



Financial Transparency, Media Coverage, and Momentum in China

Shu-Heng Chen, Xia-Ping Cao, Kun-Ben Lin, Jing-Bo Huang, Yubing Zhang & Hung-Wen Lin

To cite this article: Shu-Heng Chen, Xia-Ping Cao, Kun-Ben Lin, Jing-Bo Huang, Yubing Zhang & Hung-Wen Lin (2020): Financial Transparency, Media Coverage, and Momentum in China, Emerging Markets Finance and Trade, DOI: [10.1080/1540496X.2020.1825936](https://doi.org/10.1080/1540496X.2020.1825936)

To link to this article: <https://doi.org/10.1080/1540496X.2020.1825936>



Published online: 29 Sep 2020.



[Submit your article to this journal](#)



Article views: 163





[View related articles](#)



[View Crossmark data](#)



Financial Transparency, Media Coverage, and Momentum in China

Shu-Heng Chen ^a, Xia-Ping Cao^b, Kun-Ben Lin ^c, Jing-Bo Huang^d, Yubing Zhang^e, and Hung-Wen Lin^f

^aDepartment of Economics, National Chengchi University, Taipei, Taiwan, ROC; ^b Xi'an Jiaotong-Liverpool University, Suzhou, China; ^cSchool of Business, Macau University of Science and Technology, Macau, China; ^dLingnan College, Sun Yat-sen University, Guangzhou, China; ^eBusiness School, Nanfang College of Sun Yat-sen University, Guangzhou, China; ^fDepartment of Finance, Nanfang College of Sun Yat-sen University, Guangzhou, China

ABSTRACT

This paper digests the influences of financial transparency and media coverage in the Chinese stock market. In China, media performs under a regulatory system and media information is regarded as the direction of news. In addition, the Chinese market is dominated by retail investors and financial information is always manipulated, so the reliability of financial information is quite intriguing. The effect of ostensible financial information on the stock market through the media hype is a crucial issue. We employ media and transparency to analyze over 3,000 stocks in China. First of all, the Chinese stock market is characterized by significantly negative momentum profit and thus exhibits price reversal. However, when high media coverage and high transparency jointly come into play, the significantly negative momentum profit turns to be significantly positive. This dramatic change alters the price reversal to be price momentum. By contrast, low media coverage and low transparency still result in price reversal.

KEYWORDS

Transparency; media coverage; momentum

JEL

G0; G10; G11; G14

1. Introduction

Although the Chinese accounting system has gradually improved over the years, the manipulation of financial information is still prevalent in China (e.g., Ang and Ma 1999; Fan, Gillan, and Yu 2013; Zhu and Niu 2016). Consequently, if we wish to make investment decisions by referring to the financial reports of listed firms, it is necessary to first of all assess the financial transparency of these firms. In this regard, financial transparency is an extremely important variable that is indicative of the reliability and honesty of listed firms.

In China, the stock market is dominated by retail investors, but these investors are known to often lack sufficient professional knowledge. The media in this market is governed by a filtering regulatory system, and so media news has long been considered to be highly influential. Moreover, since investment banks are not powerful in the Chinese stock market, the large numbers of retail investors who dominate the market mainly collect information from the media by themselves (e.g., Lee et al. 2015; Yang, Lin, and Yi 2017), suggesting that the media plays a very important role in the Chinese market.

The regulatory system on the media in China is dramatically different from those in the US and Europe, while the market characteristics of these markets are different as well. It has been documented that the stock markets in the US and Europe are characterized by price momentum (e.g., Asness, Moskowitz, and Pedersen 2013; Da, Gurnun, and Warachka 2014; Hillert, Jacobs, and Müller 2014), but the Chinese stock market is known to be contrarian (e.g., Demirer, Lien, and Zhang 2015; Kang, Liu, and Ni 2002). Momentum represents price continuation in the stock market, suggesting the past price

trends of stocks will be maintained and will continue into the future. By contrast, contrarian is opposite to momentum and indicates price reversal, implying the past price trends are difficult to maintain, and that the market embodies overreaction (e.g., De Bondt and Thaler 1987, 1985). From the perspective of risk, the Chinese stock market exhibits relatively higher price risks.

Momentum is well regarded as an essential indicator for studying price trends and research in this field is first pioneered by Jegadeesh and Titman (1993). The momentum profit designed by Jegadeesh and Titman (1993) is generally used to identify price continuation and reversal. A significantly positive momentum profit suggests price continuation, whereas a significantly negative momentum profit suggests price reversal. In the US market, Hillert, Jacobs, and Müller (2014) find that high media coverage will stimulate evident price continuation. However, according to the market characteristic of the Chinese market, we deem that their opinion on the media is not suitable for the Chinese market.

It is generally considered that price trends are related to firms' financial statements (e.g., Baber, Chen, and Kang 2006; Haggard, Martin, and Pereira 2008; Healy and Palepu 1993). As discussed above, it is necessary to assess the financial transparency of listed firms before referring to the financial reports. Since the retail investors lack professional expertise, they frequently learn of the financial conditions of the firms through news disseminated by the media. These discussions show that financial transparency and media coverage very likely jointly influence momentum in the Chinese market.

Our paper grasps two obvious features. First of all, recent studies on the media shed light on the effects of how media news, news tones, and the news sensitivity of firms serve to predict stock returns (e.g., Narayan 2019; Narayan and Bannigidadmath 2017; Narayan and Narayan 2017; Narayan et al. 2017). These studies use the number of pieces of positive and negative news, a news factor (the difference between the number of positive and negative news reports), and the growth rates of positive and negative news as explanatory variables in the time-series predictive regression as well as the Fama-Macbeth regression to forecast the stock returns. Of course, these studies above have deepened our understanding of the role of the media in the stock market. From where we stand, it is indispensable to dissect the essence of listed firms before we explore the interaction between the media and stock market. Hence, we involve financial transparency into our study to evaluate the reliability of listed firms. We pioneer the effect of transparency on stock market through the assistance of media in China.

Second, existing studies detect the effects of the media in China from the perspectives of market liquidity, price crash risk, stock price synchronicity, market volatility, and information asymmetry, etc. (e.g., Gao et al. 2018, 2020; Li, Qiao, and Zhao 2019; Qiao and Su 2020; Zhao 2020; Zhu et al. 2017). Another strand of the literature has decoded the effects of transparency in China from the perspectives of investor sentiment, carbon disclosure, corporate philanthropy, firm liquidity, and IPO performance, etc. (e.g., Firth, Wang, and Wong 2015; Huang, Li, and Chen 2019; Qian, Gao, and Tsang 2015; Tang and Wang 2011; Zhou et al. 2018). So far, although transparency and media coverage are both crucial, most of the studies just detect one of them. Research on the synergistic effect of transparency and media coverage in China has not been sufficiently detailed, thereby suggesting this paper is the pioneer of this topic.

To be more direct, we show that the stocks with high media coverage give rise to negative momentum profit in China, which is in sharp contrast with Hillert, Jacobs, and Müller (2014) in the US. By separating those stocks with high transparency from those with high media coverage, we have found significantly positive momentum profit. Hence, high media coverage and high transparency activate price continuation and alleviate overreaction in the market.

In order to carry out a thorough analysis, all existing momentum portfolios are taken into consideration in this paper to examine financial transparency, media coverage, and momentum in China. These portfolios consist of interactive, break-down, and conditional momentum portfolios.¹ Compared to those studies which use one or two of them (e.g., McLean 2010; Mortal and Schill 2018), our results are more reliable.²

The remainder of this paper is organized as follows. Section 2 describes the methodology and data. In Section 3, we present the empirical results. In Section 4, we check for robustness. The last section concludes.

2. Methodology and Data

This section discusses the calculations of momentum, as well as the construction of interactive, breakdown, and conditional momentum portfolios. In addition, we further develop models of financial transparency and media coverage. The details of the data are also provided.

2.1. Momentum Calculations

According to Jegadeesh and Titman (1993), our momentum calculations are as follows. The set of all stocks in the market as a whole in period t is denoted as $\Omega_t = \{i | i = 1, 2, \dots, n_t\}$. The subscript i represents a specific stock and n_t is the number of stocks in the market. We use J to represent each past J quarters formation period and K to represent each future K quarters holding period. Consequently, the formation period is the period in which we rank stocks by past returns and the holding period is the period in which we calculate momentum profit in the future.

In the first screening quarter t , the Ω_t is classified into g groups in ascending order by the past stock returns, R^F , during the first formation period, $[t - J + 1, t]$. We have g portfolios $\Omega_t(R_1^F), \Omega_t(R_2^F), \dots, \Omega_t(R_g^F)$, where $\Omega_t = \Omega_t(R_1^F) \cup \Omega_t(R_2^F) \cup \dots \cup \Omega_t(R_g^F)$. The $\frac{1}{g}$ stocks of Ω_t with the highest R^F generate the winner portfolio, while the $\frac{1}{g}$ stocks of Ω_t with the lowest R^F are used to construct the loser portfolio. $\frac{1}{g}$ is the momentum ratio. In the first holding period, the equal-weighted portfolio return is represented by R^H . Hence, the equal-weighted holding returns of the winner and loser portfolios are $R(\Omega_{J+K}^W)^H$ and $R(\Omega_{J+K}^L)^H$, respectively. Ω_t^W is equal to $\Omega_t(R_g^F)$ and Ω_t^L is equal to $\Omega_t(R_1^F)$. During the holding period, we calculate $R(\Omega_{J+K}^W)^H - R(\Omega_{J+K}^L)^H$.

Note that the constructions of momentum portfolios are based on a rolling procedure. Hence, if we roll n times, in the n^{th} screening quarter $t + n - 1$, we proceed to use past stock returns, R^F , during the n^{th} formation period, $[t - J + n, t + n - 1]$ for stock classifications. We identify winner and loser portfolios. When approaching the n^{th} holding period, the $R(\Omega_{J+K+n}^W)^H - R(\Omega_{J+K+n}^L)^H$ is computed. The periods of winner-minus-loser return spreads are $J + K, J + K + 1, J + K + 2, \dots, J + K + n$, and $J + K + n$ is equal to S , where S is the length of the sample period. Therefore, the momentum profit is obtained by the following equation.

$$MP = \frac{1}{(S - J - K + 1)} \sum_{t=J+K}^S \left[R(\Omega_t^W)^H - R(\Omega_t^L)^H \right]$$

2.1.1. Interactive Momentum Portfolios

The term interactive momentum originally appears in Scott, Stumpp, and Xu (2003), since the stocks are classified independently by stock returns and chosen factors. We use transparency (T) and media coverage (C) as the classifying factors. The stocks classified by T or by C are divided into three levels: high level (h), medium level (m), and low level (l). The intersections of these classifications give rise to a series of two-way sorting interactive momentum portfolios.

$$Inter(R^F, T) = \begin{bmatrix} \Omega_t(T_h, R_1^F) & \Omega_t(T_h, R_2^F) & \cdots & \Omega_t(T_h, R_g^F) \\ \Omega_t(T_m, R_1^F) & \Omega_t(T_m, R_2^F) & \cdots & \Omega_t(T_m, R_g^F) \\ \Omega_t(T_l, R_1^F) & \Omega_t(T_l, R_2^F) & \cdots & \Omega_t(T_l, R_g^F) \end{bmatrix} \quad (1)$$

$Inter(R^F, C)$ portfolio is constructed in the same manner of $Inter(R^F, T)$ portfolio. The three-way sorting interactive momentum portfolios are represented by the following matrix.

$$Inter(R^F, C, T) = \begin{bmatrix} \Omega_t(T_h, C_h, R_1^F) & \Omega_t(T_h, C_h, R_2^F) & \cdots & \Omega_t(T_h, C_h, R_g^F) \\ \Omega_t(T_h, C_m, R_1^F) & \Omega_t(T_h, C_m, R_2^F) & \cdots & \Omega_t(T_h, C_m, R_g^F) \\ \Omega_t(T_h, C_l, R_1^F) & \Omega_t(T_h, C_l, R_2^F) & \cdots & \Omega_t(T_h, C_l, R_g^F) \\ \vdots & \vdots & \vdots & \vdots \\ \Omega_t(T_l, C_h, R_1^F) & \Omega_t(T_l, C_h, R_2^F) & \cdots & \Omega_t(T_l, C_h, R_g^F) \\ \Omega_t(T_l, C_m, R_1^F) & \Omega_t(T_l, C_m, R_2^F) & \cdots & \Omega_t(T_l, C_m, R_g^F) \\ \Omega_t(T_l, C_l, R_1^F) & \Omega_t(T_l, C_l, R_2^F) & \cdots & \Omega_t(T_l, C_l, R_g^F) \end{bmatrix} \quad (2)$$

2.1.2. Break-down Momentum Portfolios

The break-down momentum portfolio suggests that winner and loser stocks are classified by chosen factors. It is clear that momentum effect is broken down by the factors. In constructing the break-down momentum portfolios, we first classify all stocks based on R^F into g groups and then by T . The resulting portfolios are given in the matrix $BD(R^F, T)$. The symbols in the brackets, R^F, T , are now ordered, and to make it explicit we add a bar in each entry of the $BD(R^F, T)$, such as $\Omega_t(T_h | R_1^F)$.

$$BD(R^F, T) = \begin{bmatrix} \Omega_t(T_h | R_1^F) & \Omega_t(T_h | R_2^F) & \cdots & \Omega_t(T_h | R_g^F) \\ \Omega_t(T_m | R_1^F) & \Omega_t(T_m | R_2^F) & \cdots & \Omega_t(T_m | R_g^F) \\ \Omega_t(T_l | R_1^F) & \Omega_t(T_l | R_2^F) & \cdots & \Omega_t(T_l | R_g^F) \end{bmatrix} \quad (3)$$

Similarly, we have $BD(R^F, C)$, denoting the portfolios classified first by R^F and then by media coverage, C . The construction of $BD(R^F, T, C)$ is the same as that of $BD(R^F, T)$ except that the stocks are further classified based on C , similarly for $BD(R^F, C, T)$.

$$BD(R^F, T, C) = \begin{bmatrix} \Omega_t[C_h | (T_h | R_1^F)] & \Omega_t[C_h | (T_h | R_2^F)] & \cdots & \Omega_t[C_h | (T_h | R_g^F)] \\ \Omega_t[C_m | (T_h | R_1^F)] & \Omega_t[C_m | (T_h | R_2^F)] & \cdots & \Omega_t[C_m | (T_h | R_g^F)] \\ \Omega_t[C_l | (T_h | R_1^F)] & \Omega_t[C_l | (T_h | R_2^F)] & \cdots & \Omega_t[C_l | (T_h | R_g^F)] \\ \vdots & \vdots & \vdots & \vdots \\ \Omega_t[C_h | (T_l | R_1^F)] & \Omega_t[C_h | (T_l | R_2^F)] & \cdots & \Omega_t[C_h | (T_l | R_g^F)] \\ \Omega_t[C_m | (T_l | R_1^F)] & \Omega_t[C_m | (T_l | R_2^F)] & \cdots & \Omega_t[C_m | (T_l | R_g^F)] \\ \Omega_t[C_l | (T_l | R_1^F)] & \Omega_t[C_l | (T_l | R_2^F)] & \cdots & \Omega_t[C_l | (T_l | R_g^F)] \end{bmatrix} \quad (4)$$

2.1.3. Conditional Momentum Portfolios

Sagi and Seasholes (2007) apply the term conditional momentum portfolio when stock classifications based on specific factors take place before selections of winner and loser stocks. It begins with the chosen factors, followed by the stock returns. The following presents the two-way sorting portfolios, $Con(T, R^F)$. As in the case of the break-down momentum portfolios, the symbols in the brackets T, R^F , are ordered.

$$Con(T, R^F) = \begin{bmatrix} \Omega_t(R_1^F|T_h) & \Omega_t(R_2^F|T_h) & \cdots & \Omega_t(R_g^F|T_h) \\ \Omega_t(R_1^F|T_m) & \Omega_t(R_2^F|T_m) & \cdots & \Omega_t(R_g^F|T_m) \\ \Omega_t(R_1^F|T_l) & \Omega_t(R_2^F|T_l) & \cdots & \Omega_t(R_g^F|T_l) \end{bmatrix} \quad (5)$$

Similarly for $Con(C, R^F)$, $Con(T, C, R^F)$, and $Con(C, T, R^F)$. Using $Con(T, C, R^F)$ as an example, it is:

$$Con(T, C, R^F) = \begin{bmatrix} \Omega_t[R_1^F|(C_h|T_h)] & \Omega_t[R_2^F|(C_h|T_h)] & \cdots & \Omega_t[R_g^F|(C_h|T_h)] \\ \Omega_t[R_1^F|(C_m|T_h)] & \Omega_t[R_2^F|(C_m|T_h)] & \cdots & \Omega_t[R_g^F|(C_m|T_h)] \\ \Omega_t[R_1^F|(C_l|T_h)] & \Omega_t[R_2^F|(C_l|T_h)] & \cdots & \Omega_t[R_g^F|(C_l|T_h)] \\ \vdots & \vdots & \vdots & \vdots \\ \Omega_t[R_1^F|(C_h|T_l)] & \Omega_t[R_2^F|(C_h|T_l)] & \cdots & \Omega_t[R_g^F|(C_h|T_l)] \\ \Omega_t[R_1^F|(C_m|T_l)] & \Omega_t[R_2^F|(C_m|T_l)] & \cdots & \Omega_t[R_g^F|(C_m|T_l)] \\ \Omega_t[R_1^F|(C_l|T_l)] & \Omega_t[R_2^F|(C_l|T_l)] & \cdots & \Omega_t[R_g^F|(C_l|T_l)] \end{bmatrix} \quad (6)$$

2.2. Transparency Measure

Following Bhattacharya, Daouk, and Welker (2003), we compute earnings aggressiveness, earnings smoothing, and loss avoidance to construct a composite transparency measure.

$$Trans_{it} = \frac{Deciles(EA_{it}) + Deciles(ES_{it}) + Deciles(LA_{it})}{3} \quad (7)$$

where $Trans_{it}$ is the transparency of stock i in period t , EA_{it} is earnings aggressiveness, ES_{it} is earnings smoothing, LA_{it} is loss avoidance, and $Deciles$ is decile rankings. The details of the calculations appear in [Appendices A, B and C](#).

2.3. Media Coverage

Following Hillert, Jacobs, and Müller (2014), we use the residuals ($\hat{u}_{it,media}$) of a regression model with some adjustments for the Chinese markets to represent media coverage. We introduce the detailed procedure in [Appendix D](#).

2.4. Data Description

We have collected the data on stock prices and financial transparency from the China Stock Markets and Accounting Research (CSMAR) database. The data on the media (stock-related articles) are gathered from the China Infobank database, which includes more than 1,000 kinds of media, such as traditional and online newspapers. The seasonal data are obtained from the third quarter of 2005 to the third quarter of 2016, as the CSI300 index started to be used around the third quarter of 2005. The data set contains all the stocks listed on the Shenzhen Stock Exchange and Shanghai Stock

Table 1. Descriptive Statistics.

| Year | Momentum Profit | | | Transparency | | | Media Coverage | | |
|------------|-----------------|-----------|-------|--------------|--------|-------|----------------|--------|-------|
| | Mean | Median | Std | Mean | Median | Std | Mean | Median | Std |
| 2005 | -0.008 | -0.032 | 0.068 | 5.534 | 5.333 | 1.749 | 1.87E-16 | -0.116 | 0.708 |
| 2006 | 0.007 | -0.017 | 0.085 | 5.712 | 5.667 | 1.720 | 0.175 | 0.072 | 0.837 |
| 2007 | -0.053 | -0.059 | 0.048 | 5.478 | 5.333 | 1.687 | 0.016 | -0.091 | 0.645 |
| 2008 | -0.050 | -0.046 | 0.069 | 5.444 | 5.333 | 1.551 | -0.053 | -0.161 | 0.561 |
| 2009 | -0.088 | -0.084 | 0.096 | 5.427 | 5.333 | 1.537 | -0.130 | -0.206 | 0.461 |
| 2010 | 0.004 | 0.026 | 0.068 | 5.787 | 6.000 | 1.501 | -0.017 | -0.086 | 0.525 |
| 2011 | -0.048 | -0.055 | 0.041 | 5.718 | 5.667 | 1.565 | 0.160 | 0.064 | 0.770 |
| 2012 | -0.029 | -0.030 | 0.029 | 5.294 | 5.333 | 1.727 | -0.186 | -0.215 | 0.576 |
| 2013 | 0.0005 | 0.001 | 0.025 | 5.270 | 5.333 | 1.673 | -0.120 | -0.259 | 0.672 |
| 2014 | 0.004 | -0.013 | 0.089 | 5.489 | 5.333 | 1.758 | 0.020 | -0.094 | 0.823 |
| 2015 | -0.024 | -0.020 | 0.034 | 5.140 | 5.000 | 1.513 | 0.179 | -0.093 | 0.976 |
| 2016 | -0.026 | -0.037 | 0.042 | 5.453 | 5.333 | 1.641 | 3.81E-16 | -0.122 | 0.695 |
| Total Mean | | -0.026 | | | 5.479 | | | 0.004 | |
| t-stat | | -3.039*** | | | -0.381 | | | 0.103 | |

Displayed are the descriptive statistics for momentum profit, transparency and media coverage in each year. We calculate the mean, median, total mean value, standard deviation and t -statistic for each measure. *, ** and *** represent significance at the 10%, 5% and 1% levels, respectively.

Exchange. For our sample period, we have a total of 3,193 listed firms. The number of financial services firms is 83. A total of 343,116 stock-related articles have been collected. The descriptive statistics for momentum profit, transparency, and media coverage are presented in Table 1. The formation and holding periods are 2 quarters each ($J = K = 2$) following Jegadeesh and Titman (1993).

From Table 1, we can see that the total mean value of momentum profit is significantly negative, being -0.026 (the t -statistic is -3.039), implying that price reversal exists in China. A negative mean momentum profit also appears in many of the 12 years. The regression model of media coverage assumes that the errors have zero mean. Decile rankings let the mean decile of transparency be 5.5. Hence, media coverage and transparency are insignificantly different from 0 and 5.5, respectively (the t -statistics are 0.103 and -0.381 , respectively). Their total mean values are consistent with what we anticipate.

3. Empirical Results

The empirical results are reported in this section. In finance research, financial services firms have specific characteristics and they are always eliminated. However, eliminating financial services firms is not common in the field of momentum (e.g., Cooper, Gutierrez, and Hameed 2004; Moskowitz and Grinblatt 1999; Wahal and Yavuz 2013). Hence, we show the results for the full sample of firms and for those firms after excluding financial services firms.

3.1. The Two-way Sorting Momentum Portfolios

We construct 6 two-way sorting momentum portfolios to investigate the momentum profits under different levels of transparency or media coverage, and report the results in Table 2.

From Table 2, we can see that the results from the full sample of firms and the sample after excluding financial services firms are very close. Hence, involving financial services firms or excluding these firms has no influence on our outcomes. The momentum profits from *Inter* (RF, T), *BD* (RF, T) and *Con* (T, RF) are all negative regardless of the changes in transparency, suggesting that the contrarian profits of the Chinese stock market remain steady when we only consider the reliability of financial information in this market. In addition, there is no clear linear pattern for the negative momentum profits from high transparency to low transparency. *Inter* (RF, C), *BD* (RF, C) and *Con* (C, RF) reveal negative momentum profits in spite of the changes in media coverage, implying that

Table 2. Two-way Sorting Momentum Portfolios.

| Panel A: $Inter (R^F, T)$ Momentum | | | | Panel B: $Inter (R^F, C)$ Momentum | | | | | |
|------------------------------------|-------------|-----------|------------|------------------------------------|-------------|-----------|------------|-----------|-----------|
| | MP (Full) | t -stat | MP (EXF) | t -stat | MP (Full) | t -stat | MP (EXF) | t -stat | |
| <i>HT</i> | -0.020 | -2.487** | -0.021 | -2.533** | <i>HC</i> | -0.019 | -1.563 | -0.015 | -1.427 |
| <i>MT</i> | -0.006 | -0.837 | -0.006 | -0.870 | <i>MC</i> | -0.014 | -1.273 | -0.012 | -1.064 |
| <i>LT</i> | -0.013 | -1.936* | -0.012 | -1.858* | <i>LC</i> | -0.018 | -1.680* | -0.017 | -1.616 |
| Panel C: $BD (R^F, T)$ Momentum | | | | Panel D: $BD (R^F, C)$ Momentum | | | | | |
| | MP (Full) | t -stat | MP (EXF) | t -stat | MP (Full) | t -stat | MP (EXF) | t -stat | |
| <i>HT</i> | -0.021 | -2.467** | -0.021 | -2.511*** | <i>HC</i> | -0.017 | -1.434 | -0.014 | -1.284 |
| <i>MT</i> | -0.005 | -0.713 | -0.004 | -0.671 | <i>MC</i> | -0.027 | -2.918*** | -0.024 | -2.671*** |
| <i>LT</i> | -0.013 | -1.967** | -0.013 | -1.942* | <i>LC</i> | -0.013 | -1.249 | -0.012 | -1.146 |
| Panel E: $Con (T, R^F)$ Momentum | | | | Panel F: $Con (C, R^F)$ Momentum | | | | | |
| | MP (Full) | t -stat | MP (EXF) | t -stat | MP (Full) | t -stat | MP (EXF) | t -stat | |
| <i>HT</i> | -0.020 | -1.637 | -0.021 | -1.690* | <i>HC</i> | -0.007 | -0.511 | -0.004 | -0.307 |
| <i>MT</i> | -0.002 | -0.195 | -0.002 | -0.225 | <i>MC</i> | -0.009 | -0.650 | -0.008 | -0.520 |
| <i>LT</i> | -0.005 | -0.705 | -0.004 | -0.632 | <i>LC</i> | -0.016 | -1.259 | -0.015 | -1.190 |

Displayed are the momentum profits of two-way sorting momentum portfolios. We classify the stocks based on transparency into 3 groups: high transparency, medium transparency and low transparency (*HT*, *MT*, *LT*). The stock classifications based on media coverage also result in 3 groups: high media coverage, medium media coverage and low media coverage (*HC*, *MC*, *LC*). We classify the stocks into 5 groups based on formation stock returns to select winner and loser stocks. Some specific notations are used to represent the portfolios. For example, $Inter (W, Y)$ represents the portfolio produced by the stock classifications independently based on parameters W and Y . The construction procedures for $BD (W, Y)$ involves first classifying the stocks based on W and then based on Y . $Con (Y, W)$ first classifies stocks by Y and second by W . The formation stock returns are denoted by R^F , transparency is denoted by T , and media coverage is denoted by C . MP (Full) is the momentum profits from full firms, whereas MP (EXF) is the momentum profits from the sample after excluding financial services firms. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

contrarian profits remain steady if we only consider media coverage in China. We do not discover an evident linear pattern for the negative momentum profits from high media coverage to low media coverage.

3.2. The Three-way Sorting Momentum Portfolios

To study the joint effect of transparency and media coverage on momentum profits, we conduct 5 three-way sorting momentum portfolios. The empirical outcomes appear in Table 3.

In Table 3, the results from the full sample of firms and those after excluding financial services firms again appear to be very close. Portfolios with high media coverage and high transparency in $Con (T, C, R^F)$ and $Con (C, T, R^F)$ definitely have significantly positive momentum profits (the absolute t -statistics range from 1.7 to 1.9.) However, portfolios with low media coverage and low transparency in $Inter (R^F, C, T)$, $BD (R^F, T, C)$ and $BD (R^F, C, T)$ are sure to have significantly negative momentum profits (absolute t -statistics change from 1.7 to 3). This symmetric result indicates that high media coverage and high transparency dramatically alter the price reversal to be price continuation in China, whereas low media coverage and low transparency still result in price reversal.

4. Robustness Checks

In finance research, the weighting schemes of portfolios always include equal-weighted and value-weighted approaches. Following Jegadeesh and Titman (1993), the weighting scheme of a momentum portfolio is equal-weighted as in the previous section. Consequently, this section checks the robustness of symmetric results by using value-weighted (VW) three-way sorting momentum portfolios.

The outcomes from Table 4 indicate that the symmetric result still remains and is somewhat more evident. From all panels, all types of momentum portfolios generate significantly positive momentum

Table 3. Three-way Sorting Momentum Portfolios.

| Panel A: <i>Inter</i> (R^F , C , T) Momentum | | | | | Panel B: <i>BD</i> (R^F , T , C) Momentum | | | | |
|--|------------------|----------------|-----------------|----------------|--|------------------|----------------|-----------------|----------------|
| | <i>MP</i> (Full) | <i>t</i> -stat | <i>MP</i> (EXF) | <i>t</i> -stat | | <i>MP</i> (Full) | <i>t</i> -stat | <i>MP</i> (EXF) | <i>t</i> -stat |
| <i>HC & HT</i> | 0.017 | 0.764 | 0.017 | 0.764 | <i>HT & HC</i> | 0.028 | 0.972 | 0.028 | 0.972 |
| <i>HC & MT</i> | 0.001 | 0.061 | -0.014 | -0.471 | <i>HT & MC</i> | -0.019 | -0.756 | -0.019 | -0.756 |
| <i>HC & LT</i> | -0.033 | -1.193 | 0.002 | 0.059 | <i>HT & LC</i> | 0.006 | 0.197 | 0.002 | 0.084 |
| <i>MC & HT</i> | -0.009 | -0.347 | 0.001 | 0.061 | <i>MT & HC</i> | 0.033 | 2.022** | 0.033 | 2.022* |
| <i>MC & MT</i> | 0.042 | 1.694* | 0.042 | 1.694* | <i>MT & MC</i> | 0.029 | 1.709* | 0.029 | 1.709* |
| <i>MC & LT</i> | -0.025 | -0.878 | -0.008 | -0.381 | <i>MT & LC</i> | -0.004 | -0.149 | -0.004 | -0.149 |
| <i>LC & HT</i> | 0.002 | 0.059 | -0.033 | -1.193 | <i>LT & HC</i> | -0.004 | -0.152 | -0.004 | -0.152 |
| <i>LC & MT</i> | -0.008 | -0.381 | -0.025 | -0.886 | <i>LT & MC</i> | -0.009 | -0.345 | -0.009 | -0.345 |
| <i>LC & LT</i> | -0.036 | -2.257** | -0.036 | -2.254** | <i>LT & LC</i> | -0.058 | -1.975** | -0.058 | -1.987** |
| Panel C: <i>BD</i> (R^F , C , T) Momentum | | | | | Panel D: <i>Con</i> (T , C , R^F) Momentum | | | | |
| | <i>MP</i> (Full) | <i>t</i> -stat | <i>MP</i> (EXF) | <i>t</i> -stat | | <i>MP</i> (Full) | <i>t</i> -stat | <i>MP</i> (EXF) | <i>t</i> -stat |
| <i>HC & HT</i> | 0.043 | 1.780* | 0.043 | 1.780* | <i>HT & HC</i> | 0.066 | 1.727* | 0.066 | 1.727* |
| <i>HC & MT</i> | -0.006 | -0.284 | -0.013 | -0.481 | <i>HT & MC</i> | 0.007 | 0.225 | 0.003 | 0.079 |
| <i>HC & LT</i> | 0.001 | 0.073 | 0.000 | -0.018 | <i>HT & LC</i> | 0.041 | 1.319 | 0.041 | 1.319 |
| <i>MC & HT</i> | 0.022 | 1.175 | 0.022 | 1.175 | <i>MT & HC</i> | 0.017 | 0.703 | 0.017 | 0.703 |
| <i>MC & MT</i> | 0.000 | 0.015 | 0.000 | 0.015 | <i>MT & MC</i> | 0.018 | 0.589 | 0.018 | 0.589 |
| <i>MC & LT</i> | -0.014 | -0.677 | -0.014 | -0.677 | <i>MT & LC</i> | -0.018 | -0.607 | -0.018 | -0.607 |
| <i>LC & HT</i> | -0.017 | -0.738 | -0.017 | -0.738 | <i>LT & HC</i> | -0.029 | -1.040 | -0.029 | -1.040 |
| <i>LC & MT</i> | -0.008 | -0.288 | -0.008 | -0.288 | <i>LT & MC</i> | -0.012 | -0.512 | -0.012 | -0.512 |
| <i>LC & LT</i> | -0.040 | -1.795* | -0.041 | -1.804* | <i>LT & LC</i> | -0.022 | -0.992 | -0.022 | -1.001 |
| Panel E: <i>Con</i> (C , T , R^F) Momentum | | | | | | | | | |
| | <i>MP</i> (Full) | <i>t</i> -stat | <i>MP</i> (EXF) | <i>t</i> -stat | | | | | |
| <i>HC & HT</i> | 0.054 | 1.832* | 0.054 | 1.832* | | | | | |
| <i>HC & MT</i> | -0.005 | -0.198 | -0.005 | -0.198 | | | | | |
| <i>HC & LT</i> | 0.005 | 0.148 | 0.005 | 0.148 | | | | | |
| <i>MC & HT</i> | -0.006 | -0.237 | -0.011 | -0.366 | | | | | |
| <i>MC & MT</i> | -0.048 | -1.619 | -0.048 | -1.619 | | | | | |
| <i>MC & LT</i> | -0.007 | -0.209 | -0.008 | -0.217 | | | | | |
| <i>LC & HT</i> | 0.012 | 0.535 | 0.012 | 0.535 | | | | | |
| <i>LC & MT</i> | -0.029 | -0.900 | -0.029 | -0.900 | | | | | |
| <i>LC & LT</i> | -0.039 | -1.942* | -0.040 | -1.942* | | | | | |

Displayed are the momentum profits of the three-way sorting momentum portfolios. We classify the stocks based on transparency into 3 groups: high transparency, medium transparency and low transparency (*HT*, *MT*, *LT*). The classifications based on media coverage also consist of 3 groups: high media coverage, medium media coverage and low media coverage (*HC*, *MC*, *LC*). We classify the stocks into 5 groups based on formation stock returns to select winner and loser stocks. Some specific notations are used to represent the portfolios. For example, *Inter* (W , Y , Z) represents the portfolio produced by the independent stock classifications based on the parameters W , Y and Z . The construction procedures for *BD* (W , Y , Z) and *Con* (W , Y , Z) involve first classifying stocks based on W , then based on Y and lastly based on Z . The formation stock returns are noted by R^F , transparency is noted by T , and media coverage is noted by C . *MP* (Full) is the momentum profits from full firms, whereas *MP* (EXF) is the momentum profits from the sample after excluding financial services firms. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

profits with high media coverage and high transparency (the absolute t -statistics exceed 1.7 or even 2). Moreover, when it comes to low media coverage and low transparency, the portfolios generate significantly negative momentum profits (the absolute t -statistics are between 1.675 and 3). To be more specific, the *Con* (C , T , R^F) momentum portfolio has a significantly positive momentum profit of 0.073 with high media coverage and high transparency (the t -statistic is 2.540). In addition, the *Inter* (R^F , C , T) momentum portfolio produces a significantly negative momentum profit of -0.050 with low media coverage and low transparency (the t -statistic is -2.043).

5. Conclusions

The Chinese stock market is characterized by significantly negative momentum profit and thus embodies price reversal, suggesting there is overreaction in the market. However, the stocks with

Table 4. Three-way Sorting VW Momentum Portfolios.

| Panel A: <i>Inter</i> (R^F , C , T) Momentum | | | Panel B: <i>BD</i> (R^F , T , C) Momentum | | |
|--|---------|----------|--|---------|----------|
| | MP (VW) | t-stat | | MP (VW) | t-stat |
| <i>HC & HT</i> | 0.067 | 1.778* | <i>HT & HC</i> | 0.073 | 1.700* |
| <i>HC & MT</i> | 0.040 | 1.476 | <i>HT & MC</i> | 0.002 | 0.079 |
| <i>HC & LT</i> | -0.017 | -0.401 | <i>HT & LC</i> | 0.044 | 0.978 |
| <i>MC & HT</i> | 0.041 | 1.141 | <i>MT & HC</i> | 0.072 | 2.067** |
| <i>MC & MT</i> | 0.082 | 1.742* | <i>MT & MC</i> | 0.062 | 2.294** |
| <i>MC & LT</i> | 0.006 | 0.237 | <i>MT & LC</i> | -0.009 | -0.251 |
| <i>LC & HT</i> | 0.004 | 0.111 | <i>LT & HC</i> | 0.018 | 0.455 |
| <i>LC & MT</i> | -0.002 | -0.067 | <i>LT & MC</i> | 0.002 | 0.078 |
| <i>LC & LT</i> | -0.050 | -2.043** | <i>LT & LC</i> | -0.089 | -1.993** |
| Panel C: <i>BD</i> (R^F , C , T) Momentum | | | Panel D: <i>Con</i> (T , C , R^F) Momentum | | |
| | MP (VW) | t-stat | | MP (VW) | t-stat |
| <i>HC & HT</i> | 0.065 | 1.813* | <i>HT & HC</i> | 0.074 | 1.878* |
| <i>HC & MT</i> | 0.070 | 2.525** | <i>HT & MC</i> | 0.060 | 1.130 |
| <i>HC & LT</i> | 0.015 | 0.310 | <i>HT & LC</i> | 0.039 | 1.468 |
| <i>MC & HT</i> | 0.046 | 2.373** | <i>MT & HC</i> | 0.050 | 1.941* |
| <i>MC & MT</i> | 0.023 | 0.678 | <i>MT & MC</i> | 0.070 | 1.537 |
| <i>MC & LT</i> | 0.010 | 0.231 | <i>MT & LC</i> | -0.009 | -0.321 |
| <i>LC & HT</i> | 0.016 | 0.465 | <i>LT & HC</i> | -0.024 | -0.629 |
| <i>LC & MT</i> | -0.029 | -0.853 | <i>LT & MC</i> | 0.009 | 0.268 |
| <i>LC & LT</i> | -0.049 | -1.806* | <i>LT & LC</i> | -0.057 | -1.939* |
| Panel E: <i>Con</i> (C , T , R^F) Momentum | | | | | |
| | MP (VW) | t-stat | | | |
| <i>HC & HT</i> | 0.073 | 2.540** | | | |
| <i>HC & MT</i> | 0.039 | 1.303 | | | |
| <i>HC & LT</i> | 0.015 | 0.308 | | | |
| <i>MC & HT</i> | 0.029 | 0.885 | | | |
| <i>MC & MT</i> | 0.029 | 0.591 | | | |
| <i>MC & LT</i> | 0.001 | 0.021 | | | |
| <i>LC & HT</i> | -0.003 | -0.109 | | | |
| <i>LC & MT</i> | -0.026 | -0.731 | | | |
| <i>LC & LT</i> | -0.047 | -1.675* | | | |

Displayed are the momentum profits of the value-weighted three-way sorting momentum portfolios. We classify the stocks based on transparency into 3 groups: high transparency, medium transparency and low transparency (*HT*, *MT*, *LT*). The classifications based on media coverage also consist of 3 groups: high media coverage, medium media coverage and low media coverage (*HC*, *MC*, *LC*). We classify the stocks into 5 groups based on formation stock returns to select winner and loser stocks. Some specific notations are used to represent the portfolios. For example, *Inter* (W , Y , Z) represents the portfolio produced by the independent stock classifications based on the parameters W , Y and Z . The construction procedures for *BD* (W , Y , Z) and *Con* (W , Y , Z) involve first classifying stocks based on W , then based on Y and lastly based on Z . The formation stock returns are noted by R^F , transparency is noted by T , and media coverage is noted by C . *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

high media coverage are still not immune to negative momentum profit. The stocks with high transparency are further screened from those with high media coverage and the resulting stocks are characterized by significantly positive momentum profit. Hence, those stocks with high media coverage and high transparency give rise to price continuation.

Moreover, the above finding has some essential implications. The firm-specific financial information related to the stocks with high transparency results in their having a high degree of reliability. Besides, these stocks with high transparency are highly covered by the media as well. The firm-specific financial information thus continuously releases an influence, and so past price trends are maintained and continue into the future. The emergence of price continuation suggests high media coverage and high transparency can alleviate overreaction in China.

By contrast, the stocks with low media coverage and low transparency are still trapped in a pitfall of price reversal. These stocks are characterized by poor reliability and it is difficult for the retail investors to obtain information due to the low media coverage. The retail investors remain in murky

surroundings. Even if there is any information, the information obtained before investing and that obtained after investing are possibly inconsistent with each other. When the information received after investing goes beyond what was expected, the investors will abruptly change their past decisions, and so price reversal takes place.

Most of the stock markets in the US and Europe are characterized by price continuation (e.g., Asness, Moskowitz, and Pedersen 2013; Da, Gurun, and Warachka 2014; Hillert, Jacobs, and Müller 2014), but the Chinese market exhibits price reversal. Hence, predicting stock returns is a great challenge in China due to this characteristic. This paper dissects the interaction between financial transparency and media coverage, which reaches clear conclusions. As for the underlying driver of price reversal, the reliability of information, confidence of investors, and social culture are valuable perspectives in China.

Notes

1. We use certain factors and formation returns in order to group stocks and take the intersection between the grouping results to construct an interactive momentum portfolio (e.g., Goyal and Wahal 2015; Scott, Stumpp, and Xu 2003; Verardo 2009). As for the break-down momentum portfolio, we first group the stocks according to their formation returns, and then further group them based on the chosen factors (e.g., Demir, Muthuswamy, and Walter 2004; Fuertes, Miffre, and Rallis 2010; Grinblatt and Han 2005). Moreover, in order to construct the conditional momentum portfolio, we first sort the stocks according to the chosen factors and then further group them based on their formation returns (e.g., Avramov et al. 2007; Menkhoff et al. 2012; Novy-Marx 2012).
2. If we do not fully use the three types of momentum portfolios, we will reach unreliable conclusions. Cheema and Nartea (2014) and Naughton, Truong, and Veeraraghavan (2008) both studied the relationship between momentum and turnover. Since they used different momentum portfolios, they obtained contrasting results and reached opposite conclusions. This suggests that the conclusions of these two studies are unreliable.

ORCID

Shu-Heng Chen  <http://orcid.org/0000-0003-4584-7646>

Kun-Ben Lin  <http://orcid.org/0000-0002-1186-3640>

References

- Ang, J. S., and Y. Ma. 1999. Transparency in Chinese stocks: A study of earnings forecasts by professional analysts. *Pacific-Basin Finance Journal* 7 (2):129–55. doi:10.1016/S0927-538X(99)00006-2.
- Asness, C. S., T. J. Moskowitz, and L. H. Pedersen. 2013. Value and momentum everywhere. *The Journal of Finance* 68 (3):929–85. doi:10.1111/jofi.12021.
- Avramov, D., T. Chordia, G. Jostova, and A. Philipov. 2007. Momentum and credit rating. *The Journal of Finance* 62 (5):2503–20. doi:10.1111/j.1540-6261.2007.01282.x.
- Baber, W. R., S. Chen, and S. H. Kang. 2006. Stock price reaction to evidence of earnings management: Implications for supplementary financial disclosure. *Review of Accounting Studies* 11 (1):5–19. doi:10.1007/s11142-006-6393-0.
- Ball, R., & Shivakumar, L. (2005). Earnings quality in UK private firms: comparative loss recognition timeliness. *Journal of Accounting and Economics*, 39(1), 83–128 doi:10.1016/j.jacceco.2004.04.001
- Bhattacharya, U., H. Daouk, and M. Welker. 2003. The world price of earnings opacity. *The Accounting Review* 78 (3):641–78. doi:10.2308/accr.2003.78.3.641.
- Cheema, M. A., and G. V. Nartea. 2014. Momentum returns and information uncertainty: Evidence from China. *Pacific-Basin Finance Journal* 30:173–88. doi:10.1016/j.pacfin.2014.10.002.
- Cooper, M. J., R. C. Gutierrez Jr, and A. Hameed. 2004. Market states and momentum. *The Journal of Finance* 59 (3):1345–65. doi:10.1111/j.1540-6261.2004.00665.x.
- Da, Z., U. G. Gurun, and M. Warachka. 2014. Frog in the pan: Continuous information and momentum. *The Review of Financial Studies* 27 (7):2171–218. doi:10.1093/rfs/hhu003.
- De Bondt, W. F., and R. Thaler. 1985. Does the stock market overreact? *The Journal of Finance* 40 (3):793–805. doi:10.1111/j.1540-6261.1985.tb05004.x.
- De Bondt, W. F., and R. H. Thaler. 1987. Further evidence on investor overreaction and stock market seasonality. *The Journal of Finance* 42 (3):557–81. doi:10.1111/j.1540-6261.1987.tb04569.x.
- Dechow, P. M., Sloan, R. G., & Sweeney, A. P. 1995. Detecting earnings management. *Accounting Review*, 193–225.

- Demir, I., J. Muthuswamy, and T. Walter. 2004. Momentum returns in Australian equities: The influences of size, risk, liquidity and return computation. *Pacific-Basin Finance Journal* 12 (2):143–58. doi:10.1016/j.pacfin.2003.07.002.
- Demirer, R., D. Lien, and H. Zhang. 2015. Industry herding and momentum strategies. *Pacific-Basin Finance Journal* 32:95–110. doi:10.1016/j.pacfin.2015.02.010.
- Fan, J. P., S. L. Gillan, and X. Yu. 2013. Property rights, R&D spillovers, and corporate accounting transparency in China. *Emerging Markets Review* 15:34–56. doi:10.1016/j.ememar.2012.03.001.
- Firth, M., K. Wang, and S. M. Wong. 2015. Corporate transparency and the impact of investor sentiment on stock prices. *Management Science* 61 (7):1630–47. doi:10.1287/mnsc.2014.1911.
- Fuertes, A. M., J. Miffre, and G. Rallis. 2010. Tactical allocation in commodity futures markets: Combining momentum and term structure signals. *Journal of Banking & Finance* 34 (10):2530–48. doi:10.1016/j.jbankfin.2010.04.009.
- Gao, Y., K. Zhao, C. Wang, and C. Liu. 2020. The dynamic relationship between internet attention and stock market liquidity: A thermal optimal path method. *Physica A: Statistical Mechanics and Its Applications* 550:124180. doi:10.1016/j.physa.2020.124180.
- Gao, Y., Y. Wang, C. Wang, and C. Liu. 2018. Internet attention and information asymmetry: Evidence from Qihoo 360 search data on the Chinese stock market. *Physica A: Statistical Mechanics and Its Applications* 510:802–11. doi:10.1016/j.physa.2018.07.016.
- Goyal, A., and S. Wahal. 2015. Is momentum an echo? *Journal of Financial and Quantitative Analysis* 50 (6):1237–67. doi:10.1017/S0022109015000575.
- Grinblatt, M., and B. Han. 2005. Prospect theory, mental accounting, and momentum. *Journal of Financial Economics* 78 (2):311–39. doi:10.1016/j.jfineco.2004.10.006.
- Haggard, K. S., X. Martin, and R. Pereira. 2008. Does voluntary disclosure improve stock price informativeness? *Financial Management* 37 (4):747–68. doi:10.1111/j.1755-053X.2008.00033.x.
- Healy, P. M., and K. G. Palepu. 1993. The effect of firm's financial disclosure strategies on stock prices. *Accounting Horizons* 7 (1):1–11.
- Hillert, A., H. Jacobs, and S. Müller. 2014. Media makes momentum. *The Review of Financial Studies* 27 (12):3467–501. doi:10.1093/rfs/hhu061.
- Huang, Y. S., M. Li, and C. R. Chen. 2019. Financial market development, market transparency, and IPO performance. *Pacific-Basin Finance Journal* 55:63–81. doi:10.1016/j.pacfin.2019.03.007.
- Jegadeesh, N., and S. Titman. 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance* 48 (1):65–91. doi:10.1111/j.1540-6261.1993.tb04702.x.
- Kang, J., M. H. Liu, and S. X. Ni. 2002. Contrarian and momentum strategies in the China stock market: 1993–2000. *Pacific-Basin Finance Journal* 10 (3):243–65. doi:10.1016/S0927-538X(02)00046-X.
- Lee, B., L. Rosenthal, C. Veld, and Y. Veld-Merkoulova. 2015. Stock market expectations and risk aversion of individual investors. *International Review of Financial Analysis* 40:122–31. doi:10.1016/j.irfa.2015.05.011.
- Li, X., P. Qiao, and L. Zhao. 2019. CEO media exposure, political connection and Chinese firms' stock price synchronicity. *International Review of Economics & Finance* 63:61–75. doi:10.1016/j.iref.2018.08.006.
- McInnis, J. (2010). Earnings smoothness, average returns, and implied cost of equity capital. *The Accounting Review* 85 (1), 315–341 doi:10.2308/accr.2010.85.1.315
- McLean, R. D. 2010. Idiosyncratic risk, long-term reversal, and momentum. *Journal of Financial and Quantitative Analysis* 45 (4):883–906. doi:10.1017/S0022109010000311.
- Menkhoff, L., L. Sarno, M. Schmeling, and A. Schrimpf. 2012. Currency momentum strategies. *Journal of Financial Economics* 106 (3):660–84. doi:10.1016/j.jfineco.2012.06.009.
- Mortal, S. C., and M. J. Schill. 2018. The role of firm investment in momentum and reversal. *Journal of Empirical Finance* 48:255–78. doi:10.1016/j.jempfin.2018.07.001.
- Moskowitz, T. J., and M. Grinblatt. 1999. Do industries explain momentum? *The Journal of Finance* 54 (4):1249–90. doi:10.1111/0022-1082.00146.
- Narayan, P. K. 2019. Can stale oil price news predict stock returns? *Energy Economics* 83:430–44. doi:10.1016/j.eneco.2019.07.022.
- Narayan, P. K., and D. Bannigidadmath. 2017. Does financial news predict stock returns? New evidence from Islamic and non-Islamic stocks. *Pacific-Basin Finance Journal* 42:24–45. doi:10.1016/j.pacfin.2015.12.009.
- Narayan, P. K., D. H. B. Phan, S. Narayan, and D. Bannigidadmath. 2017. Is there a financial news risk premium in Islamic stocks? *Pacific-Basin Finance Journal* 42:158–70. doi:10.1016/j.pacfin.2017.02.008.
- Narayan, S., and P. K. Narayan. 2017. Are oil price news headlines statistically and economically significant for investors? *Journal of Behavioral Finance* 18 (3):258–70. doi:10.1080/15427560.2017.1308942.
- Naughton, T., C. Truong, and M. Veeraraghavan. 2008. Momentum strategies and stock returns: Chinese evidence. *Pacific-Basin Finance Journal* 16 (4):476–92. doi:10.1016/j.pacfin.2007.10.001.
- Novy-Marx, R. 2012. Is momentum really momentum? *Journal of Financial Economics* 103 (3):429–53. doi:10.1016/j.jfineco.2011.05.003.
- Qian, C., X. Gao, and A. Tsang. 2015. Corporate philanthropy, ownership type, and financial transparency. *Journal of Business Ethics* 130 (4):851–67. doi:10.1007/s10551-014-2109-8.

- Qiao, H., and Y. Su. 2020. Media coverage and decomposition of stock market volatility: Based on the generalized dynamic factor model. *Emerging Markets Finance and Trade* 56 (3):613–25. doi:10.1080/1540496X.2019.1686974.
- Sagi, J. S., & Seasholes, M. S. (2007). Firm-specific attributes and the cross-section of momentum. *Journal of Financial Economics* 84 (2), 389–434. doi:10.1016/j.jfineco.2006.02.002.
- Scott, J., M. Stumpp, and P. Xu. 2003. News, not trading volume, builds momentum. *Financial Analysts Journal* 59 (2):45–54. doi:10.2469/faj.v59.n2.2513.
- Tang, K., and C. Wang. 2011. Corporate governance and firm liquidity: Evidence from the Chinese stock market. *Emerging Markets Finance and Trade* 47 (sup1):47–60. doi:10.2753/REE1540-496X4701S105.
- Verardo, M. 2009. Heterogeneous beliefs and momentum profits. *Journal of Financial and Quantitative Analysis* 44 (4):795–822. doi:10.1017/S0022109009990214.
- Wahal, S., and M. D. Yavuz. 2013. Style investing, comovement and return predictability. *Journal of Financial Economics* 107 (1):136–54. doi:10.1016/j.jfineco.2012.08.005.
- Yang, W., D. Lin, and Z. Yi. 2017. Impacts of the mass media effect on investor sentiment. *Finance Research Letters* 22:1–4. doi:10.1016/j.frl.2017.05.001.
- Zhao, R. 2020. Quantifying the correlation of media coverage and stock price crash risk: A panel study from China. *Physica A: Statistical Mechanics and Its Applications* 537:122378. doi:10.1016/j.physa.2019.122378.
- Zhou, Z., H. Zhou, D. Peng, X. H. Chen, and S. H. Li. 2018. Carbon disclosure, financial transparency, and agency cost: Evidence from Chinese manufacturing listed companies. *Emerging Markets Finance and Trade* 54 (12):2669–86. doi:10.1080/1540496X.2018.1428796.
- Zhu, B., and F. Niu. 2016. Investor sentiment, accounting information and stock price: Evidence from China. *Pacific-Basin Finance Journal* 38:125–34. doi:10.1016/j.pacfin.2016.03.010.
- Zhu, Y., Z. Wu, H. Zhang, and J. Yu. 2017. Media sentiment, institutional investors and probability of stock price crash: Evidence from Chinese stock markets. *Accounting & Finance* 57 (5):1635–70. doi:10.1111/acfi.12355.

Appendix A. Earnings Aggressiveness

Following Dechow et al. (1995), we use the modified Jones model to measure earnings aggressiveness (EA):

$$EA_{it} = DisAcc_{it} = \frac{TAcc_{it}}{TA_{it-1}} - NDisAcc_{it} \quad (8)$$

where TA_{it-1} is the total assets of stock i in period $t-1$, $DisAcc_{it}$ is discretionary accruals in period t , $TAcc_{it}$ is total accruals, and $NDisAcc_{it}$ is nondiscretionary accruals. We calculate industry coefficients in advance. They are the alphas in the following model:

$$\frac{TAcc_{it}}{TA_{it-1}} = \alpha_{i1} \left(\frac{1}{TA_{it-1}} \right) + \alpha_{i2} \left(\frac{dREV_{it}}{TA_{it-1}} \right) + \alpha_{i3} \left(\frac{PPE_{it}}{TA_{it-1}} \right) + u_{it} \quad (9)$$

where $dREV_{it}$ is the difference in revenue between period t and period $t-1$, and PPE_{it} is property, plant and equipment. After we obtain the industry coefficients, we apply them to the following equation:

$$NDisAcc_{it} = \alpha_{i1} \left(\frac{1}{TA_{it-1}} \right) + \alpha_{i2} \left(\frac{dREV_{it} - dREC_{it}}{TA_{it-1}} \right) + \alpha_{i3} \left(\frac{PPE_{it}}{TA_{it-1}} \right) \quad (10)$$

where $dREC_{it}$ is the difference in net receivables between period t and period $t-1$, and α_{i1} , α_{i2} and α_{i3} are the industry coefficients.

Appendix B. Earnings Smoothing

Following the methodology of McInnis (2010), our measure for earnings smoothing (ES) is as follows

$$ES_{it} = S \left(\frac{NI_{it}}{ATA_{it}} \right) / S \left(\frac{CFO_{it}}{ATA_{it}} \right) \quad (11)$$

where NI_{it} is net income, ATA_{it} is average total assets, CFO_{it} is the cash flow from operations, and S represents the standard deviation.

Appendix C. Loss Avoidance

We use the timeliness of loss recognition as a proxy for loss avoidance. The higher timeliness of loss recognition is, the lower loss avoidance is. According to the methodology of Ball and Shivakumar (2005), the procedure is as follows:

$$ACC_{it} = \alpha_i + \beta_{i1}DCFO_{it} + \beta_{i2}CFO_{it} + \beta_{i3}DCFO_{it} \times CFO_{it} + u_{it} \quad (12)$$

where $DCFO_{it}$ is a dummy variable for the cash flow from operations. When the cash flow from operations is negative, the dummy variable takes a value of 1; otherwise it has a value of 0. CFO_{it} is the cash flow from operations and ACC_{it} is accruals. The loss recognition is calculated as follows.

$$LR_{it} = \begin{cases} |\beta_{i2}| \times 100\%CFO_{it} \geq 0 \\ |\beta_{i2} + \beta_{i3}| \times 100\%CFO_{it} < 0 \end{cases} \quad (13)$$

Appendix D. Detailed Media Model

According to Hillert, Jacobs, and Müller (2014), the following are our computations of media coverage.

$$u_{it,media} = \ln[1 + \#(Articles)]_{it} - \alpha_t - \beta_{1t}\ln(Size)_{it} - \beta_{2t}CSI_{it} - \beta_{3t}SZS_{it} - \beta_{4t}\ln[1 + \#(EE)]_{it} \quad (14)$$

where $\ln[1 + \#(Articles)]_{it}$ is the natural log of the number of news articles, $\ln(Size)_{it}$ is the natural log of market capitalization, CSI_{it} is a dummy variable taking a value of 1 if the stock is included in the CSI300 and 0 otherwise, SZS_{it} is a dummy variable taking a value of 1 if the stock is listed in Shenzhen and 0 otherwise, and $\ln[1 + \#(EE)]_{it}$ is the natural log of the number of earnings estimates.