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Stock return predictability: Evidence from moving averages of trading volume

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ABSTRACT

This study investigates the role of moving averages of trading volume on asset pricing. We find that the distance between short- and long-term moving averages of trading volume (MAVD) strongly and negatively predicts the cross-section of stock returns in the Chinese stock market. This predictive power is robust after controlling for other firm characteristics, well-known risk factors and market timing, and goes well beyond the price-based distance predictor. Moreover, the MAVD effect diminishes as portfolio holding months move further away from the portfolio formation month and even reverses at the end of the second year, which suggests that stock market overreacts to the information from MAVD and the resulting mispricing is gradually corrected. Our results also show that the MAVD effect is stronger in stocks with high limits of arbitrage and more investor attention, as well as in the periods of high sentiment and high investor overconfidence, which is consistent with behavioral mispricing explanations. Furthermore, we find that the MAVD effect is likely to be attributable to individual speculative trading behavior. Finally, the evidence indicates that the predictive power of MAVD is more pronounced among high volatility stocks rather than among low volatility stocks.

1. Introduction

Technical analysis has been used for predicting future returns by studying past information, mostly stock price and volume. Academic studies, such as Brock et al. (1992), Lo et al. (2000), Han et al. (2013) and Neely et al. (2014), provide convincing evidence on the predictive power of the moving average of past prices. Recently, Avramov et al. (2018) offer the first study that the distance between short- and long-term moving averages of past prices strongly predicts cross-sectional returns. However, most of these studies about technical analysis focus on the predictive power of moving average of past prices, ignoring the information contained in trading volume. The role of trading volume has been emphasized in previous literature (Campbell et al. 1993; Wang 1994; Lee and Swaminathan 2000). Theoretically, Blume et al. (1994) show that trading volume can provide information about the signal precision, which cannot be obtained from the price. Most recently, Liu et al. (2019) show that the moving average of past trading volume has strong predictive power and provide a theoretical model that clarifies why trading volume plays such an important role in the Chinese stock market. In addition, a number of studies argue that a volume shock is positively or negatively related with future returns (Gervais et al. 2001; Kaniel et al. 2012; Huang et al. 2011; Chae and Kang 2019), which focus on short-term relation. The difference between the short- and long-term moving averages of trading volume reflects the volume trend or recent change in volume. Thus, it is essential to explore the relation between the distance based on moving average volume, a little-explored indicator, and future returns in the short

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and even longer terms.

In this study, following Avramov et al. (2018)'s research on the price-based distance predictor, we examine the stock return predictability of the distance between short- and long-term moving averages of trading volume (MAVD), a new predictor, in the cross section. We first show that the MAVD indicator strongly and negatively predicts the cross-section of stock returns, which means that the greater the negative (positive) distance between a short-term (21-day) and a long-term (200-day) average, the higher (lower) the future average return. To test for the return predictability of MAVD, we then construct a contrarian hedge portfolio by having a long position for stocks with the lowest MAVD and a short position for stocks with the highest MAVD. We find that this hedge portfolio strategy yields an equally-weighted risk-adjusted return close to 1.70% per month and a value-weighted risk-adjusted return close to 1.11% per month. We refer to this negative return predictability as "MAVD effect". We further confirm that these return prediction results are robust to an extensive set of control variables, including firm size, book-to-market, momentum, gross margin profitability, asset growth, turnover, illiquidity, idiosyncratic volatility and short-term reversal. In robustness checks, our results are robust to alternative long-term and short-term moving average windows, can still be obtained after adjusted by other common factor models, such as Fama and French (1993) three factors, Fama–French–Carhart (1997) four factors, Fama and French (2015) five factors and a variety of factor models with the additional trend factor proposed by Liu et al. (2019), and also hold in other sample subperiods, including 1999–2009 or 2010–2019 subsamples, excluding small or illiquidity stocks, and omitting earnings announcement days.

In addition, we investigate the long-term performance of the MAVD hedge portfolio, and we find that the negative prediction relation of MAVD on future returns lasts for several months. However, this prediction relation diminishes as portfolio holding months move further away from the portfolio formation month and becomes insignificant after six months, and has reversed at the end of the second year after portfolio formation. The average excess return of the MAVD hedge portfolio drops to 0.8791% with a significant t-statistic of 4.699 in months 1–3, and is only 0.0535% with an insignificant t-statistic of 0.420 in months 7–9. Moreover, the average excess return of the MAVD hedge portfolio is equal to −0.2445% with a significant t-statistic of −2.240 in months 22–24. These results indicate that the MAVD effect tends to be a mispricing due to market overreaction, and this mispricing is gradually corrected. On the other hand, the MAVD effect diminishes over time, indicating that stock price adjusts slowly to reflect the true value of the firm as the mispricing is corrected.

To highlight the role of volume, we compare the predictive power of MAVD with the distance between short- and long-term moving averages of past prices (MAD). We find that MAVD provides incremental predictive information about future returns beyond that contained in MAD, which is consistent with the theoretical implication of Blume et al. (1994) that trading volume can provide predictive information beyond the price statistic. Specifically, a hedge portfolio that goes long in the lowest MAD in the prior month and goes short in the highest MAD in the prior month, yields an equally-weighted return of 0.52% per month. Compared with the return to the MAD strategy, the MAVD strategy significantly outperforms the MAD strategy by 1.18% in terms of monthly return. Further, we construct the price trend factor (PTR hereafter) based on MAD and the volume trend factor (VTR hereafter) based on MAVD to compare the relative pricing power of these two factors. Our empirical results confirm that the pricing power of VTR factor is stronger than that of PTR factor.

Furthermore, to better understand the economic mechanism behind the MAVD effect, we further conduct empirical tests to explore the behavioral mispricing-based and risk-based explanations. We find that the predictive relation between MAVD and future returns remains significant after controlling for the risk embodied in the sensitivities of returns to well-known risk factors. These results indicate that the predictive information extracted from MAVD is not due to the compensation for risk. In contrast, the MAVD effect could arise from mispricing. Mispricing is caused by limits of arbitrage and behavioral biases in the stock market (Daniel et al. 2001; Barberis and Shleifer 2003; Hirshleifer and Jiang 2010). The Chinese stock market mainly consists of retail investors who are more prone to behavioral biases, leading to more irrational investment behaviors, so stocks could have greater mispricing. Thus, we focus on limits of arbitrage, investor attention, aggregate investor overconfidence, investor sentiment and speculative trading behavior in examining the behavioral mispricing-based explanations for the MAVD effect in this study. First, if the MAVD premium reflects mispricing to some extent, it should be larger among stocks that are more difficult to arbitrage (Daniel et al. 2001; Barberis and Shleifer 2003; Hirshleifer and Jiang 2010). We employ three standard proxies to measure limits of arbitrage, and we find that the MAVD effect is stronger among stocks with higher idiosyncratic volatility, higher turnover and lower institutional ownership where these characteristics are typically associated with higher arbitrage costs and hence with a higher likelihood of mispricing. This evidence indicates that behavioral mispricing has strong power in explaining the MAVD premium in the Chinese stock market. We then conduct the second test to investigate the role of mispricing by examining the relation between the MAVD effect and investor attention. If high MAVD stocks do attract investor attention, then more attention from individual investor could increase the purchasing pressure of stocks with high MAVD and cause overreaction. We divide all stocks into different groups based on the investor attention proxy. Our results show that the MAVD effect is stronger among stocks that are more likely to receive more investor attention. Moreover, we conduct the third test to investigate the role of mispricing by examining the relation between the MAVD effect and investor sentiment or overconfidence. We find that the MAVD effect is stronger in the periods of high sentiment or high investor overconfidence, indicating that the MAVD effect is at least partially driven by mispricing due to investor sentiment or overconfidence in the marketplace. In addition, the Chinese stock market is populated with speculative investors. Speculative trading shows a negative effect on asset prices (Pan et al. 2016), and stocks with speculative attributes tend to be overpriced (Han and Kumar 2013). Motivated by the literature on speculative trading, we add additional evidence to understand the economic mechanism behind the MAVD effect in the Chinese stock market. Inspired by the definition of MAVD, although MAVD focuses more on reflecting the future trends in trading volume, it also reflects the change of short-term trading volume. If the increased trading volume is mostly caused by speculative trading, then these trading behaviors could affect the firm's value and fail to bring the expected positive impact. Consequently, it is worthwhile investigating whether the MAVD effect is affected by speculative characteristics. In our study, we find that the MAVD effect is stronger in stocks with speculative attributes (i.e., small-cap stocks and stocks with low analyst coverage). Our findings show that the MAVD effect is likely to be attributable to individual speculative trading behavior.

Finally, we conduct further discussions. We examine whether MAVD may be another form of volume shock (Bali et al. 2014) in a regression framework. The regression results show that the coefficient on MAVD is still significant after controlling for volume shock, which indicates that MAVD contains predictive information that volume shock cannot provide. Technical analysis is usually used by investors to make trading decisions. When stocks are volatile, fundamental signals are likely to be less precise, and hence investors tend to rely more heavily on technical signals. Therefore, we also examine the predictive power of MAVD for different groups of stocks with different degrees of volatility. As expected, we observe a stronger predictive power of MAVD among high volatility stocks. Following Han et al. (2013), we further examine whether market timing can explain the MAVD effect.

Our study has the following contributions to the literature. First, to our knowledge, we are the first to define the distance between short- and long-term moving averages of trading volume (MAVD) and to document a negative relation between MAVD and future stock returns. The MAVD hedge portfolio strategy yields an average monthly return that is not only statistically significant, but also economically large for horizons ranging from one to six months, especially after being adjusted by common factor models. Second, our study complements the existing important work on technical trading rules by Brock et al. (1992), Han et al. (2013) and Liu et al. (2019). These studies consider either moving average price strategies mostly based on binary crossing rules or moving average volume strategies. We highlight a specific distance-based trading volume rule, and we compare a specific distance-based trading volume rule with a specific distance-based price rule. We show that MAVD provides incremental predictive information about future returns beyond that contained in MAD in the Chinese stock market. On the other hand, our study also complements the existing important work on low volume premium. Third, our study also contributes to a growing literature on behavioral biases applied to explain return anomalies. Our work explains the MAVD effect from multiple perspectives of investor behavioral biases. We find that limits of arbitrage delay the incorporation of information about MAVD into stock prices, and the higher limits of arbitrage there are, the stronger MAVD effect we can observe. We also find that the MAVD effect is stronger among stocks that are more likely to receive more investor attention. Moreover, the evidence shows that the MAVD effect is stronger in the periods of high sentiment and high investor overconfidence. Furthermore, we focus on the impact of speculative characteristics on the MAVD effect, and we first conclude that our specific distance-based trading volume rule is affected by individual speculative trading. Finally, we examine the cross-sectional predictability of moving averages of volumes in different volatility portfolios. The evidence shows that the predictive power of MAVD is more pronounced among high volatility stocks rather than among low volatility stocks, indicating that investors tend to rely more heavily on technical signals when stocks are volatile.

The remainder of this paper is organized as follows. Section 2 describes the data and calculation of MAVD measures. Section 3 presents the relation between MAVD and future returns for various investment horizons, tests the predictive power of MAVD using both the portfolio test and Fama–MacBeth regression analysis, compares the predictive power of MAVD and that of MAD, and does some robustness tests. Section 4 explores the behavioral mispricing-based explanation for the MAVD effect. Section 5 conducts some further discussions about MAVD, and concluding remarks are given in Section 6.

2. Data and methodology

We consider all Chinese A-share firms listed on the Shanghai Stock Exchange and Shenzhen Stock Exchange with monthly stock return and accounting data from China Stock Market and Accounting Research Database (CSMAR). The sample period spans from January 1999 to December 2019. We match accounting data of fiscal year $t-1$ to the returns from July of year t to June of year $t+1$ to make sure that all accounting variables are available. To ensure the quality of data, we exclude the financial firms and special treatment (ST) firms in the sample.

Avramov et al. (2018) define the ratio of MA (21) and MA (200) as the distance between short- and long-term moving averages of stock price. Following Avramov et al. (2018), we propose a new technical indicator to predict the cross-section of future stock returns, which is formed as:

$$MAVD = \frac{MAV(21)}{MAV(200)} \tag{1}$$

where MAV (21) is the trading volume moving average based on approximately the past one month (21 trading days) and MAV (200) is the corresponding 200-day moving average. We define the ratio of MAV (21) and MAV (200) as the distance between short- and long-term moving averages of trading volume (MAVD).[1]

In addition to our proposed predictive variable, we also consider the following main control variables, including: (1) Size (SIZE), defined as the natural logarithm of market capitalization; (2) Book-to-market Ratio (BM), defined as book equity over market equity. We use book value from fiscal year-end $t-1$ and market value from December of year $t-1$; (3) Momentum (MOM), defined as the cumulative returns from month $t-12$ to $t-2$; (4) Gross profit (GP), defined as gross profits scaled by total assets; (5) Asset growth (AG), defined as the annual growth rate of total assets; (6) Turnover (TURN), defined as the ratio of trading volume to shares outstanding, following Chordia et al. (2011, 7) Illiquidity (ILLIQ), defined as the monthly average of daily absolute return per yuan of

[1] We also use the difference between the short-term and long-term moving averages to proxy as the distance between short- and long-term moving averages of trading volume. The results are similar to those reported in Table 2, omitted for brevity.

daily trading volume (Amihud 2002, 8) Price (PRI), defined as share price; (9) Idiosyncratic volatility (IVOL), defined as the monthly standard deviation of the residuals from regressing monthly returns over the past 12-month period (t-11 to t) on Fama and French, 1993three factors; (10) Short-term reversal (SR), defined as the one-month lagged stock return (Jegadeesh 1990, 11) Volume shocks, defined as the negative difference between illiquidity (volume) and its past 12-month average, and standardize the difference by its volatility.

Table 1 presents the summary statistics for our full sample. Panel A of Table 1 reports the time series averages of mean, standard deviation, minimum, 25th percentile, median, 75th percentile, and maximum of main variables in our study. The mean of MAVD is 1.03 and its median is 1.00. Panel B of Table 1 reports average firm characteristics of the decile portfolios, sorted by MAVD. At the end of month t, stocks are sorted into decile portfolios based on their monthly MAVD, and the portfolios are rebalanced monthly. In particular, decile 1 refers to stocks with the lowest MAVD in month t, and decile 10 refers to stocks with the highest MAVD in month t. We find that decile 1 prefers to stocks with small market value, high BM, low turnover, high illiquidity and low one-month lagged stock return, while stocks in decile 10 have the opposite characteristics. Previous papers show a positive relation between average returns and book-to-market equity (Rosenberg et al. 1985; Fama and French 1992) and illiquidity (Amihud 2002). There is a negative relation between average returns and size (Banz 1981; Fama and French 1992), asset growth (Titman et al. 2004; Cooper et al. 2008), turnover (Datar et al. 1998) and one-month lagged stock return (Jegadeesh 1990). Thus, we expect that decile 1 can yield higher subsequent returns and decile 10 can yield lower subsequent returns, which indicates that MAVD may have a negative effect on future stock returns.

3. Empirical results

In this section, we investigate the power of MAVD to predict the cross-section of future stock returns by employing portfolio analysis and Fama–MacBeth regression.

Table 1
Summary statistics.

Panel A: Descriptive statistics							
Variable	Mean	Std	Min	P25	Median	P75	Max
MAVD	1.03	0.38	0.40	0.80	1.00	1.28	2.37
MAD	0.99	0.18	0.49	0.87	0.97	1.06	1.85
SIZE	21.39	0.81	19.78	20.67	21.57	22.05	22.91
BM	0.65	0.12	0.45	0.55	0.66	0.74	0.89
MOM	0.09	0.28	−0.74	−0.10	0.06	0.22	1.09
GP	0.03	0.02	−0.01	0.02	0.04	0.04	0.06
AG	0.21	0.08	0.07	0.13	0.22	0.25	0.39
TURN	2.63	1.35	0.56	1.68	2.49	3.26	7.79
ILLIQ	0.44	0.56	0.03	0.08	0.21	0.57	3.53
PRI	13.54	4.98	4.60	10.40	12.91	16.95	33.22
IVOL	0.10	0.02	0.07	0.08	0.10	0.11	0.13
SR	0.01	0.10	−0.29	−0.04	0.01	0.06	0.34
VOSHOCK1	−0.86	2.25	−18.01	−1.28	−0.23	0.39	1.17
VOSHOCK2	0.04	0.84	−1.85	−0.50	−0.15	0.43	3.20
Panel B: Firm characteristics of portfolios							
Portfolios	SIZE	BM	AG	ILLIQ	TURN	IVOL	SR
1	21.33	0.67	0.19	0.36	1.38	0.10	−0.03
2	21.37	0.66	0.21	0.27	1.56	0.10	−0.02
3	21.39	0.66	0.23	0.26	1.68	0.10	−0.01
4	21.42	0.66	0.25	0.23	1.80	0.10	−0.01
5	21.44	0.66	0.26	0.21	1.93	0.10	−0.00
6	21.46	0.66	0.28	0.20	2.09	0.10	0.01
7	21.48	0.66	0.30	0.19	2.28	0.10	0.01
8	21.50	0.65	0.29	0.17	2.58	0.10	0.02
9	21.50	0.65	0.31	0.15	3.03	0.10	0.04
10	21.48	0.66	0.35	0.15	4.53	0.11	0.08

This table reports the time series averages of mean, standard deviation, minimum, 25th percentile, median, 75th percentile, and maximum of main variables in our study, as well as average firm characteristics of the decile portfolios, sorted by MAVD. At the end of month t, stocks are sorted into decile portfolios based on their monthly MAVD, and the portfolios are rebalanced monthly. Decile 1 refers to stocks in the lowest MAVD decile, and decile 10 refers to stocks in the highest MAVD decile. Main variables include the distance between short- and long-term moving averages of trading volume (MAVD), the distance between short- and long-term moving averages of past price (MAD), the log firm size (SIZE), book-to-market ratio (BTM), momentum (MOM), gross profitability (GP), asset growth (AG), turnover (TURN), illiquidity (ILLIQ), share price (PRI), idiosyncratic volatility (IVOL), short-term reversal (SR) and two proxies of volume shocks (VOSHOCK1/VOSHOCK2) over the full sample period. The sample period is from 1999 to 2019.

3.1. Portfolio tests

3.1.1. Single sorts on MAVD

Fig. 1 shows the performance of the equally-weighted decile portfolios, sorted by MAVD. Specifically, at the end of month t, stocks are sorted into decile portfolios based on their monthly MAVD. In particular, decile 1 refers to stocks with the lowest MAVD in month t, and decile 10 refers to stocks with the highest MAVD in month t. We find that the decile portfolio returns decrease almost monotonically with MAVD in the next month and months 2–6, 7–12, indicating that there is a negative correlation between MAVD and future stock returns in the first year. These findings are consistent with our hypothesis in Section 2. However, no obvious MAVD–return patterns are obtained in months 13–24, 25–36, 37–48, and 49–60. These results suggest that stock price adjusts slowly to reflect the firm's true value, and mispricing is gradually corrected.

Table 2 documents the average equally-weighted returns by subtracting either the risk-free yield or by using a variety of factor models (Capital Asset Pricing Model (CAPM) alpha, or three- to five-factor alphas) of the MAVD hedge portfolio. The "L–H" hedge portfolio is computed with longing the lowest MAVD decile and shorting the highest decile. The evidence indicates that MAVD negatively predicts future stock returns in the cross-section. Specifically, we find that the MAVD hedge portfolio yields average monthly return of 1.7004% (t-statistic = 6.085), or roughly 20.40% per year. In the next four columns, we control for other well-known return determinants. The MAVD hedge portfolio delivers the CAPM-adjusted return of 1.7901% (t-statistic = 6.767) per month, the Fama and French (1993) three-factor-adjusted return of 1.8299% (t-statistic = 6.268) per month, Carhart (1997) four-factor-adjusted return of 1.7990% (t-statistic = 5.742) per month, and Fama and French (2015) five-factor-adjusted return of 1.7603% (t-statistic = 6.196) per month. We find that the hedge portfolio's alpha actually increases after controlling for these factors. The factor model analysis reveals two main conclusions. First, our findings show that low (high) MAVD stocks yield high (low) subsequent returns, after controlling for common risk factors. Second, our findings are driven by the underperformance of stocks with high MAVD since the factor-adjusted return on decile 10 is significantly negative, whereas the factor-adjusted return on decile 1 is significantly positive. The results imply that investors overprice stocks with higher MAVD and underprice stocks with lower MAVD.

In Table 3, we report the factor loadings from a variety of factor models for the bottom and the top decile portfolios, as well as the MAVD hedge portfolio. The MAVD hedge portfolio has negative loadings on the market return (MKT) and HML, and positive loadings on SMB, MOM, RMW and CMA. In other words, the MAVD effect is stronger in down markets, and when small stocks, growth stocks, momentum stocks, and high profitability stocks do well. The last row of each panel of Table 3 shows the factor loadings for the hedge portfolio. Returns from the MAVD hedge portfolio cannot be explained by the Fama and French (1993) three factors, Fama–-French–Carhart (1997) four factors, Fama and French (2015) five factors, as the loadings on these factors are low and mostly insignificant.

In summary, the MAVD indicator is a strong and negative predictor of future cross-sectional stock returns in the Chinese stock market, and the MAVD effect cannot be explained by well-known risk factors.

3.1.2. Double sorts on size and MAVD

The evidence shows that momentum effect is negatively related to firm size (Jegadeesh and Titman 1993; Hong et al. 2000). Thus,

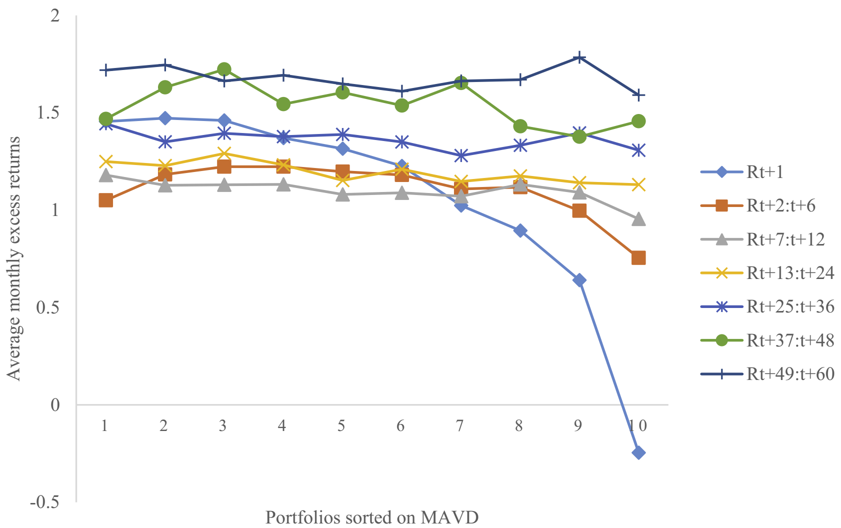

Fig. 1. The MAVD–return relation for various investment horizons.
This Figure depicts the equally-weighted average monthly excess returns of portfolios sorted on MAVD for the next month and months 2–6, 7–12, 13–24, 25–36, 37–48, and 49–60. Monthly excess return is the difference between portfolio return and monthly risk-free rate. At the end of month t, stocks are sorted into decile portfolios based on their monthly MAVD. Decile 1 refers to stocks in the lowest MAVD decile, and decile 10 refers to stocks in the highest MAVD decile.

Table 2
Decile portfolio returns.

Portfolios	R (%)	CAPMa (%)	FF3a (%)	CH4a (%)	FF5a (%)
1	1.4549**	0.8275***	0.4504**	0.4206**	0.3409**
(Low)	(2.163)	(2.714)	(2.442)	(2.181)	(2.081)
2	1.4722**	0.8104***	0.3504**	0.3485***	0.2747**
	(2.121)	(2.767)	(2.588)	(2.611)	(2.025)
3	1.4606**	0.8000***	0.3510***	0.3430***	0.2990**
	(2.111)	(2.745)	(2.930)	(2.920)	(2.376)
4	1.3701**	0.6935**	0.2250**	0.2260**	0.1711
	(1.979)	(2.469)	(2.153)	(2.249)	(1.419)
5	1.3148*	0.6328**	0.1672	0.1485	0.1056
	(1.852)	(2.185)	(1.406)	(1.309)	(0.809)
6	1.2259*	0.5347*	0.0662	0.0427	−0.0056
	(1.741)	(1.829)	(0.560)	(0.369)	(−0.043)
7	1.0237	0.3232	−0.1182	−0.1626	−0.1589
	(1.473)	(1.195)	(−1.072)	(−1.504)	(−1.314)
8	0.8950	0.2023	−0.2272*	−0.3143***	−0.3086**
	(1.288)	(0.721)	(−1.772)	(−2.613)	(−2.134)
9	0.6404	−0.0634	−0.4754***	−0.5441***	−0.5373***
	(0.912)	(−0.236)	(−3.420)	(−4.155)	(−3.549)
10	−0.2455	−0.9627***	−1.3795***	−1.3783***	−1.4193***
(High)	(−0.346)	(−3.053)	(−7.258)	(−7.104)	(−6.775)
L–H	1.7004***	1.7901***	1.8299***	1.7990***	1.7603***
	(6.085)	(6.767)	(6.268)	(5.742)	(6.196)

This table reports the equally-weighted average monthly excess returns, risk-adjusted returns of the MAVD hedge portfolio. Monthly excess return is the difference between portfolio return and monthly risk-free rate. At the end of month t, stocks are sorted into decile portfolios based on their monthly MAVD, and the portfolios are rebalanced monthly. Decile 1 refers to stocks in the lowest MAVD decile, and decile 10 refers to stocks in the highest MAVD decile. The "L–H" hedge portfolio is computed as the difference between the returns of the lowest and highest MAVD deciles. Factor returns are from CSMAR, and factor models include: CAPM model, the Fama and French (1993) three-factor model, a four-factor model including Fama–French three-factor and Carhart's (1997) momentum factor, and Fama and French (2015) five-factor model. Newey-West adjusted t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

in this subsection, we examine the performance of the portfolios double sorted on size and MAVD to test whether the return predictability of MAVD is limited to small stocks. We conduct independent double sorts on size and MAVD. At the end of each month t, we sort stocks into three size groups (small, medium, large) using the 30th and 70th market capitalization percentiles and ten MAVD decile portfolios based on their MAVD. The portfolios are rebalanced monthly. We hold these portfolios for one month and compute the monthly equally-weighted returns of these 30 (3 × 10) size–MAVD portfolios.

Panel A of Table 4 documents the average equally-weighted excess returns and risk-adjusted returns of the double sorts on size and MAVD. We find that all MAVD hedge portfolios generate significant and positive raw or risk-adjusted returns in all firm size permutations. Specifically, the MAVD hedge portfolio yields average monthly return of 2.4475% (t-statistic = 10.279) for small stocks. This average monthly return is smaller in magnitude, but still significant, at 0.8448% (t-statistic = 2.402) for large stocks. Similar patterns are obtained using risk-adjusted returns (three-, four- and five-factor alphas). The MAVD effect is not limited to small stocks and remains profitable even when constrained to large stocks. In summary, these results show that the negative predictive power of MAVD is robust after controlling for firm size.

3.1.3. Double sorts on book-to-market and MAVD

Sagi and Seasholes (2007) show that momentum effect is negatively related to firm book-to-market ratio. Thus, in this subsection, we examine the performance of the portfolios double sorted on book-to-market ratio and MAVD to test whether the return predictability of MAVD is limited to growth stocks. We conduct independent double sorts on book-to-market ratio and MAVD. At the end of each month t, we sort stocks into three book-to-market ratio groups (growth, neutral and value) using the 30th and 70th book-to-market ratio percentiles and ten MAVD decile portfolios based on their MAVD. The portfolios are rebalanced monthly. We hold these portfolios for one month and compute the monthly equally-weighted returns of these 30 (3 × 10) book-to-market ratio–MAVD portfolios.

Panel B of Table 4 provides the average equally-weighted excess returns and risk-adjusted returns of the double sorts on book-to-market and MAVD. The results show that all MAVD hedge portfolios generate significant and positive raw or risk-adjusted returns in firms with all valuation levels. Specifically, the MAVD hedge portfolio yields average monthly return of 1.7682% (t-statistic = 6.083) for growth stocks and 1.8978% (t-statistic = 5.542) for value stocks. Similar patterns are obtained using risk-adjusted returns (three-, four- and five-factor alphas). Our results demonstrate that the MAVD effect is not limited to growth stocks and remains existing for value stocks. In conclusion, these findings indicate that the negative predictive power of MAVD is robust after controlling for firm book-to-market ratio.

3.1.4. Double sorts on past one-month return and MAVD

In this subsection, we examine the performance of the portfolios double sorted on past one-month return and MAVD to test that

Table 3
Factor loading.

Panel A: Three-factor alpha loadings

Portfolios	Alpha (%)	MKT	SMB	HML
1	0.4504**	0.9024***	0.7937***	−0.2384*
(Low)	(2.442)	(35.306)	(9.127)	(−1.778)
10	−1.3795***	1.0549***	0.7737***	0.0214
(High)	(−7.258)	(28.736)	(8.073)	(0.151)
L–H	1.8299***	−0.1525***	0.0200	−0.2598
	(6.268)	(−3.009)	(0.886)	(−1.106)

Panel B: Four-factor alpha loadings

Portfolios	Alpha (%)	MKT	SMB	HML	UMD
1	0.4206**	0.9040***	0.7802***	−0.1772	−0.0041
(Low)	(2.181)	(36.478)	(8.816)	(−1.373)	(−0.088)
10	−1.3783***	1.0547***	0.7431***	0.0650	−0.0441
(High)	(−7.104)	(29.585)	(7.723)	(0.487)	(−0.617)
L–H	1.7990***	−0.1508***	0.0371	−0.2422	0.0400
	(5.742)	(−3.134)	(0.253)	(−1.083)	(0.379)

Panel C: Five-factor alpha loadings

Portfolios	Alpha (%)	MKT	SMB	HML	RMW	CMA
1	0.3409**	0.9181***	0.8077***	−0.2061	0.0149	0.1821
(Low)	(2.081)	(28.569)	(6.324)	(−1.500)	(0.077)	(1.203)
10	−1.4193***	1.0565***	0.7241***	0.1138	−0.2454	−0.1225
(High)	(−6.775)	(25.974)	(7.590)	(1.039)	(−1.292)	(−0.593)
L–H	1.7603***	−0.1384**	0.0836	−0.3199	0.2603	0.3047
	(6.196)	(−2.574)	(0.676)	(−1.603)	(0.941)	(1.307)

This table reports risk-adjusted returns and factor loadings for the bottom and the top decile portfolio sorted by MAVD, as well as the MAVD hedge portfolio. At the end of month t, stocks are sorted into decile portfolios based on their monthly MAVD, and the portfolios are rebalanced monthly. Decile 1 refers to stocks in the lowest MAVD decile, and decile 10 refers to stocks in the highest MAVD decile. The "L–H" hedge portfolio is computed as the difference between the returns of the lowest and highest MAVD deciles. Factor returns are from CSMAR, and factor models include: the Fama and French (1993) three-factor model, a four-factor model including Fama–French three-factor and Carhart's (1997) momentum factor and Fama and French (2015) five-factor model. Newey-West adjusted t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

MAVD–return pattern is not a repackage of short-term reversal. We conduct independent double sorts on past one-month return and MAVD. At the end of each month t, we sort stocks into three return groups using the 30th and 70th one-month lagged return percentiles and ten MAVD decile portfolios based on their MAVD. The portfolios are rebalanced monthly. We hold these portfolios for one month and compute the monthly equally-weighted returns of these 30 (3 × 10) past one-month return–MAVD portfolios.

Panel C of Table 4 provides the average equally-weighted excess returns and risk-adjusted returns of the double sorts on past one-month return and MAVD. The results show that all MAVD hedge portfolios generate significant and positive raw or risk-adjusted returns among different levels of short-term reversal portfolios. Similar patterns are obtained using risk-adjusted returns (three-, four- and five-factor alphas). Our results demonstrate that the MAVD effect is not subsumed by short-term reversal effect. Overall, these results suggest that the negative predictive power of MAVD is robust after controlling for short-term reversal.

3.1.5. Double sorts on momentum and MAVD

In this subsection, we examine the impact of momentum on MAVD by forming double-sorted portfolios on MAVD and momentum. At the end of each month t, we sort stocks into three momentum groups and ten MAVD decile portfolios. The portfolios are rebalanced monthly. We hold these portfolios for one month and compute the monthly equally-weighted returns of these 30 (3 × 10) momentum–MAVD portfolios. Panel D of Table 4 reports the average equally-weighted excess return and risk-adjusted returns for these portfolios. We find that all MAVD hedge portfolios earn significant and positive raw returns in all three momentum groups, which are 1.9280%, 1.8697% and 1.8756%, respectively. Similar patterns are obtained using risk-adjusted returns (three-, four- and five-factor alphas). In conclusion, these findings suggest that the negative predictive power of MAVD is robust after controlling for momentum.

3.2. Fama–MacBeth regression

In the subsection, we test the return predictability of MAVD in a regression framework while controlling for other well-documented characteristics that affect stock returns in the cross-section. Specifically, we conduct the following regressions in each month:

Table 4
Independent double sorting controlling for size, BM, Past one-month return and momentum.

Portfolios	Low	High	L–H	FF3a	CH4a	FF5a
Panel A. Size						
Small	2.2422***	−0.2053	2.4475***	2.5285***	2.5263***	2.4009***
	(2.976)	(−0.267)	(10.279)	(9.794)	(9.460)	(8.992)
Medium	1.4718**	−0.4166	1.8884***	2.0096***	2.0240***	1.9896***
	(2.087)	(−0.601)	(7.096)	(6.793)	(6.480)	(6.792)
Large	0.7058	−0.1390	0.8448***	1.0014***	0.9161**	0.8252**
	(1.140)	(−0.193)	(2.402)	(2.831)	(2.472)	(2.476)
Panel B. BM						
Low	1.3592**	−0.4090	1.7682***	1.8255***	1.8416***	1.8195***
	(2.038)	(−0.561)	(6.083)	(6.225)	(6.103)	(5.781)
Med	1.4471**	−0.2762	1.7233***	1.7930***	1.7887***	1.8087***
	(2.084)	(−0.397)	(6.952)	(6.576)	(6.170)	(6.562)
High	1.6263**	−0.2715	1.8978***	2.0598***	2.0574***	1.9436***
	(2.348)	(−0.372)	(5.542)	(5.668)	(5.314)	(5.794)
Panel C. Past one-month return						
Low	1.8383***	0.4276	1.4107***	1.5375***	1.5286***	1.4604***
	(2.664)	(0.583)	(4.522)	(4.939)	(4.645)	(5.284)
Med	1.5114**	0.0344	1.4770***	1.6490***	1.5804***	1.5377***
	(2.308)	(0.049)	(4.599)	(4.952)	(4.390)	(4.769)
High	1.1725	−0.7097	1.8822***	2.0238***	1.8243***	1.9372***
	(1.530)	(−0.973)	(5.000)	(5.632)	(4.866)	(5.495)
Panel D. Momentum						
Low	1.4349**	−0.4931	1.9280***	2.0277***	1.9452***	1.9704***
	(1.996)	(−0.642)	(6.863)	(7.158)	(6.335)	(6.743)
Med	1.5145**	−0.3553	1.8697***	2.0268***	1.9963***	1.9306***
	(2.176)	(−0.509)	(6.466)	(6.391)	(5.702)	(6.660)
High	1.6251**	−0.2505	1.8756***	1.9605***	1.8634***	1.8196***
	(2.464)	(−0.363)	(5.981)	(5.833)	(5.383)	(5.479)

This table reports the equally-weighted average monthly excess returns, risk-adjusted returns of portfolios independently double sorts on size (book-to-market ratio, past one-month return, momentum) and MAVD. At the end of each month t, we sort stocks into three size (book-to-market ratio, past one-month return, momentum) groups and ten MAVD decile portfolios based on their MAVD. The portfolios are rebalanced monthly. The "L–H" hedge portfolio is computed as the difference between the returns of the lowest and highest MAVD deciles. Factor returns are from CSMAR, and factor models include: the Fama and French (1993) three-factor model, a four-factor model including Fama–French three-factor and Carhart's (1997) momentum factor, and Fama and French (2015) five-factor model. Newey-West adjusted t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

$$R_{i,t+1} = \alpha_t + \beta_1 \times MAVD_{i,t} + \beta_2 \times SIZE_{i,t} + \beta_3 \times BM_{i,t} + \beta_4 \times MOM_{i,t} + \beta_5 \times GP_{i,t} + \beta_6 \times AG_{i,t} + \beta_7 \times TURN_{i,t} + \beta_8 \times ILLIQ_{i,t} + \beta_9 \times PRI_{i,t} + \beta_{10} \times IVOL_{i,t} + \beta_{11} \times SR_{i,t} + \varepsilon_{i,t+1} \tag{2}$$

where $R_{i,\ t+1}$ is the realized return on stock i in month t + 1, $MAVD_{i,\ t}$ is the ratio of MAV (21) and MAV (200) for stock i in month t. Other control variables are defined in Section 2.

Table 5 provides the results of Fama and MacBeth (1973) regressions in full sample. We find that these results are consistent with our portfolio analysis results in Section 3.1. The coefficients on MAVD are significantly negative in all specifications. For instance, in column 1, before controlling for well-known firm characteristics, the coefficient on MAVD is −0.0102 with a t-statistic of −5.933. The difference in the mean of MAVD between the top and bottom MAVD deciles is about 1.7730, indicating that the difference in return between the bottom and top MAVD deciles is approximately 1.8084% (=0.0102 × 1.7730) per month, which is similar in size to our portfolio analysis results. Moreover, the coefficients on other control variables are also consistent with prior literature: size, turnover and short-term reversal variables are negatively correlated with future returns, while book-to-market, momentum and illiquidity are positively correlated with future returns. Overall, the evidence from portfolio tests and Fama–MacBeth regressions shows that MAVD is a strong and negative predictor of future cross-sectional stock returns even after controlling for a broad set of well-documented firm characteristics.

3.3. Long-term return predictability

In this subsection, we explicitly examine the long-term return predictability of MAVD in the cross section. The MAVD hedge portfolios are formed based on one-month lagged MAVD, which is computed with longing the lowest MAVD decile and shorting the highest decile. The hedge portfolio is held over the period covering month t + a through t + b after portfolio formation.

Table 6 reports the monthly average equally-weighted excess return and alphas for the MAVD hedge portfolio over the two years following portfolio formation (covering months t + 1 through t + 24). During months 1–3 after portfolio formation, we find that the average excess return of the MAVD hedge portfolio is equal to 0.8183% with a t-statistic of 4.699, which drops significantly compared with the first month after portfolio formation, and is only 0.2758% for months 4–6 (t-statistic = 1.740). The predictive power of MAVD

Table 5
Fama–MacBeth regression.

Variable	Regression 1	Regression 2
Intercept	0.0222***	0.1125***
	(3.592)	(3.497)
MAVD	−0.0102***	−0.0036***
	(−5.933)	(−2.880)
SIZE		−0.0045***
		(−3.394)
BM		0.0066**
		(2.173)
MOM		0.0069**
		(2.003)
GP		0.0003
		(0.061)
AG		−0.0002
		(−0.383)
TURN		−0.0039***
		(−7.418)
ILLIQ		0.0548***
		(3.200)
PRI		0.0000
		(0.396)
IVOL		−0.0042
		(−0.323)
SR		−0.0300***
		(−3.550)

This table reports the average coefficients and their respective Newey-West adjusted t-statistics from monthly cross-sectional regressions of the return in that month on lagged variables including MAVD and other control variables. Following Fama and French (1992), we match accounting data for all fiscal year-ends in calendar year t − 1 with the returns for July of year t to June of year t + 1 to ensure that the accounting variables are known before the returns they are used to explain. The dependent variable is the monthly excess return. The explanatory variables include MAVD, firm size (SIZE), book-to-market ratio (BM), momentum (MOM), gross profitability (GP), asset growth (AG), turnover (TURN), illiquidity (ILLIQ), share price (PRI), idiosyncratic volatility (IVOL) and short-term reversal (SR). Fama–MacBeth t-statistics are reported below the coefficient estimates. Coefficients marked with *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

Table 6
Longer-term return predictability.

	$R_{t+1:t+3}$	$R_{t+4:t+6}$	$R_{t+7:t+9}$	$R_{t+10:t+12}$	$R_{t+16:t+18}$	$R_{t+22:t+24}$
1	1.1587*	1.0859	1.0241	1.2965*	1.2462*	1.1341
(Low)	(1.853)	(1.597)	(1.531)	(1.665)	(1.754)	(1.562)
10	0.3404	0.8100	0.9707	0.8671	1.0738	1.3786*
(High)	(0.518)	(1.234)	(1.398)	(1.291)	(1.507)	(1.846)
L–H	0.8183***	0.2758*	0.0535	0.4294	0.1724	−0.2445**
	(4.699)	(1.740)	(0.420)	(1.757)	(1.230)	(−2.240)
FF3a	0.8791***	0.2878**	0.0542	0.3260	0.1581	−0.2001*
	(5.439)	(1.930)	(0.448)	(1.636)	(1.130)	(−1.817)
CH4a	0.8735***	0.3179**	0.0218	0.2881	0.1826	−0.2059*
	(5.270)	(2.180)	(0.177)	(1.393)	(1.334)	(−1.821)
FF5a	0.8446***	0.2573**	0.0228	0.2394	0.1927	−0.2486**
	(5.261)	(2.002)	(0.175)	(1.212)	(1.350)	(2.005)

This table reports the longer-term equally-weighted average monthly returns and alphas of the MAVD hedge portfolio which buys stocks in the bottom MAVD decile and shorts stocks in the top MAVD decile. We sort stocks into decile portfolios at the end of each month and track monthly returns from one to 24 months ahead after portfolio formation. Decile 1 refers to stocks in the lowest MAVD decile, and decile 10 refers to stocks in the highest MAVD decile. The "L–H" hedge portfolio is computed as the difference between the returns of the lowest and highest MAVD deciles. Factor returns are from CSMAR, and factor models include: the Fama and French (1993) three-factor model, a four-factor model including Fama–French three-factor and Carhart's (1997) momentum factor, and Fama and French (2015) five-factor model. Newey-West adjusted t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

on future returns diminishes as one moves further away from the portfolio formation month and becomes insignificant after six months. Furthermore, we find that the average excess return of the MAVD hedge portfolio is equal to −0.2445% with a significant t-statistic of −2.240 in months 22–24, indicating that there is a tendency for a subsequent return reversal. Similar patterns are obtained using risk-adjusted returns. This predictability pattern over time suggests that stock markets overreact to the information from MAVD, and the resulting mispricing is gradually corrected, which makes prices gradually back toward a valuation consistent with the firm's fundamentals. In short, this negative predictive power of MAVD persists in a few months, however, reverses in the longer term.

3.4. Comparison with MAD

3.4.1. The predictive power of MAVD and MAD

Avramov et al. (2018) show that the distance between short- and long-term moving averages of prices strongly predict cross-sectional returns. Blume et al. (1994) show that trading volume can provide information that cannot be obtained from the price. Most recently, Liu et al. (2019) provide a theoretical model, which indicates that any exogenous variable (especially trading volume) that is correlated with the noise trader demand has the predictive power to future stock returns. Chinese stock market has a critical feature, which is that individual investors contribute about 80% of the whole market volume. Thus, we explore whether the predictive power of MAVD can exceed that of MAD.

Table 7 documents the average monthly equally-weighted excess return and Fama–French five-factor alpha of the MAD hedge portfolio in full sample and other subsamples. Specifically, at the end of month t, stocks are sorted into decile portfolios based on their monthly MAD, and the portfolios are rebalanced monthly. In particular, decile 1 refers to stocks with the lowest MAD in month t, and decile 10 refers to stocks with the highest MAD. The MAD hedge portfolio is computed with longing the lowest MAD decile and shorting the highest decile. "Δ" is the difference between the MAVD hedge portfolio returns and the MAD hedge portfolio returns. We find that the returns of the MAD hedge portfolio are not always significant, and are lower in size than the returns of the MAVD hedge portfolio. Specifically, the MAD hedge portfolio yields average monthly excess return of 0.5159% (t-statistic = 1.744) in full sample, 0.4092% (t-statistic = 0.862) in 1999–2009 subsample, and 0.6235% (t-statistic = 1.764) in 2010–2019 subsample. The differences between the MAVD hedge portfolio's monthly excess return and the MAD hedge portfolio's monthly excess return are 1.1845% (t-statistic = 3.045) in full sample, 1.4539% (t-statistic = 2.373) in 1999–2009 subsample, and 0.9128% (t-statistic = 1.919) in

Table 7
Return predictability of MAD and MAVD.

Portfolios	R (%)	FF5a (%)	MKT	SMB	HML	RMW	CMA
Panel A: Full sample portfolio returns							
1	1.1662	0.0223	1.0120***	0.8065***	−0.2892***	−0.2112	−0.0135
(Low)	(1.619)	(0.117)	(28.724)	(8.110)	(−2.666)	(−1.120)	(−0.074)
10	0.6503	−0.4902**	1.0283***	0.7277***	−0.0266	0.1158	−0.2279
(High)	(0.972)	(−2.314)	(28.218)	(6.132)	(−0.164)	(0.458)	(−1.108)
$(L–H)_{MAD}$	0.5159*	0.5126**	−0.0163	0.0788	−0.2626	−0.3270	0.2144
	(1.744)	(1.884)	(−0.336)	(0.698)	(−1.162)	(−1.034)	(0.871)
$(L–H)_{MAVD}$	1.7004***	1.7603***	−0.1384**	0.0836	−0.3199	0.2603	0.3047
	(6.085)	(6.196)	(−2.574)	(0.676)	(−1.603)	(0.941)	(1.307)
△	1.1845***	1.2477***	−0.1222*	0.0048	−0.0573	0.5872*	0.0903
	(3.045)	(3.691)	(−1.798)	(0.026)	(−0.288)	(1.890)	(0.307)
Panel B: 1999–2009 portfolio returns							
1	1.7038	0.3498	1.0079***	0.8636***	−0.3391**	−0.0306	0.3325
(Low)	(1.424)	(1.093)	(23.594)	(7.044)	(−2.227)	(−0.099)	(0.971)
10	1.2945	−0.2955	1.0404***	0.6576***	0.2691	0.3682	0.0324
(High)	(1.191)	(−0.856)	(19.522)	(3.920)	(0.997)	(0.938)	(0.079)
$(L–H)_{MAD}$	0.4092	0.6453	−0.0325	0.2060	−0.6081*	−0.3988	0.3001
	(0.862)	(1.449)	(−0.540)	(1.144)	(−1.723)	(−0.823)	(0.689)
$(L–H)_{MAVD}$	1.8632***	1.9129***	−0.0760*	0.0550	−0.1670	0.3401	0.2211
	(4.424)	(4.158)	(−1.788)	(0.468)	(−0.637)	(0.844)	(0.543)
Δ	1.4539**	1.2676**	−0.0435	−0.1510	0.4411**	0.7389*	−0.0790
	(2.373)	(2.213)	(−0.702)	(−0.793)	(2.455)	(1.726)	(−0.182)
Panel C: 2010–2019 portfolio returns							
1	0.6242	−0.2156	1.0243***	0.6694***	−0.3980***	−0.2639	−0.3247**
(Low)	(0.784)	(−0.947)	(16.341)	(5.251)	(−3.188)	(−1.521)	(−2.403)
10	0.0007	−0.7643***	0.9824***	0.6001***	−0.2406	−0.1610	−0.1707
(High)	(0.001)	(−3.071)	(29.594)	(3.486)	(−1.342)	(−0.623)	(−0.886)
$(L–H)_{MAD}$	0.6235*	0.5487*	0.0419	0.0694	−0.1574	−0.1029	0.1540
	(1.764)	(1.776)	(0.579)	(0.408)	(−0.698)	(−0.409)	(−0.619)
$(L–H)_{MAVD}$	1.5363***	1.5017***	−0.2922***	0.0202	−0.3923	−0.0450	0.5212**
	(4.181)	(4.424)	(−2.857)	(0.109)	(−2.031)	(−0.147)	(2.126)
Δ	0.9128*	0.9530**	−0.3341***	−0.0492	−0.2349	0.0578	0.6753**
	(1.919)	(2.099)	(−3.367)	(−0.194)	(−1.121)	(0.155)	(2.179)

This table reports the equally-weighted average monthly excess returns, risk-adjusted returns and factor loadings of the MAVD and MAD hedge portfolio, and the difference between the MAVD hedge portfolio returns and the MAD hedge portfolio returns. At the end of month t, stocks are sorted into decile portfolios based on their monthly MAD (MAVD). Decile 1 refers to stocks in the lowest MAD (MAVD) decile, and decile 10 refers to stocks in the highest MAD (MAVD) decile. The "L–H" hedge portfolio is computed as the difference between the returns of the lowest and highest MAD (MAVD) deciles. "Δ" is the difference between the MAVD hedge portfolio returns and the MAD hedge portfolio returns. Newey-West adjusted t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

2010–2019 subsample, which are all significant. Similar patterns are obtained from Fama–French five-factor alpha. These findings are consistent with Blume et al. (1994) and Liu et al. (2019).

In summary, our findings show that MAD negatively predicts the cross-section of stocks returns, but this return predictability is time-varying while the return predictability of MAVD is robust to alternative sample. The evidence also indicates that MAVD can provide predictive information beyond MAD.

3.4.2. The pricing power of VTR and PTR

In this subsection, we further compare the relative pricing power of VTR and PTR. First, following Han et al. (2016), we construct the price trend factor (PTR) based on MAD and the volume trend factor (VTR) based on MAVD. We sort all stocks into ten decile portfolios by their MAD (MAVD). The portfolios are equally-weighted and rebalanced every month. The return difference between the decile portfolio of the lowest MAD (MAVD) and the decile portfolio of the highest is defined as the return on the trend factor based on MAD (MAVD). Second, we construct 25 portfolios from independent sorts of stocks into five size groups and five book-to-market ratio groups, and 25 portfolios from independent sorts of stocks into five size groups and five momentum groups. To compare the relative pricing power of PTR and VTR factor, we add them into the three-factor model and the five-factor model to compare the performance of these models following the literature (Fama and French 2015).

Following Fama and French (2015), we use the average absolute value of the intercept in the regressions and the GRS F-test (Gibbons et al. 1989) to evaluate the performance of the models. The lower the absolute value of an intercept implies the better the performance of the model by leaving less of the average variation in portfolio returns unexplained. GRS F-test can test whether an intercept is significantly different from zero. Table 8 reports the absolute values of intercepts and GRS statistics of the multi-factor models, including Fama–French three-factor model, two four-factor models as extensions of Fama–French three-factor model with the additional PTR or VTR factor, Fama–French five-factor model, and two six-factor models as extensions of Fama–French five-factor model with the additional PTR or VTR factor. We find that the incorporation of VTR factor in the model improves its performance, and the incorporation of PTR factor in the model cannot always improve its performance. More importantly, models with VTR factor perform better than models with PTR factor. For example, for portfolios sorted on size and book-to-market ratio or momentum in Panel A, the four-factor model with VTR factor has the lowest GRS F-test values (3.1232 and 1.7363, respectively) and the lowest absolute value of the intercepts (0.2290% and 0.2314%, respectively), while the GRS F-test values are 3.3516 and 2.1659 and the absolute value of the intercepts are 0.2434% and 0.2506% for the four-factor model with PTR factor. Similar results are obtained from Fama–French five-factor model with the additional PTR or VTR factor in Panel B.

In summary, our findings suggest that the pricing power of VTR factor is stronger than that of PTR factor, which also indicates that trading volume can provide information that cannot be obtained from the price.

3.5. Other robustness tests

3.5.1. Value-weighted results

We also conduct empirical tests to explore the results of the average value-weighted returns of the MAVD hedge portfolio. The results of these tests are omitted for brevity, but we find that the return patterns are similar with equally-weighted results reported in Table 2. Specifically, the MAVD hedge portfolio yields the value-weighted return of 1.1063% (t-statistic = 2.803) per month, or roughly 13.28% per year. Similar results are obtained using risk-adjusted returns.

3.5.2. Alternative windows

We consider short-term moving averages of 5, 21 and 25 trading days and long-term moving averages of 200 and 250 days. Table 9 reports the results of Fama and MacBeth (1973) regressions for MAVD in different windows, including MAVD (5, 200), MAVD (25,

Table 8
Pricing power of VTR and PTR.

	25 Size-BM			25 Size-MOM		
	GRS-stat	GRS-P	|a|	GRS-stat	GRS-P	|a|
Panel A: Based on Fama-French three factor model						
FF3	3.3387	0.0000	0.2548	1.9340	0.0067	0.2483
FF3 plus VTR factor	3.1232	0.0000	0.2290	1.7363	0.0199	0.2314
FF3 plus PTR factor	3.3516	0.0000	0.2434	2.1659	0.0017	0.2506
Panel B: Based on Fama-French five factor model						
FF5	3.0798	0.0000	0.2653	1.9067	0.0078	0.2538
FF5 plus VTR factor	2.9377	0.0000	0.2355	1.7586	0.0178	0.2234
FF5 plus PTR factor	3.0497	0.0000	0.2440	2.1096	0.0024	0.2489

This table reports the model evaluation results of the multi-factor models. We construct the price trend factor (PTR) based on MAD, and the volume trend factor (VTR) based on MAVD. We sort all stocks into ten portfolios by their MAD (MAVD). The portfolios are equal-weighted and rebalanced every month. The return difference between the decile portfolio of the lowest MAD (MAVD) and the decile portfolio of the highest is defined as the return on the trend factor based on MAD (MAVD). We then construct 25 portfolios from independent sorts of stocks into five size groups and five book-to-market ratio groups, and 25 portfolios from independent sorts of stocks into five size groups and five momentum groups. GRS-stat shows the value of the GRS statistics. GRS-P shows the corresponding P value of the GRS statistics. |a| denotes the average absolute value of the intercept.

Table 9
Cross-sectional regression of alternative windows.

	MAVD (5, 200)		MAVD (25, 200)		MAVD (21, 250)	
	Regression 1	Regression 2	Regression 3	Regression 4	Regression 5	Regression 6
Intercept	0.0206***	0.1118***	0.0224***	0.1096***	0.0214***	0.1132***
	(3.291)	(3.447)	(3.610)	(3.454)	(3.463)	(3.503)
MAVD	−0.0088***	−0.0060***	−0.0105***	−0.0036***	−0.0096***	−0.0034***
	(−7.446)	(−8.095)	(−5.717)	(−2.902)	(−6.281)	(−3.724)
SIZE		−0.0042***		−0.0044***		−0.0045***
		(−3.201)		(−3.345)		(−3.384)
BM		0.0057*		0.0067**		0.0068**
		(1.882)		(2.186)		(2.302)
MOM		0.0072**		0.0071**		0.0064*
		(2.120)		(2.060)		(1.914)
GP		0.0009		0.0005		0.0002
		(0.190)		(0.0102)		(0.049)
AG		−0.0002		−0.0002		−0.0000
		(−0.361)		(−0.392)		(−0.001)
TURN		−0.0038***		−0.0040***		−0.0037***
		(−7.811)		(−7.585)		(−7.399)
ILLIQ		0.0485***		0.0714***		0.0526***
		(3.187)		(3.247)		(3.492)
PRI		−0.0000		0.0000		−0.0000
		(−0.025)		(0.477)		(−0.099)
IVOL		−0.0072		−0.0030		−0.0089
		(−0.548)		(−0.234)		(−0.692)
SR		−0.0159*		−0.0317***		−0.0305***
		(−1.827)		(−3.759)		(−3.610)

This table reports the average coefficients and their t-statistics from monthly cross-sectional regressions of the return in that month on lagged variables including MAVD and other control variables. We consider short-term moving averages of 5, 21 and 25 trading days and long-term moving averages of 200 and 250 days. Following Fama and French (1992), we match accounting data for all fiscal year-ends in calendar year t − 1 with the returns for July of year t to June of year t + 1 to ensure that the accounting variables are known. The dependent variable is the monthly excess return. The explanatory variables include MAVD, firm size (SIZE), book-to-market ratio (BM), momentum (MOM), gross profitability (GP), asset growth (AG), turnover (TURN), illiquidity (ILLIQ), share price (PRI), idiosyncratic volatility (IVOL) and short-term reversal (SR). Fama–MacBeth t-statistics are reported below the coefficient estimates. Coefficients marked with *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

200) and MAVD (21, 250). We find that the coefficients of all MAVD indicators are significantly negative. Overall, the return predictability of MAVD is robust to considering alternative long-term and short-term moving average windows.

3.5.3. *Alternative samples*

We examine whether the predictive power of MAVD varies across time. We divide our full sample period into 1999–2009 and 2010–2019. We then repeat our empirical analysis from Table 5 for each subperiod. Table 10 reports the results of Fama and MacBeth (1973) regressions in 1999–2009 and 2010–2019 subperiods. The coefficients of MAVD are all significantly negative after controlling for well-known firm characteristics. For both subperiods, we find consistent results that MAVD is a strongly negative predictor of future cross-sectional stock returns.

3.5.4. *Excluding microcap, illiquidity stocks and omitting earnings announcement days*

Information events or stock-specific illiquidity shocks can cause a large change in trading volume. Meanwhile, previous literature suggests that smaller stocks are on average less liquid, covered less by analysts, and more expensive to trade (e.g., Carhart (1997); Keim and Stambaugh, 1986; Brennan et al., 1998; Novy-Marx and Velikov, 2016). In this section, we investigate whether the negative relation between MAVD and future stock returns is driven by illiquid, microcap stocks or earnings announcements.

Panels A and B of Table 11 report the average equally-weighted excess returns and risk-adjusted returns of the MAVD hedge portfolio by excluding microcap or illiquidity stocks. Stocks with market capitalization or illiquidity below the 20 percentile are excluded. Our findings show that the average monthly excess return of the MAVD hedge portfolio is slightly lower than that of the whole sample in the Table 2. Specifically, the MAVD hedge portfolio yields average monthly return of 1.4952% with a significant t-statistic of 5.281 in Panel A and 1.5529% with a significant t-statistic of 5.083 in Panel B. These results suggest that illiquidity and size cannot solely explain the negative relation between MAVD and future stock returns.

Panel C of Table 11 presents the average equally-weighted excess returns and risk-adjusted returns of the MAVD hedge portfolio by omitting earnings announcement days. We omit the 12 days around earnings announcement to exclude the impact of earnings announcement on the MAVD effect. The average monthly excess return of the MAVD hedge portfolio is economically and statistically significant. Similar patterns are obtained using risk-adjusted returns (three-, four- and five-factor alphas). Overall, the evidence indicates that the MAVD effect is still strong after omitting volume around earnings announcement days.

Table 10
Cross-sectional regression of alternative samples.

	1999–2009		2010–2019	
	Regression 1	Regression 2	Regression 3	Regression 4
Intercept	0.0284***	0.1000**	0.0159**	0.1251***
	(3.013)	(2.200)	(1.997)	(2.737)
MAVD	−0.0114***	−0.0050**	−0.0089***	−0.0031**
	(−4.390)	(−2.540)	(−3.988)	(−1.980)
SIZE		−0.0037*		−0.0052***
		(−1.893)		(−2.971)
BM		0.0122***		0.0009
		(2.788)		(0.221)
MOM		0.0068		0.0070*
		(1.217)		(1.734)
GP		−0.0025		0.0031
		(−0.345)		(0.474)
AG		−0.0000		−0.0005***
		(−0.0028)		(−3.015)
TURN		−0.0051***		−0.0027***
		(−5.627)		(−5.275)
ILLIQ		−0.0018		0.1119***
		(−0.263)		(3.392)
PRI		−0.0000		0.0000
		(0.137)		(0.882)
IVOL		−0.0068		−0.0016
		(−0.266)		(−0.360)
SR		−0.0222		−0.0308***
		(−1.639)		(−2.748)

This table reports the average coefficients and their respective Newey-West adjusted t-statistics from monthly cross-sectional regressions of the return in that month on lagged variables including MAVD and other control variables. The sample periods include 1999–2009 and 2010–2019. We match accounting data for all fiscal year-ends in calendar year t − 1 with the returns for July of year t to June of year t + 1 to ensure that the accounting variables are known. The dependent variable is the monthly excess return. The explanatory variables include MAVD, firm size (SIZE), book-to-market ratio (BM), momentum (MOM), gross profitability (GP), asset growth (AG), turnover (TURN), illiquidity (ILLIQ), share price (PRI), and idiosyncratic volatility (IVOL). Fama–MacBeth t-statistics are reported below the coefficient estimates. Coefficients marked with *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

Table 11
Decile portfolio returns by excluding microcap, illiquidity stocks and omitting earnings announcement days.

Portfolios	R (%)	FF3a (%)	CH4a (%)	FF5a (%)
Panel A: Excluding microcap stocks				
Low	1.1945*	0.2584	0.2320	0.1974
	(1.815)	(1.333)	(1.126)	(1.164)
High	−0.3007	−1.3885***	−1.3934***	−1.4071***
	(−0.427)	(−6.761)	(−6.663)	(−6.277)
L–H	1.4952***	1.6469***	1.6254***	1.6045***
	(5.281)	(5.360)	(4.976)	(5.498)
Panel B: Excluding illiquidity stocks				
Low	1.1832*	0.2363	0.2075	0.1470
	(1.777)	(1.106)	(0.945)	(0.807)
High	−0.3697	−1.5007***	−1.4956***	−1.5614***
	(−0.519)	(−7.388)	(−7.176)	(−6.867)
L–H	1.5529***	1.7370***	1.7031***	1.7084***
	(5.083)	(5.452)	(5.093)	(5.641)
Panel C: Omitting earnings announcement days				
Low	1.3881**	0.3803**	0.3679*	0.2964*
	(2.070)	(2.070)	(1.869)	(1.755)
High	−0.2469	−1.3798***	−1.3675***	−1.4011***
	(−0.351)	(−7.295)	(−7.094)	(−6.699)
L–H	1.6349***	1.7601***	1.7354***	1.6975***
	(5.919)	(5.979)	(5.452)	(5.873)

This table reports the equally-weighted average monthly excess returns, risk-adjusted returns of the MAVD hedge portfolio by excluding microcap, illiquidity stocks or omitting earnings announcement days. Stocks with market capitalization or illiquidity below the 20 percentile are excluded. We omit the 12 days around earnings announcement to exclude the effect of earnings announcement on the MAVD effect. The "L–H" hedge portfolio is computed as the difference between the returns of the lowest and highest MAVD deciles. Factor returns are from CSMAR, and factor models include: the Fama and French (1993) three-factor model, a four-factor model including Fama–French three-factor and Carhart's (1997) momentum factor, and Fama and French (2015) five-factor model. Newey-West adjusted t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

3.5.5. Risk-adjusted returns based on LZZ trend factor

Liu et al. (2019) propose a trend factor (LZZ trend factor hereafter) for the Chinese stock market that includes the impact of trends in volume. Thus, in this subsection, we examine the performance of MAVD in predicting future returns after controlling for this trend factor.

Table 12 documents the risk-adjusted returns of the portfolios sorted on MAVD by using a variety of factor models with the additional LZZ trend factor. Panel A reports the results of full sample. We find that the MAVD hedge portfolio generates significant and positive risk-adjusted returns when the LZZ trend factor is included. For example, the risk-adjusted return by the LZZ four-factor model proposed by Liu et al. (2019) is 1.3801% with a significant t-statistic of 4.902. Similar results are obtained from other factor models, including Fama–French three-factor model with the additional LZZ trend factor and Fama–French five-factor model with the additional LZZ trend factor. Panel B and Panel C report the results in 1999–2009 and 2010–2019 subperiods, which are consistent with that of Panel A. In summary, the MAVD effect cannot be explained by the LZZ trend factor.

4. Underlying mechanisms

Our previous analysis indicates that MAVD strongly and negatively predicts the cross-section of stocks returns. If pricing is rational, the predictive relation between MAVD and future returns should reflect compensation for some form of risk associated with MAVD. From the portfolio analysis of Table 2, we find that this predictive relation is robust after controlling for well-known risk factors. Although we may not be able to properly control for some unknown risk factors that may still explain our findings, at least partially, our results show that current well-known risk factors cannot explain the MAVD effect. Thus, to better understand the economic mechanism behind the MAVD effect, we also conduct empirical tests to explore the behavioral mispricing-based explanations. Daniel et al. (2001), Barberis and Shleifer (2003), and Hirshleifer and Jiang (2010) show that mispricing is caused by limits of arbitrage and behavioral biases in the stock market. Thus, we focus on limits of arbitrage, investor attention, aggregate investor overconfidence, investor sentiment and speculative trading behavior in examining the behavioral mispricing-based explanations for the MAVD effect in this section.

4.1. Limits of arbitrage

Existing works empirically examine the role of limits of arbitrage on various market anomalies, including book-to-market effect (Ali et al. 2003), momentum (Nagel 2005), accrual anomaly (Mashruwala et al. 2006), asset growth anomaly (Lam et al., 2011), idiosyncratic volatility effect (Gu et al., 2018) and technical trading effect (Ma et al. 2020). When a stock is mispriced, the arbitrage activity can push the convergence of market price to fundamentals. However, limits of arbitrage create risks and costs for the arbitrage process, which delays the adjustment of stock prices and hinders the correction of mispricing. Therefore, we expect to observe a stronger MAVD effect for stocks with higher limits of arbitrage. In this subsection, we examine the role of limits of arbitrage behind the negative prediction relation between MAVD and future returns.

Limits of arbitrage contain transaction cost, trading constraint, and information uncertainty (Gu et al., 2018). We use idiosyncratic volatility, turnover, institutional ownership as our proxies of limits of arbitrage. Shleifer and Vishny (1997) and Pontiff (2006) identify idiosyncratic volatility risk as the primary arbitrage holding cost, indicating higher idiosyncratic volatility reflects higher limits of arbitrage. Higher turnover reflects higher information asymmetry (Jiang et al. 2018). Akbas et al. (2017) show that institutional ownership is associated with short selling costs, indicating that lower institutional ownership reflects higher limits of arbitrage. In summary, stocks with characteristics of higher idiosyncratic volatility, higher turnover and lower institutional ownership have higher limits of arbitrage and thus greater mispricing.

Table 13 reports the average equally-weighted excess returns and risk-adjusted returns of the double sorts on each limit of arbitrage proxy and MAVD. At the end of each month t, we sort stocks into three limit of arbitrage groups (low, med, high) based on the 30th and 70th percentiles of the ranked values of a limit of arbitrage proxy, and we then sort stocks in each limit of arbitrage group based on their MAVD into ten decile portfolios. The portfolios are rebalanced monthly.

The results in panels of Table 13 show that the MAVD hedge portfolio yields higher returns among stocks with higher limits of arbitrage, such as stocks with higher idiosyncratic volatility, higher turnover, and lower institutional ownership. For example, in Panel A, the MAVD hedge portfolio yields average monthly return of 1.3049% (t-statistic = 4.344) for low idiosyncratic volatility stocks and 2.2803% (t-statistic = 6.979) for high idiosyncratic volatility stocks. The difference in average monthly excess returns of the MAVD hedge portfolio between the highest and lowest idiosyncratic volatility groups is 0.9754% (t-statistic = 3.561). The last three rows of each panel of Table 13 show the results of the risk-adjusted returns for the MAVD hedge portfolio, consistent with the results of excess returns. Furthermore, we obtain similar patterns from turnover and institutional ownership. In conclusion, the evidence provides support for our prediction that the MAVD effect is stronger among stocks with higher limits of arbitrage and thus greater mispricing.

4.2. Investor attention

Limited attention from investors as a cognitive bias can have an impact on asset prices in financial markets (Seasholes and Wu 2007; Da et al. 2011; Mondria and Wu 2013). Previous studies show that stock prices underreact to public information about stock fundamentals and characteristics due to limited investor attention (Hirshleifer et al. 2009; Bali et al. 2014). Barber and Odean (2008) argue that individual investors are net buyers of attention-grabbing stocks, which generates price pressure and makes stocks overvalued. Thus, more attention from individual investor could increase the purchasing pressure on high MAVD stocks. If the MAVD effect

Table 12
Risk-adjusted returns based on LZZ trend factor.

Portfolios	R (%)	(FF3 plus ER_{Trend})a (%)	(FF5 plus ER_{Trend})a (%)	LZZ4a (%)
Panel A: Full sample				
Low	1.4549**	0.2401	0.1553	0.4842***
	(2.163)	(1.044)	(0.742)	(3.164)
High	−0.2455	−1.1244***	−1.1761***	−0.8959***
	(−0.346)	(−5.239)	(−5.251)	(−5.302)
L–H	1.7004***	1.3645***	1.3314***	1.3801***
	(6.085)	(3.684)	(3.797)	(4.902)
Panel B: 1999–2009				
Low	2.0053*	0.6469**	0.5702*	0.5258**
	(1.850)	(2.054)	(1.937)	(2.449)
High	0.1421	−1.2895***	−1.2628***	−0.9054***
	(0.122)	(−4.270)	(−3.664)	(−3.132)
L–H	1.8632***	1.9364***	1.8329***	1.4312***
	(4.424)	(3.958)	(3.764)	(4.300)
Panel C: 2010–2019				
Low	0.9000	0.2753	0.1130	0.0599
	(1.137)	(1.038)	(0.581)	(0.273)
High	−0.6363	−0.7479***	−0.9267***	−0.7717***
	(−0.786)	(−3.369)	(−3.909)	(−3.644)
L–H	1.5363***	1.0232**	1.0397***	0.8315***
	(4.181)	(2.233)	(2.421)	(2.694)

This table reports the risk-adjusted returns of the portfolios sorted on MAVD by using a variety of factor models with the additional LZZ trend factor. LZZ trend factor is proposed by Liu et al. (2019). At the end of month t, stocks are sorted into decile portfolios based on their monthly MAVD, and the portfolios are rebalanced monthly. The "L–H" hedge portfolio is computed as the difference between the returns of the lowest and highest MAVD deciles. Other factor returns are from CSMAR, and factor models include: the Fama and French (1993) three-factor model and Fama and French (2015) five-factor model. Newey-West adjusted t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

is related to investor attention, we should observe a stronger effect for stocks that receive more investor attention.

To test our conjecture, following Barber and Odean (2008), we use abnormal return and trading volume to proxy for degree of investor attention.[2] Abnormal return is defined as the absolute value of the difference between individual stock return and market return, and trading volume is defined as the number of shares traded. Stocks with characteristics of higher abnormal return and higher trading volume are more likely to receive investor attention. Table 14 reports the average equally-weighted excess returns and risk-adjusted returns of the double sorts on each investor attention proxy and MAVD. Specifically, at the end of each month t, we sort stocks into three investor attention groups (low, med, high), and we then sort stocks in each investor attention group based on their MAVD into ten decile portfolios. Panel A of Table 14 reports that the MAVD hedge portfolio yields average monthly return of 0.7780% (t-statistic = 2.606) for group with low abnormal return stocks while 2.4215% (t-statistic = 7.215) for group with high abnormal return stocks. The difference in average monthly excess returns of the MAVD hedge portfolio between two groups is 1.6435% (t-statistic = 5.277), which is economically and statistically significant. Panel B of Table 14 documents that the MAVD hedge portfolio yields average monthly return of 0.5389% (t-statistic = 2.009) for group with low trading volume stocks while 1.8232% (t-statistic = 4.840) for group with high trading volume stocks. The difference in average monthly excess returns of the MAVD hedge portfolio between these two groups is 1.2843% (t-statistic = 3.449). We obtain similar return patterns from risk-adjusted returns in the last three rows of each panel of Table 14. These results suggest that the MAVD effect is stronger among stocks that are more likely to receive more investor attention, indicating that the MAVD effect is at least partially driven by mispricing due to investor attention.

4.3. Investor sentiment and overconfidence

Many studies empirically show that investor sentiment has explanatory power on some well-known market anomalies, such as size effect (Lemmon and Portniaguina 2006) and momentum effect (Antoniou et al. 2013). Stambaugh et al. (2012, 2014) show that a broad set of anomalies are stronger following higher levels of investor sentiment, which provides the evidence that investor sentiment plays an important role in affecting the degree of mispricing behind anomalies. When investor sentiment is high, they may become more irrational. Therefore, if the MAVD effect is at least partially caused by mispricing due to investor sentiment, we expect to observe a stronger MAVD effect following higher levels of investor sentiment. Moreover, theoretical and empirical studies have extensively documented that investor overconfidence affects asset prices. Previous literature shows that overconfidence as a behavioral bias is considered as an explanation for various anomalies (De Bondt and Thaler 1985; Lakonishok et al. 1994; Daniel et al. 2001). Overconfidence means having mistaken valuations and believing in certain information too strongly. Daniel et al. (1998, 2001) and Epstein and Schneider (2008) show that when investors are overconfident and thus overweight their signals, asset returns would appear to

[2] As a robustness test, we also use turnover and the Baidu search volume index as other proxies of investor attention, the results of this test are omitted for brevity.

Table 13
Dependent double sorting based on limits of arbitrage and MAVD.

Portfolios	Low	2	High	H–L
Panel A. Idiosyncratic volatility				
Low	1.4688**	1.5168**	1.4376**	
	(2.227)	(2.248)	(2.068)	
High	0.1639	−0.2765	−0.8427	
	(0.233)	(−0.390)	(−1.173)	
L–H	1.3049***	1.7933***	2.2803***	0.9754***
	(4.344)	(6.158)	(6.979)	(3.561)
FF3a	1.4963***	1.9305***	2.3476***	0.8512***
	(5.053)	(6.322)	(6.839)	(3.195)
CH4a	1.4723***	1.9431***	2.2922***	0.8199***
	(4.407)	(5.743)	(6.528)	(2.984)
FF5a	1.4880***	1.8294***	2.2444***	0.7564***
	(5.306)	(6.040)	(6.278)	(2.770)
Panel B. Turnover				
Low	1.3815**	1.6353**	1.2706*	
	(2.126)	(2.303)	(1.727)	
High	1.2154*	0.7147	−1.1769	
	(1.857)	(1.030)	(−1.626)	
L–H	0.1661	0.9206***	2.4475***	2.2814***
	(0.535)	(3.628)	(8.345)	(7.294)
FF3a	0.1576	0.8245***	2.3724***	2.2148***
	(0.545)	(3.339)	(8.051)	(7.721)
CH4a	0.0161	0.7695***	2.2697***	2.2536***
	(0.056)	(3.010)	(7.747)	(7.729)
FF5a	0.0855	0.7431***	2.2778***	2.1923***
	(0.313)	(3.417)	(7.557)	(7.482)
Panel C. Institutional ownership				
Low	1.0094	1.4790**	0.6944	
	(1.490)	(2.204)	(1.092)	
High	−0.1578	−0.1318	0.0808	
	(−0.228)	(−0.202)	(0.103)	
L–H	1.1671***	1.6108***	0.6136	−0.5536
	(2.986)	(5.528)	(1.424)	(−1.056)
FF3a	1.1933***	1.6668***	0.8597**	−0.3336
	(2.943)	(4.919)	(2.336)	(−0.676)
CH4a	1.1203***	1.5788***	0.8442**	−0.2761
	(2.665)	(4.458)	(2.224)	(−0.592)
FF5a	1.2139***	1.6388***	0.7752**	−0.4386
	(2.772)	(4.389)	(2.104)	(−0.868)

This table reports the equally-weighted average monthly excess returns, risk-adjusted returns of portfolios dependently double sorts on each limits of arbitrage proxy and MAVD. We use idiosyncratic volatility, turnover, institutional ownership as our proxies of limits of arbitrage. At the end of each month t, we sort stocks into three limit of arbitrage groups, and we then sort stocks in each limit of arbitrage group based on their MAVD into ten decile portfolios. The portfolios are rebalanced monthly. The "L–H" hedge portfolio is computed as the difference between the returns of the lowest and highest MAVD deciles. "H–L" is the difference of returns of the MAVD hedge portfolio between the highest and lowest each limits of arbitrage proxy deciles. Factor returns are from CSMAR, and factor models include: the Fama and French (1993) three-factor model, a four-factor model including Fama–French three-factor and Carhart's (1997) momentum factor, and Fama and French (2015) five-factor model. Newey-West adjusted t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

overreact to the signals. Consequently, it is worthwhile investigating examine the role of investor overconfidence behind the negative prediction relation between MAVD and future returns.

In this subsection, we investigate the effects of investor sentiment and overconfidence behind the MAVD effect. We use two proxies for aggregate investor sentiment, including ISI index and market turnover obtained from CSMAR. We divide all the data by months into low and high sentiment based on the mean of a sentiment proxy for the entire sample period. Glaser and Weber (2009) show that past market returns strengthen investor overconfidence. Following Cooper et al. (2004), we use two measures to proxy for investor overconfidence: lagged 12-month or 36-month cumulative market returns.[3] If the lagged 12-month (lagged 36-month) cumulative market return is nonnegative for the entire sample period, then the level of overconfidence is identified as "high", "low" otherwise. Thus, if the MAVD effect is at least partially caused by mispricing due to investor overconfidence, we expect to observe a stronger MAVD effect following higher past market returns.

Table 15 reports the average equally-weighted excess returns and risk-adjusted returns of the MAVD hedge portfolio under different investor sentiment or overconfidence levels. We find that the MAVD hedge portfolio yields higher returns in the periods of high

[3] As a robustness test, we also use 24-month lagged market returns as another proxy of investor overconfidence, the results of this test are omitted for brevity.

Table 14
Dependent double sorting based on investor attention and MAVD.

Portfolio	Low	2	High	H-L
Panel A. Abnormal return				
Low	1.0785	1.4854**	1.8490***	
	(1.533)	(2.234)	(2.712)	
High	0.3005	0.1009	−0.5725	
	(0.408)	(0.143)	(−0.790)	
L-H	0.7780***	1.3845***	2.4215***	1.6435***
	(2.606)	(4.910)	(7.215)	(5.277)
FF3a	1.0136***	1.5116***	2.4783***	1.4647***
	(3.452)	(4.882)	(7.497)	(5.006)
CH4a	0.9481***	1.5361***	2.3958***	1.4477***
	(3.068)	(4.775)	(6.981)	(5.065)
FF5a	0.9688***	1.5333***	2.4251***	1.4563***
	(3.555)	(5.288)	(7.166)	(5.216)
Panel B. Trading volume				
Low	1.5977**	1.4269**	0.8544	
	(2.369)	(2.061)	(1.261)	
High	1.0588	0.2166	−0.9688	
	(1.554)	(0.303)	(−1.309)	
L-H	0.5389**	1.2103***	1.8232***	1.2843***
	(2.009)	(4.189)	(4.840)	(3.449)
FF3a	0.6100***	1.2692***	1.9583***	1.3482***
	(2.595)	(3.953)	(4.960)	(3.566)
CH4a	0.6381***	1.3431***	1.9344***	1.2963***
	(2.672)	(4.326)	(4.880)	(3.381)
FF5a	0.6997***	1.3755***	2.0993***	1.3997***
	(2.828)	(4.542)	(5.630)	(3.793)

This table reports the equally-weighted average monthly excess returns, risk-adjusted returns of portfolios dependently double sorts on each investor attention proxy and MAVD. We use abnormal return and trading volume as our proxies of investor attention. At the end of each month t, we sort stocks into three investor attention groups, and we then sort stocks in each investor attention group based on their MAVD into ten decile portfolios. The portfolios are rebalanced monthly. The "L–H" hedge portfolio is computed as the difference between the returns of the lowest and highest MAVD deciles. "H–L" is the difference of returns of the MAVD hedge portfolio between the highest and lowest each investor attention proxy deciles. Factor returns are from CSMAR, and factor models include: the Fama and French (1993) three-factor model, a four-factor model including Fama–French three-factor and Carhart's (1997) momentum factor, and Fama and French (2015) five-factor model. Newey-West adjusted t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

sentiment from the results of Panel A and Panel B. Specifically, Panel A shows that the MAVD hedge portfolio yields Fama–French three-factor alpha of 2.3990% (t-statistic = 4.708) in the periods of high ISI index, which is higher than the three-factor alpha of 1.7293% (t-statistic = 4.517) in the periods of low ISI index. Similarly, Panel B reports that the MAVD hedge portfolio yields Fama–French three-factor alpha of 1.1956% (t-statistic = 5.039) in the periods of high market turnover while 2.9072% (t-statistic = 5.204) in the periods of low market turnover. Similar results are obtained from raw or other risk-adjusted returns.

In addition, we also find that the MAVD hedge portfolio yields higher returns in the periods of high investor overconfidence from the results of Panel C and Panel D. Panel C shows that the MAVD hedge portfolio yields Fama–French three-factor alpha of 1.5625% (t-statistic = 6.961) in the periods of low investor overconfidence. The analogous figure for the hedge portfolio in the periods of high investor overconfidence is 2.1734% (t-statistic = 5.085). We obtain similar patterns from other proxies of investor overconfidence, and raw or other risk-adjusted returns.

Overall, the evidence shows that subsequent returns are more sensitive to MAVD in the periods of high sentiment or high investor overconfidence, indicating that the MAVD effect is at least partially caused by mispricing due to investor sentiment or overconfidence.

4.4. Individual speculative trading behavior

The Chinese stock market is the world's largest emerging market, mainly consisting of individual investors (Ng and Wu 2007). Individual investors pay more attention to stock price fluctuations and short-term returns, and conduct more speculative trading, leading to more irrational investment behaviors. Pan et al. (2016) indicate that speculative trading negatively affects asset prices in the Chinese stock market. Han and Kumar (2013) show that stocks with a high proportion of retail trading have strong lottery features and attract individual investors with a strong gambling propensity. These stocks tend to be overpriced and yield significantly negative returns. According to the analysis of the above sections, the higher the MAVD, the higher the recent trading volume compared with the long term and the larger the upward trend in trading volume. If the increased trading volume is mostly caused by speculative trading, then these trading behaviors could affect the firm's value and fail to bring the expected positive impact. Therefore, we expect that the MAVD effect is stronger in stocks with speculative attributes.

To investigate this conjecture, we use firm size and analyst coverage to proxy for degree of speculation. Hvidkjaer (2008) and Andrade et al. (2013) indicate that stocks with small market capitalization, or with low analyst coverage tend to have speculative attributes. Firstly, small stocks tend to face expensive buying and short selling costs (D'Avolio 2002), and their returns have a high

Table 15
The MAVD effect, investor sentiment and overconfidence.

Portfolios	Low	High	L-H	FF3a	CH4a	FF5a
Panel A. ISI index						
Low	1.4995*	−0.1169	1.6164***	1.7293***	1.6263***	1.4359***
	(1.791)	(−0.123)	(3.522)	(4.517)	(3.591)	(3.232)
High	1.8071	−0.3816	2.1887***	2.3990***	2.3399***	1.9848***
	(1.325)	(−0.264)	(3.941)	(4.708)	(4.327)	(3.586)
Panel B. Market turnover						
Low	0.1752	−1.1739*	1.3491***	1.1956***	1.3195***	1.2216***
	(0.295)	(−1.810)	(5.877)	(5.039)	(5.221)	(4.882)
High	3.8468***	1.4897	2.3571***	2.9072***	2.9705***	3.0514***
	(2.670)	(0.937)	(3.451)	(5.204)	(5.402)	(4.925)
Panel C. Lagged 36-month market return						
Low	1.1523	−0.4062	1.5585***	1.5625***	1.3848***	1.4869***
	(1.480)	(−0.529)	(4.404)	(6.961)	(4.383)	(4.853)
High	1.4990	−0.4333	1.9322***	2.1734***	2.1642***	1.9473***
	(1.237)	(−0.338)	(3.943)	(5.085)	(5.101)	(4.251)
Panel D. Lagged 12-month market return						
Low	0.8104	−0.9534	1.7638***	1.4590***	1.5517***	1.4877***
	(0.972)	(−1.125)	(7.814)	(4.697)	(4.715)	(4.605)
High	1.9313*	0.1336	1.7977***	1.9195***	1.8620***	1.8778***
	(1.893)	(0.121)	(3.690)	(4.267)	(3.830)	(3.888)

This table reports the equally-weighted average monthly excess returns, risk-adjusted returns of the MAVD hedge portfolio under different investor sentiment or overconfidence levels. We use two proxies for aggregate investor sentiment, including ISI index and market turnover obtained from CSMAR. Following Cooper et al. (2004), we use two measures to proxy for investor overconfidence: lagged 12-month or 36-month cumulative market returns. At the end of month t, stocks are sorted into decile portfolios based on their monthly MAVD, and the portfolios are rebalanced monthly. The "L–H" hedge portfolio in the fourth column is computed as the difference between the returns of the lowest and highest MAVD deciles. Factor returns are from CSMAR, and factor models include: the Fama and French (1993) three-factor model, a four-factor model including Fama–French three-factor and Carhart (1997) momentum factor, and Fama and French (2015) five-factor model. Newey-West adjusted t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

degree of idiosyncratic variation, which leads to a higher level of risk. Baker and Wurgler (2007) argue that the stocks that are speculative, difficult-to-arbitrage, including small stocks, would be more sensitive to investor sentiment and their prices deviate more from the fundamental value. Thus, small stocks are more likely to contain a bubble component in their prices and are more susceptible to speculative behavior. Second, analysts play an important role in the Chinese stock market given its unique institutional setting (with quite low institutional ownership). Information production and dissemination by financial analysts have a significant effect on the efficiency of stock prices. Apart from the role of information production and dissemination, Andrade et al. (2013) suggest that analysts could also mitigate bubbles by coordinating the investors' beliefs to reduce the dispersion, resulting in reducing the resale option component of asset prices. Thus, speculative trading is more likely to be in stocks with low analyst coverage due to the lack of co-ordination mechanism. Consequently, the MAVD effect is mainly produced in small stocks or low analyst coverage stocks.

Panel A of Table 16 reports the average equally-weighted excess returns and risk-adjusted returns of the double dependent sorts on firm size and MAVD. At the end of each month t, we sort stocks into three size groups (small, medium, large), and we then sort stocks in each size group based on their MAVD into ten decile portfolios. The portfolios are rebalanced monthly. The MAVD hedge portfolio yields large average monthly return of 2.3270% (t-statistic = 9.681) for small stocks but smaller returns of 1.0825% (t-statistic = 3.111) for large stocks. The difference in average monthly excess returns of the MAVD hedge portfolio between the smallest and largest groups is economically and statistically significant; that is 1.2445% (t-statistic = 4.100). We obtain similar patterns from other risk-adjusted returns. The evidence confirms our conjecture that the MAVD–return pattern is significantly strengthened in small stocks with high speculative tendency.

Panel B of Table 16 presents the average equally-weighted excess returns and risk-adjusted returns of the double dependent sorts on analyst coverage and MAVD. We first sort stocks into three groups based on the level of coverage measured by the number of analysts, and we then sort stocks in each analyst coverage group based on their MAVD into ten decile portfolios. The MAVD hedge portfolio generates large monthly average returns of 1.8614% (t-statistic = 5.338) for low analyst coverage stocks but much smaller returns of 0.7876% (t-statistic = 1.777) for high analyst coverage stocks. Furthermore, the difference in average monthly excess returns of the MAVD hedge portfolio between the lowest and highest analyst coverage groups is 1.0738% (t-statistic = 3.062), which is highly significant. These results indicate that the negative MAVD–return pattern is significantly stronger in stocks with low analyst coverage, driven by speculative trading.

In conclusion, the MAVD effect is stronger in stocks with speculative attributes. Our findings show that the MAVD effect is likely to be attributable to individual speculative trading behavior.

Table 16
Dependent double sorting based on speculative attributes and MAVD.

Portfolios	Low	2	High	L–H
Panel A. Size				
Low	2.2013***	1.4442**	0.7639	
	(2.945)	(2.055)	(1.233)	
High	−0.1257	−0.4054	−0.3186	
	(−0.167)	(−0.580)	(−0.447)	
L–H	2.3270***	1.8496***	1.0825***	1.2445***
	(9.681)	(7.145)	(3.111)	(4.100)
FF3a	2.3799***	1.9632***	1.2714***	1.1085***
	(9.204)	(6.966)	(3.557)	(3.709)
CH4a	2.4020***	1.9802***	1.2361***	1.1659***
	(9.018)	(6.764)	(3.390)	(3.735)
FF5a	2.2313***	1.9469***	1.1473***	1.0839***
	(8.377)	(6.870)	(3.343)	(3.547)
Panel B. The number of analyst coverage				
Low	2.0293**	1.6240**	1.4147*	
	(2.436)	(2.123)	(1.898)	
High	0.1679	−0.0112	0.6271	
	(0.191)	(−0.013)	(0.715)	
L–H	1.8614***	1.6352***	0.7876*	1.0738***
	(5.338)	(3.917)	(1.777)	(3.062)
FF3a	1.9852***	1.8941***	0.9590**	1.0262***
	(6.266)	(4.360)	(2.520)	(3.127)
CH4a	1.9647***	1.8547***	0.8773**	1.0874***
	(5.887)	(4.025)	(2.251)	(3.153)
FF5a	2.0645***	1.8094***	0.9938**	1.0707***
	(6.084)	(4.466)	(2.468)	(3.219)

This table reports the equally-weighted average monthly excess returns, risk-adjusted returns of portfolios dependently double sorts on size (analyst coverage) and MAVD. At the end of each month t, we sort stocks into three size (analyst coverage) groups, and we then sort stocks in each size (analyst coverage) group based on their MAVD into ten decile portfolios. The portfolios are rebalanced monthly. The "L–H" hedge portfolio is computed as the difference between the returns of the lowest and highest MAVD deciles. "L–H" in the last column is the difference of returns of the MAVD hedge portfolio between the highest and lowest speculative tendency. Factor returns are from CSMAR, and factor models include: the Fama and French (1993) three-factor model, Carhart's (1997) four-factor factor, and Fama and French (2015) five-factor model. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

5. Further discussion

5.1. MAVD, volume premium and volume shocks

Volume shock (Bali et al. 2014) is related to investor attention and visibility of stocks (Barber and Odean 2008). In this subsection, we examine whether MAVD–return pattern is a repackage of volume shock effect in a regression framework that includes both MAVD and volume shocks. Following Bali et al. (2014) and Zhong et al. (2018), we construct two proxies of volume shocks, including (1) VOSHOCK1, defined as the negative difference between illiquidty and its past 12-month average, and standardize the difference by its volatility; (2) VOSHOCK2, defined as the difference between volume and its past 12-month average, and standardize the difference by its volatility.

Table 17 provides the results of Fama and MacBeth (1973) regressions. We find that the coefficients on MAVD are significantly negative in all specifications after controlling for volume shocks. For example, in regression (1), before controlling for other well-known firm characteristics, the coefficient on MAVD is −0.0102 with a significant t-statistic of −5.933, while the coefficient on VOSHOCK1 is 0.0010 with an insignificant t-statistic of 1.125. In regression (3), the coefficient on MAVD is −0.0062 with a t-statistic of −2.813, while the coefficient on VOSHOCK2 is −0.0026 with a t-statistic of −3.339. Similar results are obtained after controlling for other well-known firm characteristics in Regression (2) and Regression (4).

Overall, our findings show that MAVD–return pattern is not a repackage of volume shock effect, that is, MAVD also contains predictive information that volume shock cannot provide. Inspired by moving average-based crossing rules, we define MAVD as the difference between the short- and long-term moving averages of trading volume. Thus, MAVD focuses more on reflecting the future trends in trading volume while volume shock focuses more on reflecting the current changes in trading volume.

5.2. MAVD and volatility

In this subsection, we examine the predictive power of MAVD for different groups of stocks that are characterized by different degrees of volatility. Han et al. (2013) are the first to examine the cross-sectional profitability of moving averages of past prices in different volatility portfolios. Technical analysis is usually used by investors to make trading decisions. When stocks are volatile, fundamental signals are likely to be less precise, and hence investors tend to rely more heavily on technical signals. Therefore, we expect to observe a stronger predictive power of MAVD among high volatility stocks.

Table 17
MAVD, volume premium and volume shocks.

	Regression 1	Regression 2	Regression 3	Regression 4
Intercept	0.0207***	0.1061***	0.0179***	0.0492
	(3.315)	(3.311)	(2.806)	(1.544)
MAVD	−0.0101***	−0.0038***	−0.0062***	−0.0052***
	(−6.224)	(−3.018)	(−2.813)	(−3.194)
VOSHOCK1	0.0010	0.0011*		
	(1.125)	(1.840)		
VOSHOCK2			−0.0026***	−0.0027***
			(−3.339)	(−4.495)
SIZE		−0.0042***		−0.0018
		(−3.216)		(−1.396)
BM		0.0064**		0.0068**
		(2.107)		(2.100)
MOM		0.0063*		0.0029
		(1.879)		(0.856)
GP		0.0002		0.0019
		(0.048)		(0.356)
AG		−0.0002		−0.0005
		(−0.337)		(−0.772)
TURN		−0.0038***		−0.0026***
		(−7.144)		(−5.227)
ILLIQ		0.0617***		0.0982***
		(3.629)		(4.819)
PRI		0.0000		0.0000
		(0.367)		(0.403)
IVOL		−0.0030		−0.0056
		(−0.229)		(−0.427)
SR		−0.0305***		−0.0360***
		(−3.616)		(−4.254)

This table reports the average coefficients and their respective Newey-West adjusted t-statistics from cross-sectional regressions of the return in that month on lagged variables including MAVD, volume shocks and other control variables. Following Bali et al. (2014) and Zhong et al. (2018), we construct two proxies of volume shocks, including (1) VOSHOCK1, defined as the negative difference between illiquidty and its past 12-month average, and standardize the difference by its volatility; (2) VOSHOCK2, defined as the difference between volume and its past 12-month average, and standardize the difference by its volatility. The dependent variable is the monthly excess return. The explanatory variables include MAVD, volume shocks, firm size (SIZE), book-to-market ratio (BM), momentum (MOM), gross profitability (GP), asset growth (AG), turnover (TURN), illiquidity (ILLIQ), share price (PRI), idiosyncratic volatility (IVOL) and short-term reversal (SR). Fama–MacBeth t-statistics are reported below the coefficient estimates. Coefficients marked with *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

To test our conjecture, we divide our sample into subsamples based on the stock volatility. Specifically, at the end of each month t, we sort stocks into five groups by their monthly standard deviations estimated using the daily returns, and we then sort stocks in each group into five portfolios based on their MAVD. Table 18 reports the average equally-weighted excess returns and risk-adjusted returns of the MAVD hedge portfolio in different volatility-sorted portfolios. We find that the average monthly excess returns of the MAVD hedge portfolio increase monotonically from the lowest volatility group to the highest volatility group, and the MAVD hedge portfolio in the highest volatility group generates an average monthly excess returns that is about four times (1.6290%/0.4808%) as large as that generated by the MAVD hedge portfolio in the lowest group. The difference in average monthly excess returns of the MAVD hedge portfolio between the highest and lowest volatility groups is 1.1482% with a significant t-statistic of 3.864. We obtain similar results from risk-adjusted returns. Overall, the evidence indicates that the predictive power of MAVD is more pronounced among high volatility stocks rather than among low volatility stocks.

5.3. *Other explanations*

In this subsection, we examine whether market timing can explain the MAVD effect. Following Han et al. (2013), we employ two popular methods to explore this issue. The first method is the quadratic regression of Treynor and Mazuy (1966):

$$R_{j,t} = \alpha_j + \beta_{j1} R_{mkt,t} + \beta_{j2} R_{mkt,t}^2 + \epsilon_{\mathrm{j,t}} \tag{3}$$

where $R_{j,\,t}$ is the excess return on portfolio j in month t, $R_{mkt,\,t}$ is market excess return, $R^2_{mkt,\,t}$ is the squared market excess return. The second is the regression of Henriksson and Merton (1981):

$$R_{j,t} = \alpha_j + \beta_j R_{mkt,t} + \gamma_j R_{mkt,t} I_{R_{mkt}>0} + \epsilon_{\mathrm{j,t}} \tag{4}$$

where $I_{R_{mkt}>0}$ is the indicator function taking the value of one when the market excess return is above zero, otherwise taking the value of zero.

Table 19 provides the results of the above two regressions. Panel A reports the coefficients of the quadratic regression and

Table 18
MAVD in volatility-sorted portfolios.

Portfolios	Low	2	3	4	High	H–L
Low	1.2538*	1.5786**	1.8162**	1.5911**	0.9359	
	(1.865)	(2.280)	(2.499)	(2.213)	(1.293)	
High	0.7730	0.9857	0.7334	0.4222	−0.6931	
	(1.198)	(1.401)	(1.027)	(0.566)	(−0.973)	
L–H	0.4808**	0.5929**	1.0828***	1.1688***	1.6290***	1.1482***
	(2.101)	(2.198)	(4.033)	(3.958)	(5.384)	(3.864)
FF3a	0.4675*	0.5933**	1.0302***	1.1590***	1.6967***	1.2292***
	(1.846)	(2.125)	(3.810)	(4.239)	(6.156)	(4.238)
CH4a	0.4968*	0.6679**	1.0576***	1.1652***	1.5931***	1.0963***
	(1.824)	(2.399)	(3.814)	(4.388)	(5.552)	(3.582)
FF5a	0.5039**	0.5647**	0.9867***	1.1253***	1.6783***	1.1744***
	(2.215)	(2.191)	(3.859)	(3.927)	(5.705)	(4.039)

This table reports the equally-weighted average monthly excess returns, risk-adjusted returns of portfolios dependently double sorts on volatility and MAVD. At the end of each month t, we sort stocks into five groups by their monthly standard deviations estimated using the daily returns, and we then sort stocks in each group into five portfolios based on their MAVD. The portfolios are rebalanced monthly. The "L–H" hedge portfolio is computed as the difference between the returns of the lowest and highest MAVD portfolios. "H–L" is the difference of returns of the MAVD hedge portfolio between the highest and lowest volatility portfolios. Factor returns are from CSMAR, and factor models include: the Fama and French (1993) three-factor model, a four-factor model including Fama–French three-factor and Carhart's (1997) momentum factor, and Fama and French (2015) five-factor model. Newey-West adjusted t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

Table 19
The MAVD effect and market timing.

	TM regression			HM regression		
	Alpha (%)	MKT	MKT_2	Alpha (%)	MKT	MKT_I
Panel A: The MAVD effect						
Low	1.0144***	0.9915***	−0.3247	1.0734**	1.0372***	−0.0878
	(2.817)	(16.775)	(−0.673)	(2.008)	(13.597)	(−0.483)
High	−1.0020***	1.1304***	0.0521	−1.1550***	1.0976***	0.0635
	(−2.952)	(19.147)	(0.130)	(−2.756)	(15.695)	(0.448)
L–H	2.0164***	−0.1389***	−0.3768	2.2284***	−0.0603	−0.1513
	(7.560)	(−2.799)	(−1.106)	(5.896)	(−1.172)	(−1.071)
Panel B: The MAVD effect in volatility-sorted portfolios						
Low volatility	0.5304**	−0.0468	−0.0325	0.4924	−0.0501	0.0064
	(2.199)	(−1.109)	(−0.114)	(1.519)	(−1.140)	(0.057)
2	0.6758***	−0.0303	−0.1054	0.5770*	−0.0365	0.0121
	(2.718)	(−0.668)	(−0.331)	(1.672)	(−0.755)	(0.092)
3	1.2287***	−0.0133	−0.2280	1.2757***	0.0198	−0.0636
	(4.470)	(−0.310)	(−0.729)	(3.297)	(0.436)	(−0.488)
4	1.0760***	−0.0298	0.1859	0.9202**	−0.0777	0.0923
	(4.145)	(−0.592)	(0.494)	(2.355)	(−1.349)	(0.609)
High volatility	1.8152***	−0.0319	−0.2751	1.9510***	0.0221	−0.1040
	(5.500)	(−0.601)	(−0.695)	(3.780)	(0.363)	(−0.623)

This table reports the coefficients of the quadratic regression and Henriksson and Merton's regression of the portfolios based on MAVD, and the MAVD hedge portfolio under different volatility-sorted portfolios. Newey-West adjusted t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

Henriksson and Merton's regression of the portfolios based on MAVD. Following Han et al. (2013), Panel B documents the coefficients of the quadratic regression and Henriksson and Merton's regression of the MAVD hedge portfolio under different volatility-sorted portfolios. We find that market timing alone does not explain the MAVD effect. For example, in Panel A, the alphas of the MAVD hedge portfolio are still significantly positive, 2.0164% with a t-statistic of 7.560 in the quadratic regressions and 2.2284% with a t-statistic of 5.896 in the Henriksson and Merton's regression. In Panel B, from the lowest to the highest volatility groups, the alphas of the MAVD hedge portfolio monotonically increase from 0.5304% to 1.8152%, which are all significant. Thus, our findings suggest that the MAVD effect is not subsumed by the market timing.

6. Conclusion

In this study, we examine the stock return predictability of the distance between short- and long-term moving averages of trading volume (MAVD) in the cross section. We find that MAVD strongly and negatively predicts the cross-section of stocks returns. More importantly, MAVD also contains predictive information that volume shock cannot provide. This predictive power is robust after controlling for other well-documented characteristics that affect stock returns in the cross-section, including firm size, book-to-market, momentum, gross profitability, asset growth, turnover, illiquidity, share price, idiosyncratic volatility and short-term reversal. This negative relation is also robust to a variety of factor models with the additional trend factor proposed by Liu et al. (2019), and to alternative samples, including excluding small or illiquidity stocks and omitting earnings announcement days. Moreover, the predictive power of MAVD on future returns diminishes as portfolio holding months move further away from the portfolio formation month, and becomes insignificant after six months and even reverses at the end of the second year. This predictability pattern over time suggests that stock markets overreact to the information from MAVD and the resulting mispricing is gradually corrected. In addition, the evidence indicates that MAVD provides significant incremental predictive information about future returns beyond that contained in the distance between short- and long-term moving averages of past prices (MAD).

We further investigate whether the predictive information of MAVD is due to risk compensation or mispricing. We find that the MAVD hedge portfolio still yields super normal profits in the context of a variety of factor models, which indicates that this return predictability is not a compensation for bearing more risk. We further provide alternative explanations for the MAVD effect, associated with irrational mispricing. First, we find that the MAVD effect is stronger among stocks with higher limits of arbitrage and more investor attention. Second, we also find that the MAVD effect is stronger in the periods of high sentiment and high investor overconfidence, indicating that the MAVD effect is at least partially caused by mispricing due to investor sentiment and overconfidence. These findings are consistent with the mispricing-based explanations of behavioral finance. Third, the MAVD effect is associated with individual speculative trading, and is stronger in small stocks and stocks with low analyst-coverage. Thus, investors should avoid high volume trend stocks with speculative attributes, which are more likely to be overvalued. However, the MAVD effect cannot explained by the market timing. In further analysis, we find that the predictive power of MAVD is stronger among high volatility stocks, which is consistent with the explanation that investors tend to rely more heavily on technical signals when stocks are volatile.

Declaration of Competing Interest

None.

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