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Expected return, volume, and mispricing[☆]

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Abstract

We find that expected return is related to trading volume positively among underpriced stocks but negatively among overpriced stocks. As such, trading volume amplifies mispricing. Our results are robust to alternative mispricing and trading volume measures, alternative portfolio formation methods, and controlling for variables that are known to have amplification effects on mispricing. By attributing trading volume to investor disagreement, we show that our results are consistent with the recent theoretical model of Atmaz and Basak (2018) in that investor disagreement predicts stock returns conditional on expectation bias.

Keywords: Turnover, Trading volume, Mispricing, Disagreement, Expectation bias

JEL classification: G12, G14, G17, D03

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1. Introduction

Trading volume plays an important role for price discovery, risk sharing, and liquidity provision in the stock market. It affects stock returns as this inherently multi-faceted variable can be related to investor disagreement, volatility, liquidity, investor attention, private information, etc. Cochrane (2007, 2017) argues for a more central role of trading volume and calls such research the *next revolution* of asset pricing.[1] Building on the recent advancement of the anomaly literature, in this paper, we show there exists a novel *volume amplification effect*, and explore its economic mechanism through which trading volume affects stock returns.

Specifically, we find that mispricing is concentrated among high volume stocks as expected return is related to trading volume positively among underpriced stocks but negatively among overpriced stocks. With a five-by-five independent double sort on the mispricing score (MISP) of Stambaugh, Yu, and Yuan (2015) and trading volume from July 1965 to December 2019, among underpriced stocks, the monthly Fama and French (2015) five-factor (FF5) alpha increases in trading volume, from -0.02% for the low volume portfolio to 0.51% for the high volume portfolio. Among overpriced stocks, however, the monthly FF5 alpha decreases in trading volume, from -0.28% for the low volume portfolio to -0.68% for the high volume portfolio. Hence, the monthly FF5 alpha of the underpriced-minus-overpriced (UMO) portfolio is 0.26% among low volume stocks and 1.18% among high volume stocks, with the difference, dubbed the volume amplification effect, equal to 0.93% (t-value $= 4.24$) per month. These results suggest that the volume-return relation is heterogeneous and depends on mispricing, and that mispricing is concentrated among high volume stocks.[2]

In addition to MISP, we consider two alternative mispricing measures that are popular and easy to compute. The first is CAPM alpha, which is the primary performance measure investors use in making their capital allocation decisions and in assessing fund managers (Barber, Huang, and

[1] https://www.johnhcochrane.com/news-op-eds-all/efficient-markets-today.

[2] In this paper, we use "volume-return relation" and "volume amplification effect" interchangeably.

Odean, 2016; Berk and van Binsbergen, 2016). A stock is overpriced if its CAPM alpha is negative and underpriced otherwise. The second measure is a composite alpha, which is the average alpha from five leading asset pricing factor models. A double sort on the CAPM (composite) alpha and trading volume yields similar results to the double sort on MISP and trading volume.

We show that trading volume is different from those variables that are known to have amplification effects on mispricing, consisting of idiosyncratic volatility (IVOL), size, illiquidity, institutional ownership, skewness, and capital gain overhang (Stambaugh, Yu, and Yuan, 2015; Nagel, 2005; Barberis, Jin, and Wang, 2021). After controlling for these competing variables, the volume amplification effect remains significant. Our results continue to hold with several other robustness tests. First, the volume amplification effect is persistent and remains strong up to two years after portfolio formation. Second, while we primarily rely on independent sorts, we find similar results by using NYSE breakpoints and sequential sorts. Third, while we focus on all-but-microcap stocks in our main analyses, the volume amplification effect applies to microcap stocks. Lastly, our results are robust to three alternative measures of trading volume.

To understand the underlying economic mechanism, Atmaz and Basak (2018) provide an insight. In a theoretical model, they consider the average expectation bias and investor disagreement on a stock jointly, and define them as the cross-sectional mean and standard deviation of investors' expectation biases. In equilibrium, after good news, optimistic investors' beliefs get supported and become relatively wealthier through their investment in the stock, which in turn increases their weight in the average expectation bias and makes the overall view on the stock more optimistic. Similarly, after bad news, the overall view on the stock becomes more pessimistic. Moreover, Atmaz and Basak (2018) show that investor disagreement has an amplification effect on the average expectation bias. When the average bias is positive, it is positively related to disagreement and an increase in disagreement leads to more optimism, implying a negative disagreement-return relation. In contrast, when the average bias is negative, it implies a positive disagreement-return relation. In essence, investor disagreement can amplify mispricing when investors' average expectation is biased.

Our main finding that trading volume amplifies mispricing is consistent with Atmaz and Basak's (2018) model if trading volume captures investor disagreement and MISP captures investor expectation bias. Indeed, these two facts are well recognized in the finance literature. For example, Diether, Malloy, and Scherbina (2002), Boehme, Danielsen, and Sorescu (2006), and Banerjee (2011), among many others, measure investor disagreement with trading volume. Also, Stambaugh, Yu, and Yuan (2015) motivate MISP from the perspective of investors' biased expectations, which is further highlighted by Engelberg, McLean, and Pontiff (2018). In this paper, we provide new supporting evidence that analyst forecast bias is concentrated among high volume stocks and the volume amplification effect is weakened substantially after accounting for the amplification effect of analysts' return (or earnings) forecast dispersion.

Our conclusion that trading volume amplifies mispricing could suffer from a potential identification issue. It is possible that there is an omitted variable that drives both trading volume and stock returns. To mitigate this concern, we identify two natural experiments, Regulation Fair Disclosure (Reg FD) and the 9/11 terrorist attacks, to explore how an exogenous shock to trading volume and disagreement affects our volume amplification effect. We show that the implementation of Reg FD increases trading volume and disagreement, consistent with Bailey, Li, Mao, and Zhong (2003), and consequently, the volume amplification effect becomes stronger. In contrast, after 9/11, stocks that suffer from analyst casualties in the terrorist attacks experience a significant reduction in trading volume and disagreement, and the volume amplification effect becomes weaker among these affected stocks. Since both Reg FD and 9/11 are exogenous and they affect trading volume and disagreement, our results provide some additional support that trading volume amplifies mispricing.

Because trading volume could contain information beyond investor disagreement, we consider four alternative explanations (arbitrage costs, liquidity, investor attention, and information asymmetry), and find that none of them undermines our explanation that trading volume mainly captures investor disagreement. This finding supports Hong and Stein (2007), Daniel and Hirshleifer (2015), and Barberis (2018), who all suggest that investor disagreement is arguably the most sensible explanation to trading volume.

We also analyze the investment implications of the volume amplification effect. Following the literature, we have focused on using the FF5 to assess abnormal returns. But a portfolio strategy using the MISP of Stambaugh, Yu, and Yuan (2015) is likely to generate FF5 abnormal returns as MISP is unexplained by the FF5. On the other hand, the strategy may not add any investment value if its returns can be explained by the Stambaugh and Yuan (2017) four-factor model (SY4) because an investor can trade the four factors instead. Hence, the volume amplification effect (or any other related anomaly effects) should be assessed by using the corresponding factor model that explains the mispricing scores.[3] In this paper, the volume amplification effect is still significant relative to SY4, but it is weaker both economically and statistically. The reason is that our measure of the volume amplification effect is related to MISP, and so is affected to some degree by the underlying factors. For example, if we use another measure of mispricing, such as the firm-level alpha from the SY4 model itself, the volume amplification effect becomes stronger. In short, from an investment perspective, trading volume together with a mispricing score can identify even more underpriced and overpriced stocks, with economic value going beyond trading the original factors.

Our paper focuses on mispricing interpretations. However, some may argue that there is no such a thing as mispricing. The MISP and the CAPM (composite) alpha could alternatively be interpreted as measures that reflect time-varying risk premiums in a rational asset pricing model. An interesting question is that if the original mispricing or anomalies can be explained by rational models, what rational model can explain both the original anomalies and the volume amplification effect. We leave this as an open issue for future research.

Our paper contributes significantly to the trading volume literature. Theoretically, the famous no-trade theorem implies zero volume in a perfect market with rational investors of common knowledge (see, e.g., Back, 2017). To explain the vast real world trading volume, traditional

[3]We are extremely grateful to the referee for this and numerous other important comments and suggestions that have helped us improve the paper immensely.

models assume that investors are heterogeneous in their information and private investment opportunities [see Lo and Wang (2009) for a review]. But the volume-return relation is typically one direction only in those models. While consistent with Atmaz and Basak (2018), our empirical results support and call for a more general theory of trading volume that models trading volume and mispricing directly, along with IVOL and other important variables, to isolate and understand better the role of trading volume in return dynamics. In other words, our paper provides unique empirical evidence that can be useful for building models for the next revolution of asset pricing.

Empirically, our paper is closely related to Conrad, Hameed, and Niden (1994) and Lee and Swaminathan (2000), but is different in three important aspects. First, Conrad, Hameed, and Niden (1994) find a positive volume-return relation among past one-week losers and Lee and Swaminathan (2000) find a negative volume-return relation among past medium horizon losers, but they do not observe a significant relationship among past winners. That is, they do not find both positive and negative volume-return relations for different stocks at the same time. Second, the results start to reverse in one week in Conrad, Hameed, and Niden (1994) and one year in Lee and Swaminathan (2000), but our results do not display such a reversal pattern. Third, Conrad, Hameed, and Niden (1994) argue that their results are consistent with microstructure theories and interpret trading volume as private information, and Lee and Swaminathan (2000) relate trading volume to market misperceptions (i.e., high volume stocks are more likely to be glamour stocks), whereas we attribute trading volume to investor disagreement.

The rest of the paper is organized as follows. Section 2 describes data. Section 3 presents the main empirical results and a number of robustness tests along several dimensions. Section 4 explores the economic rationales and exploit the two exogenous events. Section 5 shows that the volume amplification effect continues to show up when the Stambaugh and Yuan (2017) model is used as the benchmark. Section 6 concludes.

2. Data

We obtain monthly stock returns from the Center for Research in Security Prices (CRSP) from July 1963 to December 2019. Since some variables require two years of initial data, our portfolios and regression analyses start from July 1965, except for those with data only available since the 1980s (e.g., institutional ownership). We include all domestic common stocks listed on the NYSE, Amex, and Nasdaq exchanges (CRSP share code of 10 or 11). Every month, we exclude stocks without valid previous price (with the CRSP return code of "C"), not trading on the current exchange in that month (with the CRSP return code of "B"), and with missing return due to missing price in that month (with the CRSP return code of "−99.0"). We also drop stocks whose prices are less than five dollars at portfolio formation. Since microcap stocks represent only 3% of the total market capitalization but account for 60% of the number of stocks (Hou, Xue, and Zhang, 2020), in our main analyses we drop microcap stocks, i.e., stocks that are smaller than the 20th percentile of market equity for NYSE stocks. Our sample has approximately 998,000 firm-month observations.

A key variable of interest is trading volume, i.e., the past three-month average turnover (we use log turnover in regressions to reduce the concern of skewness). The monthly turnover is the number of shares traded during a month divided by the number of shares outstanding at the end of the month (see, e.g., Datar, Naik, and Radcliffe, 1998; Nagel, 2005). To address the double counting issue, we follow Gao and Ritter (2010) and divide the volume of Nasdaq stocks by 2.0 before January 2001, by 1.8 for the rest of 2001, by 1.6 for 2002-2003, and leave it unchanged after that. Lo and Wang (2009) examine turnover, share volume, dollar volume, number of trades, trading days per year, and contracts traded, and recommend turnover as the most natural measure of stock market trading volume, because it is more consistent with standard portfolio theory and equilibrium asset pricing models. Nevertheless, we also explore five alternative trading volume measures in Section 3.5, and find qualitatively similar results with three alternative measures of trading volume.

Another key variable of interest is the mispricing score (MISP) of Stambaugh, Yu, and Yuan (2015), which is a rank variable ranging from 1 to 100, with high value indicating overpricing and low value indicating underpricing. This measure is proposed to capture the mispricing of a stock by averaging its ranking percentile for each of the 11 anomalies, consisting of net stock issues, composite equity issues, accruals, net operating assets, asset growth, investment to assets, financial distress, O-score, momentum, gross profitability, and return on assets. Other variables are defined where they are used.

3. Empirical results

In this section, we present our main empirical results: The volume-return relation depends on mispricing, positive among underpriced stocks and negative among overpriced stocks. As a result, mispricing is concentrated among high volume stocks.

3.1. Mispricing and trading volume

The simplest way to see our results is to examine portfolios from a double sort on MISP and trading volume.[4] Specifically, at the end of each month, we form five-by-five portfolios with an independent double sort on MISP and trading volume. We value-weight these 25 MISP-volume portfolios and hold them for one month.

Table 1 presents the main finding of this paper. Panel A reports the average returns of the 25 MISP-volume portfolios. Among underpriced stocks, the average return increases monotonically in trading volume, from 0.61% for the low volume portfolio to 1.01% for the high volume portfolio, with the high-minus-low (H-L) portfolio's average return equal to 0.40% (t-value $= 1.89$). In contrast, among overpriced stocks, the average return decreases monotonically in trading volume, from 0.35% for the low volume portfolio to -0.25% for the high volume portfolio, with the H-L

[4] A single sort on trading volume yields an insignificant volume-return relation, and the results are reported in the Online Appendix.

portfolio's average return equal to −0.59% (t-value = −2.36). For stocks with relatively medium MISP, the average returns of the H-L portfolios are insignificant from zero.

According to Panel A, the volume-return relation is positive among underpriced stocks and negative among overpriced stocks. As a result, the underpriced-minus-overpriced (UMO) portfolio has a much higher average return in the high volume quintile than that in the low volume quintile. Specifically, the average return of the UMO portfolio is 0.27% (t-value = 1.92) among low volume stocks and 1.26% (t-value = 6.58) among high volume stocks, and therefore, the latter is four times larger than the former, which is vividly depicted by the top panel of Fig. 1.

Although the average return of the H-L portfolio among overpriced stocks is slightly larger in magnitude than that among underpriced stocks (−0.59% vs. 0.40%), the average return of the H-L portfolios across the MISP quintiles is equal to 0.08%. The reason is that the average returns of the H-L portfolios in the second to fourth MISP quintiles are all positive (0.27%, 0.30%, and 0.03%). Indeed, the average return of 0.08% after controlling for MISP is close to the insignificant average return of the H-L portfolio with a single sort on trading volume (0.03%). This finding explains why one cannot detect a significant volume-return relation in an unconditional setting.

To examine whether risks can explain the volume-return relation, Panel B of Table 1 reports the FF5 alphas of the 25 MISP-volume portfolios. Similar to Panel A, among underpriced stocks, the FF5 alpha increases from −0.02% for the low volume portfolio to 0.51% for the high volume portfolio, with the difference equal to 0.53% (t-value = 3.16). In contrast, among overpriced stocks, the FF5 alpha decreases from −0.28% for the low volume portfolio to −0.68% for the high volume portfolio, with the difference equal to −0.39% (t-value = −2.16). For stocks in the second and third MISP quintiles, the FF5 alphas also increase in general, and the H-L portfolios' FF5 alphas are significantly positive. For stocks in the fourth MISP quintile, the H-L portfolio's FF5 alpha is statistically indifferent from zero. Taken together, the FF5 alpha is 0.27% for the low volume UMO portfolio and 1.26% for the high volume UMO portfolio, and the difference, dubbed the volume amplification effect, is equal to 0.93% (t-value = 4.24). The bottom panel of

Fig. 1 plots the FF5 alphas of the UMO portfolios across the volume quintiles and indicates that the mispricing in high volume stocks is much stronger than that in low volume stocks.

Panel C of Table 1 reports the Hou, Xue, and Zhang (2015) q-factor alphas. Due to the factors availability, the sample period in this panel is January 1967 to December 2019. The results are similar to Panel B, and the volume-return relation continues to be positive among underpriced stocks and negative among overpriced stocks. Hence, mispricing is concentrated among high volume stocks.

As mispricing is time-varying (Stambaugh, Yu, and Yuan, 2015), we expect the volume amplification effect to also fluctuate over time. Also, Schwert (2003), McLean and Pontiff (2016) and Green, Hand, and Zhang (2017), among others, show that most of the anomalies attenuate or disappear after academic publications. A natural question is whether this decaying pattern applies to the volume amplification effect. We address this question in two ways. First, we calculate the monthly average returns and FF5 alphas of the UMO portfolios within each year and plot the time-series dynamics in Fig. 2, where the FF5 alpha in year t is the average pricing error of year t (i.e., the intercept plus the average residual within year t) from the full sample regression of the UMO portfolio returns on the FF5 factors. Second, following Novy-Marx (2012), we run Fama-MacBeth regressions of one-month-ahead stock returns on MISP, volume, and their interaction with a ten-year rolling window approach. Fig. 3 plots the regression coefficient on the interaction, which represents the volume amplification effect in a regression setting. Consistent with the literature, both figures show that the volume amplification effect increases from 1980, reaches its maximum in 2003, declines thereafter, and becomes insignificant in the past two years. As put forth by Green, Hand, and Zhang (2017) in explaining the declining profits of characteristics-based anomalies, the likely reasons are the passing of the Sarbanes-Oxley Act, the accelerating of 10-Q and 10-K filing requirements by the SEC, and the introduction of autoquoting by the NYSE, which lead to falling costs of exploiting mispricing. In addition, the increased computing power may also have dampened the arbitrage costs and mispricing.

In the Online Appendix, we present two more robustness results. First, while we focus on all-but-microcap stocks in our main analyses, the volume amplification effect applies to microcap stocks. Recent studies, such as Novy-Marx and Velikov (2016) and Hou, Xue, and Zhang (2020), suggest that arbitrage costs are a dominant factor in driving mispricing among microcap stocks. This is the reason our main analyses focus on all-but-microcap stocks. When applying the same MISP-volume double sort procedure to the microcap stocks, we find that the mispricing magnitude is larger among the microcap stocks than that among the non-microcap stocks. More importantly, the volume-return relation remains the same as Table 1. Second, complementing the earlier portfolio formation, we consider two alternatives. The first is to form portfolios using breakpoints of the NYSE stocks, and the second is to use a sequential sort. The results show that the volume amplification is not affected by these alternative portfolio formation methods.

Trading volume has been widely studied in the finance literature, but its relation with expected return is ambiguous. Theoretically and empirically, it can be positive, negative, or insignificant (see, e.g., Kyle, 1985; Campbell, Grossman, and Wang, 1993; Wang, 1994; Blume, Easley, and O'Hara, 1994; He and Wang, 1995; Lee and Swaminathan, 2000; Chordia, Subrahmanyam, and Anshuman, 2001; Gervais, Kaniel, and Mingelgrin, 2001; Scheinkman and Xiong, 2003; Johnson, 2008; Banerjee, 2011; Kaniel, Ozoguz, and Starks, 2012; Barberis, Greenwood, Jin, and Shleifer, 2018; Hou, Xue, and Zhang, 2020; Israeli, Kaniel, and Sridharan, 2020). This subsection reconciles the literature and shows that the failure to find a significant volume-return relation is because the relation is positive among underpriced stocks and negative among overpriced stocks. This heterogeneous relation implies that mispricing is concentrated among high trading volume stocks.

3.2. Alternative mispricing measures

Since the volume-return relation depends critically on MISP, it is useful to know how sensitive the results are to alternative measures of mispricing. We consider below two types of alpha measures, which are considerably easier to compute than MISP.

The first is CAPM alpha. It is a widely used performance measure by investors in making portfolio allocation decisions (Barber, Huang, and Odean, 2016; Berk and van Binsbergen, 2016). The second is a composite alpha, which is the average alpha of five factor models, including the CAPM model, Fama-French three-factor model, Fama-French three factors plus a momentum factor model, Fama-French five-factor model, and Hou, Xue, and Zhang (2015) q-factor model.

Each month, we estimate the alpha of each individual stock for each factor model with its past two-year observations. Theoretically, a negative alpha indicates overpricing, and a positive alpha indicates underpricing. As in the previous section, we form five-by-five portfolios with an independent double sort on the CAPM (composite) alpha and trading volume. All portfolios are value-weighted and held for one month.

Panel A of Table 2 reports the FF5 alphas of portfolios sorted by the CAPM alpha and trading volume. Similar to Table 1, among the positive CAPM alpha (underpriced) stocks, the FF5 alpha increases from 0.16% for the low volume portfolio to 0.62% for the high volume portfolio, with the difference equal to 0.46% (t-value = 2.41). Among the negative CAPM alpha (overpriced) stocks, the FF5 alpha decreases from −0.19% for the low volume portfolio to −0.60% for the high volume portfolio, with the difference equal to −0.41% (t-value = −2.35). Hence, the FF5 alpha of the positive-minus-negative alpha (PMN) portfolio increases monotonically in trading volume, from 0.34% (t-value = 1.55) among the low volume stocks to 1.22% (t-value = 5.58) among the high volume stocks. Therefore, the volume amplification effect equals 0.87% (t-value = 3.71), implying that mispricing is concentrated among high volume stocks.

Panel B of Table 2 reports the FF5 alphas of portfolios sorted by the composite alpha and trading volume. Apparently, the FF5 alpha increases in trading volume among the stocks with positive composite alphas, but decreases in trading volume among the stocks with negative composite alphas. As a result, the FF5 alpha of the positive-minus-negative alpha (PMN) portfolio monotonically increases from 0.26% (t-value = 1.32) for the low volume portfolio to 1.11% (t-value = 5.60) for the high volume portfolio. In this case, the volume amplification effect is 0.85%

(t-value $= 3.83$). Collectively, Table 2 shows that the finding that volume amplifies mispricing continues to exist when we use alternative mispricing measures.[5]

Note that our results show a persistence pattern in the CAPM alpha and are consistent with Grundy and Martin (2001), who find that a momentum strategy based on alpha can be more profitable than one based on raw returns. However, this finding is different from Horenstein (2020) who finds a CAPM alpha reversal pattern. The reason is that he forms portfolios annually at the end of each December, and holds them for the next one year. In contrast, we construct portfolios monthly and hold them only for one month. Hence, both papers are consistent with the notion that alpha is persistent in a short horizon and reversing in a medium horizon.

We note that our methodology can be further extended to nonlinear models. The reason is that alpha can be defined for any asset pricing model,

$$\alpha_t = \mathrm{E}_t(R_{t+1}) - \mathrm{E}_t(m_{t+1}R_{t+1}), \tag{1}$$

where m_{t+1} is the stochastic discount factor and R_{t+1} is the excess return. Theoretically, a stock is underpriced if its alpha is positive and overpriced otherwise. A natural question is whether the CAPM (composite) alpha or MISP captures more information in the interaction with trading volume. To address this question, we perform a double sort on MISP and CAPM alpha. The Online Appendix shows that the predictive power of the CAPM alpha is subsumed by MISP in terms of excess returns. Indeed, the superior information of MISP is not surprising if one notes that it is measured as of time t with more timely information, while the alpha is an average of the mispricing over the estimation horizon.

To sum up, our main finding that volume amplifies mispricing is robust to alternative mispricing measures.

[5] Instead of two-year rolling windows, we also consider five-year rolling windows and find quantitatively similar results, which are reported in the Online Appendix.

3.3. *Other amplification effects*

While our paper seems the first to study the impact of the interaction between MISP and volume, we cannot claim that trading volume is the only variable that exerts an amplification effect on mispricing. Indeed, there are at least six other variables in the literature that have varying degrees of amplification effects.

Stambaugh, Yu, and Yuan (2015) posit that IVOL captures arbitrage costs and it has an amplification effect on mispricing. Besides, firm size, illiquidity, and institutional ownership also are recognized as arbitrage costs measures and can amplify mispricing (see, e.g., Sadka and Scherbina, 2007; Nagel, 2005; Fama and French, 2016). More recently, Barberis, Jin, and Wang (2021) show that prospect theory-motivated skewness and capital gain overhang (Grinblatt and Han, 2005), together with stock volatility, can explain a dozen of anomalies. Thus, an important question is whether the volume amplification effect still exists after controlling for the effects of these competing variables.

We apply two approaches to address this question. The first approach is to use the popular triple sort to control for one of the effects at a time. We report the results of controlling for the IVOL and size effects in the Online Appendix, and omit the results of controlling for the other four as they have much weaker impacts on the volume-return relation, which can be easily seen from the second approach. We have three observations. First, the volume amplification effect is not subsumed by the IVOL effect. The FF5 alpha is 0.50% (t-value $= 2.35$) among low IVOL stocks and 1.29% (t-value $= 4.26$) among high IVOL stocks. Second, the volume amplification effect remains strong after controlling for the size effect. It is 0.55% (t-value $= 2.35$) among small stocks and 0.84% (t-value $= 3.58$) among large stocks, with the latter about 50% larger than the former. This result implies that trading volume is unlikely attributable to arbitrage costs or financial constraints, which are generally stronger among small stocks.

Third, the heterogeneous volume-return relation remains significant among underpriced stocks, but becomes insignificant in general among overpriced stocks after controlling for the IVOL or size effects. For example, among the underpriced large stocks, the FF5 alpha increases from -0.05% for the low volume portfolio to 0.47% for the high volume portfolio. In contrast, among the overpriced large stocks, although the corresponding value decreases in trading volume, the difference between the high and low volume portfolios is only -0.31% and statistically insignificant. This result seems to suggest that while trading volume could contain information overlapping with IVOL and size among the overpriced stocks, it goes beyond them and contains unique information among the underpriced stocks (Sections 4.1 and 4.4 examine IVOL and trading volume further).

The second approach is to use adjusted volume. Specifically, each month we first estimate adjusted volume as the residual from a cross-sectional regression of trading volume on one or more amplification variables, and then apply the earlier double sort to MISP and the adjusted volume. Compared to the triple sort approach, the adjusted volume approach allows us to control for multiple amplification effects simultaneously.

Panel A of Table 3 reports the FF5 alphas of the 25 MISP-adjusted volume portfolios after controlling for IVOL. The volume-return pattern shown in Table 1 continues to hold, albeit weaker. The main reason is that the volume-return relation becomes insignificant among overpriced stocks after controlling for the IVOL effect. Nevertheless, the magnitude of mispricing among the high volume stocks is still much larger than that among the low volume stocks. The FF5 alpha is 0.87% (t-value $= 5.05$) for the high volume UMO portfolio and 0.40% (t-value $= 2.96$) for the low volume UMO portfolio, leaving the volume amplification effect equal to 0.46% (t-value $= 2.24$). In short, after controlling for IVOL, the volume amplification effect remains statistically significant. In Panel B, we obtain virtually the same results when we control for both the IVOL and size effects.

In Panel C, we simultaneously control for IVOL, size, illiquidity, and institutional ownership, while in Panel D we include two more controls, skewness and capital gain overhang. In these two panels, we find stronger results than Panels A and B. For example, the volume amplification effect is 0.46% in Panel A when controlling for IVOL alone, whereas it is 0.70% when controlling for all the six amplifying variables simultaneously. The reason is that the volume amplification effect has become stronger since 1980s, and the starting period for Panels C and D is March 1980 due to data availability. Overall, IVOL seems the most likely variable that can weaken the volume amplification effect.

In sum, while the volume amplification effect is weakened to some extent after controlling for other mispricing amplifying variables, it remains statistically and economically significant.

3.4. Duration of volume amplification effect

Once portfolios are formed in month t, we follow their returns into the future for h months. Table 4 presents the FF5 alphas of the 25 MISP-volume portfolios in months $t+6$, $t+12$, $t+24$, $t+36$, $t+48$, and $t+60$, respectively. The volume amplification effect decays gradually and lasts two years into the future. For example, the volume amplification effect is 0.82% (t-value $= 3.86$) in month $t+6$ and 0.41% (t-value $= 1.87$) in month $t+24$. It is still significant at the 10% level in month $t+36$ if we use a one-sided test (0.33% with a 1.41 t-value). However, after $t+36$, the volume amplification effect completely disappears.

In the literature, Lee and Swaminathan (2000) find a negative volume-return relation among past losers. They interpret the high volume stocks are more likely to be glamour stocks, suggesting that the losers are largely over-priced by our measure, and hence their result is consistent with ours. However, based on past winners, there is no clear volume-return relation, suggesting that past returns alone cannot tell a complete story about the volume-return relation. Additionally, their winner-minus-loser portfolio return tends to reverse after one year since portfolio formation, whereas Table 4 shows that the volume amplification effect does not reverse but decays gradually. Overall, their results and motivations are different from ours and their volume-return relation is limited to loser stocks.

3.5. Alternative volume measures

Following Lo and Wang (2009) and many others, we focus on the level of trading volume in this paper. In the literature, however, for different research purposes, trading volume can be measured differently. Here we review five major alternatives, three of which measure the level of trading activity and two measure information beyond the level.

The first is transaction-based volume. Conrad, Hameed, and Niden (1994) define trading volume as the growth rate in the number of trades, rather than shares, and explore the volume-return relation at a weekly horizon. We extend it to our framework and sort stocks based on MISP and monthly growth in the number of trades. Different from Conrad, Hameed, and Niden (1994), we use TAQ data and include all common stocks traded on the NYSE, AMEX, and Nasdaq exchanges. As such, our sample period is January 1993 to December 2019. Panel A of Table 5 shows that our main finding is robust to this alternative definition. The FF5 alpha is 0.38% for the low volume UMO portfolio and 0.84% for the high volume UMO portfolio, with the volume amplification effect equal to 0.46% (t-value = 1.90).

The second is earnings-adjusted volume. Theoretically, He and Wang (1995) argue that trading volume should increase around earnings announcement days. Empirically, Berkman, Dimitrov, Jain, Koch, and Tice (2009) find that trading volume does spike around the earnings announcement days. The question is whether it is the volume spikes that drive our findings. To address this issue, following Gervais, Kaniel, and Mingelgrin (2001), we exclude three days' trading volume around earnings announcements in computing our volume measure. Panel B shows that the results are similar to Table 1.

The third is based on alternative formation and holding periods. Instead of defining trading volume based on the past three-month average turnover, we consider using the past six-month average turnover as in Lee and Swaminathan (2000) and Hou, Xue, and Zhang (2020). Panel C of Table 5 shows that this measure generates similar results to those with the past three-month average turnover. With other formation and holding periods, the results are similar and reported in the Online Appendix.

The fourth is abnormal volume or shock to trading volume. In their influential paper, Gervais, Kaniel, and Mingelgrin (2001) find that abnormal volume positively predicts future stock returns, and attribute it to investor attention, which in turn affects the demand and price of the stock. To extend their analysis to our framework, for each stock each month, by comparing its last week trading volume of the month to the average of its previous nine weeks' trading volume, we assign it a score from one to five, with five representing the highest volume shock. We then combine the volume shock score with MISP and do an independent double sort to form 25 portfolios. Since a stock with high abnormal volume can possibly have the same level of trading volume as a stock with low abnormal volume, we do not expect that the interaction between MISP and abnormal volume produces the same pattern as the interaction between MISP and the level of volume. Indeed, Panel D of Table 5 shows that the abnormal volume-return relation is always positive, regardless of whether a stock is overpriced or underpriced. This result confirms Gervais, Kaniel, and Mingelgrin (2001) and suggests that abnormal volume seems a convincing attention measure, whereas the level of trading volume captures something different (Section 4.1 ties it to investor disagreement).

The fifth is dollar volume, which is measured as the shares traded in the month times the stock price. Brennan, Chordia, and Subrahmanyam (1998) find a negative relation between returns and dollar volume and attribute the latter to a proxy for liquidity. Panel E of Table 5 reports the results from a double sort on MISP and dollar volume. There are two observations. First, conditional on MISP, dollar volume does not have any predictive power on future stock returns. Second, there is no significant difference in mispricing between the low and high dollar volume stocks. As a result, there is no dollar volume amplification effect.

In sum, the volume amplification effect continues to exist with the three level measures of trading volume, but it disappears for abnormal volume and dollar volume.

4. Economic interpretation

In this section, we turn to a behavioral interpretation for our empirical findings. In a theoretical model, Atmaz and Basak (2018) consider the average expectation bias and investor disagreement on a stock jointly, and define them as the cross-sectional mean and standard deviation of investors' expectation biases. In equilibrium, after good news, optimistic investors' beliefs get supported and become relatively wealthier through their investment in the stock, which in turn increases their weight in the average expectation bias and makes the overall view on the stock more optimistic. Similarly, after bad news, the overall view on the stock becomes more pessimistic. Moreover, Atmaz and Basak (2018) show that investor disagreement has an amplification effect on the average expectation bias. When the average bias is positive, it is positively related to disagreement and an increase in disagreement leads to more optimism, implying a negative disagreement-return relation. In contrast, when the average bias is negative, it is negatively related to disagreement, and an increase in disagreement leads to more pessimism, implying a positive disagreement-return relation. In sum, investor disagreement alone does not generate mispricing, but it can amplify mispricing when investors' average expectation is biased. In the context of this paper, the heterogeneous volume-return relation is consistent with Atmaz and Basak (2018) if trading volume measures investor disagreement and MISP measures investor expectation bias. We show below that it is indeed the case.

4.1. Investor disagreement

Consider first the link between trading volume and investor disagreement. The survey studies of Hong and Stein (2007), Daniel and Hirshleifer (2015), and Barberis (2018) illustrate that a trade, in general, is driven by one of the three motives: liquidity needs, private information, and disagreement due to speculation/overconfidence. While the first two motives may qualitatively explain the relation between volume and return, it is unlikely to quantitatively explain the magnitude of trading volume. By estimating a structural model, Kelley and Tetlock (2013) find that, without investor disagreement, trading volume would be smaller by a factor of 100 than what is observed, which suggests that investor disagreement is the dominant driver of trading volume. This evidence is perhaps why numerous studies, such as Diether, Malloy, and Scherbina (2002) and Banerjee (2011), use trading volume to measure investor disagreement. Jones, Kaul, and Lipson (1994, p.633) note that "the apparent consensus even among academics that volume....reflects the extent of disagreement about a security's value based on either differential information or differences of opinion." Similarly, Chen, Hong, and Stein (2001) posit that "...trading volume proxies for the intensity of disagreement."

Although the literature that proxies trading volume for investor disagreement is vast, we provide some new empirical evidence. We show that trading volume is positively associated with two economically clean disagreement measures, analysts' return forecast dispersion and earnings forecast dispersion. While the literature has widely used earnings forecast dispersion as a disagreement measure since Diether, Malloy, and Scherbina (2002), there are only a few studies on analysts' return forecasts (see, e.g., Engelberg, McLean, and Pontiff, 2020). We seem the first to proxy investor disagreement with return forecast dispersion. The intuition is that, unlike earnings forecasts, return forecasts provide direct and actionable information to explicitly guide investors to trade a stock, either buy or hold or sell. The advantage of using these two dispersion measures is that they are constructed based on expectations directly.

Specifically, we measure return forecast dispersion as the cross-sectional standard deviation of analysts' return forecasts, where return forecasts of a stock are defined as the 12-month-ahead analysts' target prices forecasted in month t divided by the actual stock price at the beginning of month t. Similarly, we measure earnings forecast dispersion as the cross-sectional standard deviation of analysts' earnings forecasts scaled by stock price. The sample period is April 1999 to December 2019 for return forecast dispersion and May 1982 to December 2019 for earnings forecast dispersion.

Panel A of Table 6 presents the value-weighted return forecast dispersions and earnings forecast dispersions of the 25 MISP-volume portfolios at portfolio formation. Within each MISP quintile, both dispersion measures increase in trading volume. For example, return forecast dispersion increases from 8.48% to 13.70% among underpriced stocks and from 9.29% to 20.50% among overpriced stocks, respectively. Also, the two dispersion measures are strictly larger among high volume stocks than among low volume stocks. This finding confirms Diether, Malloy, and Scherbina (2002) that trading volume is a reasonable disagreement measure, and lends direct support to Atmaz and Basak (2018) that investor disagreement has an amplification effect on investor expectation bias.

In Panel B, we assess how return or earnings forecast dispersion affects the volume amplification effect. We address this question via Fama-MacBeth regressions. All independent variables are cross-sectionally normalized so that the regression coefficient on each variable represents the change in expected stock return in response to one standard deviation increase in that variable. Regressions 1 through 4 are about return forecast dispersion and Regressions 5 through 8 are about earnings forecast dispersion. Specifically, Regression 1 regresses one-month-ahead stock returns on MISP, volume, and their interaction, and yields a significantly negative regression coefficient on the interaction between MISP and volume (i.e., the volume amplification effect), thereby reaffirming Table 1 that trading volume amplifies mispricing. Regression 2 replaces trading volume with IVOL and also delivers a negative coefficient on the interaction between MISP and IVOL. This result has two interpretations. First, as argued by Stambaugh, Yu, and Yuan (2015), IVOL captures arbitrage costs and exacerbates mispricing. Second, according to Atmaz and Basak (2018), IVOL can be also driven by investor disagreement. Indeed, some empirical studies, such as Boehme, Danielsen, and Sorescu (2006) and Berkman, Dimitrov, Jain, Koch, and Tice (2009) have proposed to measure investor disagreement with IVOL or return volatility. This explains our earlier results that the volume amplification effect can be weakened after controlling for IVOL.

Regression 3 is a direct test of Atmaz and Basak (2018), which shows that return forecast dispersion has strong power in predicting future stock returns, positively among underpriced stocks and negatively among overpriced stocks. Regression 4 is the general case. When volume, IVOL, and disagreement are considered simultaneously, the regression coefficients on the interactions of

MISP with volume and IVOL become insignificant and marginally significant, respectively. In contrast, the interaction of MISP with return forecast dispersion remains relatively stable. This result suggests that the disagreement amplification effect almost subsumes the volume and IVOL amplification effects and provides support for Atmaz and Basak (2018) that both volume and IVOL are likely driven by investor disagreement.

Regressions 5 and 6 repeat the tests in Regressions 1 and 2, but extend the sample period by almost 20 years to 1982. Over this extended period, both the volume and IVOL amplification effects become stronger with larger regression coefficients in magnitude on their interactions with MISP. Regression 7 replaces return forecast dispersion with earnings forecast dispersion and yields a similar result as Regression 3. In Regression 8, when considered simultaneously, the volume and IVOL amplification effects are weakened substantially, although they are still significant. The regression coefficients on the interactions of mispricing with volume and IVOL decrease in magnitude from -0.68 to -0.43 and from -0.85 to -0.49, respectively. The corresponding value with earnings forecast dispersion also reduces but with a smaller magnitude.

Collectively, Table 6 suggests that trading volume and IVOL can be proxies for investor disagreement, and their effects on stock returns are weakened substantially after controlling for analysts' return or earnings forecast dispersion.[6]

4.2. Investor expectation bias

Consider now the link between MISP and investor expectation bias. Stambaugh, Yu, and Yuan (2015) motivate their MISP by arguing that investors have biased expectations. Subsequent studies show that MISP is closely linked to investor expectation bias. For instance, by analyzing institutional trading of anomalies, Edelen, Ince, and Kadlec (2016) find that institutions tend to buy overpriced stocks and argue that expectation bias, rather than limits-to-arbitrage, is more likely the

[6]This result does not necessarily mean that return or earnings forecast dispersion is a better measure for investor disagreement, because trading volume can be used for firms with rare or no analyst coverage. For example, it can be used to measure investor disagreement before the 1980s when analyst forecast data are unavailable. Also, trading volume can measure disagreement beyond institutional investors.

key driver of mispricing. Engelberg, McLean, and Pontiff (2018) extend Stambaugh, Yu, and Yuan (2015) to 97 anomalies and show that expectation bias is likely the only explanation.

In this section, we test two implications from Atmaz and Basak (2018). The first implication is about expectation bias in the cross section, which is defined as realized earnings minus the median of analyst forecasts divided by stock price (Livnat and Mendenhall, 2006). Among the underpriced stocks that are more likely to have experienced negative news, the expectation biases are more likely to be dominated by pessimistic investors. As a result, the ex post analyst forecast errors are expected to be positive, and the higher the trading volume/investor disagreement, the more positive the forecast errors (i.e., the more negative the expectation biases). Similarly, among the overpriced stocks, we expect that the higher the trading volume, the more negative the forecast errors (i.e., the more positive the expectation biases).

Panel A of Table 7 reports the ex post analyst forecast errors of the 25 MISP-volume portfolios. As expected, the forecast errors are positive among the underpriced stocks and negative among the overpriced stocks. This finding suggests that on average, investors are pessimistic about underpriced stocks and optimistic about overpriced stocks. That is, when the trading volume increases, the expectation biases become more negative among underpriced stocks and more positive among overpriced stocks. As such, extreme forecast biases are concentrated in high volume/disagreement stocks, consistent with our hypothesis that MISP captures the average expectation bias of individual investors.

The second implication is about expectation bias in time series. Since expectation bias is driven by investor disagreement and it varies over time, we expect that the volume amplification effect to be also time-varying. Following Stambaugh, Yu, and Yuan (2015), we use the Baker and Wurgler (2006) investor sentiment index to proxy for the aggregate expectation bias, and examine how the volume amplification effect varies in the high and low sentiment periods, where a high (low) sentiment month is one in which the value of the Baker and Wurgler (2006) orthogonalized sentiment index at the end of the previous month is above (below) the median value over the July

1965 to December 2018 sample period.[7]

For each of the 25 MISP-volume portfolios, we run the following regression:

$$R_{i,t} = a_H d_{H,t} + a_L d_{L,t} + b\text{MKT}_t + c\text{SMB}_t + d\text{HML}_t + e\text{RMW}_t + f\text{CMA}_t + \varepsilon_{i,t}, \tag{2}$$

where $d_{H,t}$ and $d_{L,t}$ are dummy variables indicating the high or low sentiment period in month t. Table 8 presents the estimates of a_H, a_L, and $a_H - a_L$, respectively. As expected, the negative volume-return relation among the overpriced stocks is more pronounced in the high sentiment periods. Among the overpriced stocks in Panel A, the FF5 alpha monotonically decreases in trading volume, from -0.14% for the low volume portfolio to -0.93% for the high volume portfolio, resulting a difference of -0.79% (t-value $= -3.17$). In comparison, following the low sentiment periods among the overpriced stocks in Panel B, the FF5 alpha does not monotonically decrease and the differential between the high and low volume portfolios has a negligible FF5 alpha of -0.01% (t-value $= -0.04$), which is consistent with Stambaugh, Yu, and Yuan (2015) that overpricing is concentrated in high sentiment periods.

Interestingly, the positive volume-return relation among the underpriced stocks is significant in both the high- and low-sentiment periods. The volume amplification effect is also stronger in the high sentiment periods. Following the high sentiment periods, among the underpriced stocks, the FF5 alpha increases from 0.03% for the low volume portfolio to 0.70% for the high volume portfolio, with the difference equal to 0.67% (t-value $= 2.34$). In contrast, following the low sentiment periods, the FF5 alpha increases from -0.07% for the low volume portfolio to 0.39% for the high volume portfolio, with the difference equal to 0.46% (t-value $= 2.14$). These results suggest that arbitrage costs in Stambaugh, Yu, and Yuan (2015) are unlikely to explain the positive volume-return relation among the underpriced stocks.

Panel C of Table 8 presents the difference between Panels A and B. The FF5 alpha differential

[7] The results with the Baker and Wurgler (2006) raw sentiment index are similar and reported in the Online Appendix.

of the UMO portfolios between the high and low sentiment periods is -0.19% among the low volume stocks and 0.82% among the high volume stocks. As a result, the volume amplification effect is 1.00% stronger in the high sentiment periods than that in the low sentiment periods. In the Online Appendix, we show that this result continues to hold when we examine the volume amplification effect in the aggregate high and low disagreement periods. Overall, Table 8 shows that the volume amplification effect is stronger among the overpriced stocks during the high sentiment periods.

4.3. Exogenous shocks to trading volume

On our volume amplification results, there could be a potential identification issue. It is possible that there is an omitted variable that affects trading volume and stock returns simultaneously. To mitigate this concern, in this section, we identify two natural experiments to show how exogenous shocks to trading volume and disagreement affect the volume amplification effect.

4.3.1. The Reg FD effect

To reduce information disparities between individual and institutional market participants, the Securities and Exchange Commission (SEC) has implemented Regulation Fair Disclosure (Reg FD) since October 23, 2000. It prohibits firms from disclosing material information to subsets of market participants before its public dissemination. The purpose is to improve the flow of information to financial markets.

In assessing the impacts of Reg FD, Bailey, Li, Mao, and Zhong (2003) find that trading volume and investor disagreement rise around earnings announcement days after the introduction of Reg FD, which are especially pronounced among small, information-poor, and unprofitable firms (Agrawal, Chadha, and Chen, 2006). They conclude that Reg FD impairs the ability of financial analysts to form opinions and reach consensus on interpreting earnings information, which consequently increases disagreement and stimulates trading volume. In this sense, Reg FD provides us with a unique setting to assess how an exogenous increase in trading volume affects the volume amplification effect.

In the spirit of Bailey, Li, Mao, and Zhong (2003), we define October 2000 as the event month and post (pre) Reg FD period as November 2000 to October 2001 (October 1999 to September 2000). We use panel regressions to show whether the volume amplification effect becomes stronger in the post Reg FD period. To proceed, we define a dummy that equals one in the post Reg FD period and zero otherwise. For all panel regressions, we control for firm characteristics such as size and book-to-market, and use standard errors that are double clustered by firm and time.

First, we show that the adoption of Reg FD increases trading volume and investor disagreement significantly. We use monthly trading volume, rather than the abnormal trading volume in Bailey, Li, Mao, and Zhong (2003), to make the results consistent with our setup. Also, as shown in Section 4.1, because analysts' return forecast dispersion better subsumes the predictive information in trading volume, we use it as the investor disagreement measure in this section. The first two columns of Panel A in Table 9 show that trading volume and investor disagreement increase significantly after implementing Reg FD. In these two columns, we control for firm fixed effects but not time fixed effects, because the latter are collinear with the Reg FD dummy. In the post Reg FD period, trading volume and investor disagreement increase by 1% and 3.7%, which are highly significant.

Then, to examine how Reg FD affects the volume amplification effect, we run the following panel regression:

$$
\begin{aligned}
R_{i,t+1} \quad = \quad & \beta_1 \mathrm{MISP}_{i,t} + \beta_2 \mathrm{Volume}_{i,t} + \beta_3 \mathrm{MISP}_{i,t} * \mathrm{Volume}_{i,t} + \beta_4 \mathrm{MISP}_{i,t} * \mathrm{Volume}_{i,t} * \mathrm{Reg\ FD}_t \\
& + \beta_5 \mathrm{IVOL}_{i,t} + \beta_6 \mathrm{MISP}_{i,t} * \mathrm{IVOL}_{i,t} + \beta_7 \mathrm{MISP}_{i,t} * \mathrm{IVOL}_{i,t} * \mathrm{Reg\ FD}_t \\
& + \gamma' \mathrm{Controls}_{i,t} + \alpha_i + \alpha_t + \alpha_0 + \varepsilon_{i,t+1}. \qquad (3)
\end{aligned}
$$

The regression coefficient of interest is β_4. It represents the increase in the volume amplification effect because of implementing Reg FD, and is expected to be significantly negative. The dummy variables α_i and α_t are the firm and time fixed effects. Besides firm characteristics, we also control for the IVOL effect, as it is the most likely variable that can weaken the volume amplification effect (see Table 3). The result is reported in the forth column of Panel A in Table 9. As expected, β_4 is -0.314 with a t-value of -5.91, suggesting that the volume amplification effect in the post Reg FD period is statistically stronger than that in the pre Reg FD period.

To mitigate the concern that our volume amplification effect could be driven by other possible market-wide events around the Reg FD, we conduct a placebo test. We check all the one year windows and find that the performances of the market and value factors over April 1981 to March 1982 are the closest to that over the period of November 2000 to October 2001; the market and value returns are -2.20% and 2.70% over April 1981 to March 1982, and they are -2.32% and 2.74% over November 2000 to October 2001. This period is the only period where the return differences are less than 20% for both the market and value factors. Therefore, we choose March 1981 as the pseudo-event month in the placebo test, and examine the effects of this pseudo-Reg FD over the March 1980 to March 1982 period.

The third and fifth columns of Panel A in Table 9 reports the results of the placebo test. In column 3, trading volume does not increase, but decreases with an insignificant magnitude of 0.2% after this pseudo-event. In column 5, the volume-amplification effect is not significant, and even has an opposite sign, compared with that after the actual Reg FD implementation. Hence, our result that the adoption of Reg FD exaggerates the volume amplification effect seems unlikely to be driven by other unobserved shocks.

To sum up, Reg FD, which affects stock returns via the trading volume and disagreement channels, provides a direct support for our main finding that trading volume amplifies mispricing.

4.3.2. The 9/11 effect

On September 11, 2001, some financial analysts are killed in the terrorist attacks, especially those working for Keefe, Bruyette & Woods and Sandler O'Neill & Partners in the World Trade

Center, and many others are heavily affected. This provides an event that allows for assessing how terrorism-induced analyst casualties affect the volume amplification effect.

Our tests are motivated by Cuculiza, Antoniou, Kumar, and Maligkris (2021), who show that a salient event such as 9/11 can have disproportional effect on the behavior of analysts who cover the same stocks but with different distances to the center of the event. Specifically, they find that, after terrorist attacks, analysts located near the attacks issue relatively more pessimistic earnings forecasts compared with other analysts who cover the same firm. These pessimistic forecasts are more likely below the consensus forecast and more accurate, and they are independent of any preexisting trends in analyst pessimism and current economic conditions. In our setting, we treat the loss of analysts on a stock as a salient event for that stock and this shall affect the behavior of the remaining analysts who cover the same stock as they are close to the lost analyst. Because the affected analysts who could have been overly optimistic now issue more pessimistic and more accurate forecasts, we expect lower analyst forecast dispersion and trading volume for a firm that experiences analyst casualties. Based on this implication, we examine the volume amplification effect among the affected firms after 9/11.

We identify 31 analyst casualties by matching the 9/11 Memorial with the IBES analyst recommendation files, and track 337 firms they cover as the affected firms.[8] To mitigate the concern that the affected firms are different from those unaffected by 9/11, we identify control firms by matching the sample in terms of size, number of analysts, and industry before 9/11. Specifically, each month, we independently sort stocks into 25 groups according to firm size, 5 groups according to the number of analysts, and the Fama-French 17 industries according to the SIC code. For each affected stock, we match it to stocks that have the same firm size, number of analysts, and industry. In doing so, we construct a control group consisting of 756 stocks over the pre-9/11 period.

In Panel B of Table 9, we explore whether 9/11 causes a decrease in trading volume and investor

[8] http://edition.cnn.com/SPECIALS/2001/memorial/lists/by-name/index.html.

disagreement for the affected firms relative to the unaffected firms over the September 2000 to September 2002 event period, which ranges from one year before to one year after 9/11. We define two dummy variables, Post_t and Treat_i, where Post_t is a time dummy that equals one after 9/11 and zero otherwise, and Treat_i is a firm dummy that equals one for affected firms and zero for control firms. With panel regressions of trading volume and investor disagreement on $\text{Post}_t * \text{Treat}_i$, we find that both trading volume investor disagreement in the affected firms experience a significant decrease after 9/11.

In the third column of Panel B in Table 9, we explore whether the volume amplification effect becomes weaker after 9/11 among the affected firms that experience volume and disagreement reductions. To this end, we run the following difference-in-difference panel regression:

$$\begin{aligned}
R_{i,t+1} \quad = \quad & \beta_1 \text{MISP}_{i,t} + \beta_2 \text{Volume}_{i,t} + \beta_3 \text{MISP}_{i,t} * \text{Volume}_{i,t} + \beta_4 \text{MISP}_{i,t} * \text{Volume}_{i,t} * \text{Post}_t \\
& + \beta_5 \text{MISP}_{i,t} * \text{Volume}_{i,t} * \text{Treat}_i + \beta_6 \text{MISP}_{i,t} * \text{Volume}_{i,t} * \text{Post}_t * \text{Treat}_i \\
& + \beta_7 \text{Post}_t * \text{Treat}_i + \beta_8 \text{IVOL}_{i,t} + \beta_9 \text{MISP}_{i,t} * \text{IVOL}_{i,t} + \beta_{10} \text{MISP}_{i,t} * \text{IVOL}_{i,t} * \text{Post}_t \\
& + \beta_{11} \text{MISP}_{i,t} * \text{IVOL}_{i,t} * \text{Treat}_i + \beta_{12} \text{MISP}_{i,t} * \text{IVOL}_{i,t} * \text{Post}_t * \text{Treat}_i \\
& + \gamma' \text{Controls}_{i,t} + \alpha_i + \alpha_t + \alpha_0 + \varepsilon_{i,t+1}. \qquad (4)
\end{aligned}$$

Similar to Reg FD, we control for the IVOL effect. The dummy variables α_i and α_t represent the firm and time fixed effects. We are interested in β_6 and expect it to be statistically positive. Empirically, the result confirms our conjecture. β_6 equals 0.402 with a t-value of 2.35. Therefore, the volume amplification effect is attenuated among the affected firms after 9/11. Because 9/11 is purely exogenous, our results and explanations to trading volume seem not suffering from the identification concern.

4.4. Other possible explanations

In the previous sections, we have shown that trading volume is a sensible measure of investor disagreement and its heterogeneous relation with stock returns can be explained by the recently developed disagreement theory in Atmaz and Basak (2018). However, the literature has also proposed several other explanations, and it is possible that trading volume contains information beyond investor disagreement. In this section, we consider four alternative explanations that could also generate a heterogeneous volume-return relation (i.e., arbitrate costs, illiquidity, investor attention, and private information), and show that our results and explanations are robust after taking them into account.

The first alternative explanation is that trading volume captures arbitrage costs. Since trading volume is positively correlated with IVOL and its relation with stock returns is similar to the IVOL-return relation in Stambaugh, Yu, and Yuan (2015), one may posit that trading volume proxies for arbitrage costs like IVOL. However, this explanation seems unlikely in our context. First, it is unlikely that high volume stocks have higher arbitrage costs than low volume stocks. Second, empirically, in Section 3.3 we show that the volume amplification effect continues to exist even after controlling for IVOL. Instead, as shown in Section 4.1, IVOL could be a proxy for investor disagreement and its effect on stock returns is weakened dramatically after controlling for return or earnings forecast dispersion.

The second alternative explanation is that trading volume captures illiquidity. The lower the volume, the higher the illiquidity. According to Kyle (1985), to compensate for illiquidity, a stock with a higher trading volume requires a lower risk premium, suggesting an unconditional, negative volume-return relation. However, in the spirit of Stambaugh, Yu, and Yuan (2015), illiquidity deters arbitrage activities for both under and overpriced stocks, and so the volume-return relation can be conditional and heterogeneous. Among underpriced stocks, the lower the volume (higher illiquidity), the higher the underpricing, implying a negative volume-return relation. In contrast, among overpriced stocks, the lower the volume (higher illiquidity), the higher the overpricing, implying a positive volume-return relation, which suggests that mispricing is concentrated in low volume stocks. Thus, if trading volume in our context measures illiquidity, its relation with stock returns can be heterogeneous, but it is the opposite from what we have found: It attenuates, rather than amplifies, mispricing.

The third alternative is that trading volume captures investor attention. Attention is a scarce resource, and Gervais, Kaniel, and Mingelgrin (2001) find that limited attention causes investors to overlook useful information and thus some stocks that are out of investors' radar are undervalued. As attention rises, there are more buyers to drive up stock prices, which results in a positive attention-return relation. In the meantime, investors tend to buy stocks with attention-grabbing events (Barber and Odean, 2008). If too much attention is paid to a stock, it may lead to overvaluation, which results in a negative attention-return relation.

The last alternative explanation is that trading volume captures information asymmetry (private information). Wang (1994) and Blume, Easley, and O'Hara (1994) argue that informed investors are more likely to trade on stocks with large mispricing, and trading volume captures the degree of private information. Among underpriced stocks, higher trading volume indicates more underpricing, while among overpriced stocks, higher trading volume indicates more overpricing. As such, mispricing is concentrated among actively traded stocks, and informed trading can produce results similar to ours.

To capture the above four alternative explanations, we consider IVOL, bid-ask spread, abnormal volume (Gervais, Kaniel, and Mingelgrin, 2001), and net arbitrage trading (Chen, Da, and Huang, 2019), as well as their interactions with MISP. We use Fama-MacBeth regressions to examine their impacts on the volume amplification effect while controlling for firm characteristics such as size and book-to-market. In the Online Appendix we show that our results are robust to more alternative measures, such as institutional ownership (Nagel, 2005), Amihud (2002) illiquidity, analyst coverage, and probability of informed trading (PIN) of Easley, Kiefer, O'Hara, and Paperman (1996).

Table 10 presents the results. All independent variables are cross-sectionally normalized so that the regression coefficient on each variable represents the change in expected stock return in response to one standard deviation increase in that variable. The first regression includes MISP, trading volume, and their interaction, but does not include other competing variables. All the coefficients are statistically significant, and their signs are consistent with the double sort results in Table 1. In particular, the coefficient of trading volume is positive, whereas its interaction with MISP is negative, suggesting that trading volume positively predicts future stock returns among underpriced stocks but negatively predicts future stock returns among overpriced stocks.

The second regression controls for the IVOL effect. In this case, the coefficient on the interaction between MISP and volume (i.e, the volume amplification effect) decreases in magnitude from -0.47 to -0.26, but it is still statistically significant. Again, this result is not surprising if one views IVOL as an alternative disagreement measure. Alternatively, if one views that IVOL captures limit-to-arbitrage, then our results show that the volume amplification effect remains significant after taking into account the impact of limit-to-arbitrage. The third regression controls for bid-ask spread. As expected, bid-ask spread predicts future stock returns positively among underpriced stocks but negatively among overpriced stocks. Interestingly, bid-ask spread does not attenuate, but enhance, the volume amplification effect. The fourth regression controls for abnormal volume, a proxy for investor attention. The result shows that abnormal volume predicts future stock returns, reaffirming Gervais, Kaniel, and Mingelgrin (2001), but its interaction with MISP is not significant, suggesting that investor attention does not affect the volume amplification effect.

The fifth regression controls for net arbitrage trading, which is a proxy for private information and measured by the difference between quarterly abnormal hedge fund holdings and abnormal short interest (Chen, Da, and Huang, 2019). In this case, the volume amplification effect becomes even stronger with a larger regression coefficient in absolute value. In the Online Appendix, we find similar results when net arbitrage trading is replaced by PIN, another well-known private information measure. Thus, private information is unlikely to be a successful explanation to the volume amplification effect. Finally, when including all variables into one regression, we find that only the volume and IVOL amplification effects remain significant, while others lose power. Therefore, we conclude that our results are robust to the four alternative explanations.

In sum, our results show that, although trading volume could have multiple facets, it is most likely a measure of investor disagreement, and its amplification effect is robust to alternative explanations.

5. Investment implications

Mispricing is a relative concept that depends on the benchmark model. So far, we have used MISP to identify mispriced stocks that are not explained by the FF5, and then any meaningful trading strategy based on these mispriced stocks is likely to generate FF5 alphas. Hence, to assess the "pure" volume amplification effect, we need to remove part of the FF5 alphas attributable to MISP.

In this paper, the Stambaugh and Yuan (2017) four-factor model (SY4) is the benchmark that explains MISP, and so we should examine whether the volume amplification effect still has a significant alpha relative to SY4. This also has an important investment implication. If the alpha is not significant, then the volume amplification effect is of no value to an investor who trades the SY4 factors. Instead, if the alpha is significant, then the volume amplification effect improves the investor's opportunity set, yielding extra economic values.

Panel A of Table 11 shows that, relative to the SY4, the abnormal return is -0.04% for the low volume UMO portfolio and 0.41% for the high volume UMO portfolio. As a result, the volume amplification effect has an SY4 alpha of 0.45% (t-value $= 1.99$). In contrast to the earlier results, say the FF5 alpha of 0.93% (t-value = 4.24), the magnitude reduces by about half, which in turn reduces the t-value by about half.

There are two notables in the above result. First, the abnormal return of the volume amplification effect decreases once the SY4 is used. Recall that we measure the volume amplification effect by using the diff-in-diff result (i.e., the high volume UMO portfolio minus the low volume UMO portfolio). Any alpha due to MISP (from either the under- or over-pricing) is canceled out. Ideally, if volume has no incremental information about expected returns relative to MISP, our volume amplification measure should have a zero mean. Otherwise, volume does contain incremental information that goes beyond MISP. However, given that the volume amplification effect arises from the interaction between trading volume and the mispricing score, it may have a multiplicative component that depends on the alpha of the mispricing score, consistent with Atmaz and Basak (2018). In terms of their model, the amplification depends on both expectation bias and investor disagreement, where the expectation bias is captured by the mispricing score and the investor disagreement is captured by volume. This explains why the SY4 alpha is smaller than the FF5 alpha.

Second, the amplification effect remains modestly significant both economically and statistically even it is adjusted by the SY4. Economically, the magnitude is comparable with other major anomalies [such as the study by Novy-Marx (2013)] and is typically viewed as significant. Statistically, if the amplification effect were viewed as a new anomaly, it is a conditional one, and depends on the 11 major anomalies in constructing MISP. Hence, the probability of its existence is different from that of a standard new anomaly. Moreover, there are economic rationales for its existence as argued earlier. Therefore, it appears reasonable for us to interpret the statistical significance of the amplification by the usual significance level, and it is indeed significant at the conventional 5% level, when using the SY4 as the benchmark model.

There is a novel "placebo" test of the amplification effect.[9] To see whether the volume is really important or not, we replace it by each of the 11 anomalies in the MISP-volume double sort and examine the resulting amplification effect. Empirically, none of the 11 anomalies can produce a significant amplification effect (see the Online Appendix). This re-assures in a unique way that trading volume is special and its interaction with mispricing generates an amplification effect.

While we do not have an optimal way to extract the maximum amplification effect from a given benchmark asset pricing model, the previous amplification effect can be improved given the SY4 as the benchmark. We can use the firm-level SY4 alpha as the mispricing measure, which is exactly the usual sense of mispricing if we treat the SY4 as the true asset pricing model. By definition, it

[9]We are extremely grateful to the co-editor for this and numerous other insightful comments.

is the firm-level return that cannot be explained by the SY4 model. Panel B of Table 11 reports the results. The abnormal return is 0.25% for the low volume PMN (i.e., positive-minus-negative alpha) portfolio, and 0.89% for the high volume PMN portfolio. Hence, the volume amplification effect has an SY4 alpha of 0.64% (t-value $= 2.72$). Replacing volume by the IVOL and size adjusted volume, Panel C shows that the volume amplification effect remains strong, with an SY4 alpha of 0.72% (t-value $= 3.17$).

In summary, the volume amplification effect is still present when the SY4 is used as the benchmark, and it can significantly expand the investment opportunity set even when an investor trades the SY4 factors.

6. Conclusion

The volume-return relation is one of the fundamental problems in asset pricing and is still an area in great need of research. In this paper, unlike existing empirical results that are largely inconclusive, we document a new finding about the heterogeneity of the volume-return relation across stocks with different levels of mispricing. Among underpriced stocks, the volume-return relation is positive. In sharp contrast, among overpriced stocks, the relation is negative. Therefore, mispricing is concentrated in high volume stocks. Our results are robust to alternative measures of mispricing, to alternative volume levels, and to a number of controls. The results are also alive and well in two natural experiments.

On the economic driving forces, we argue that our results can be explained by the theoretical model of Atmaz and Basak (2018) if trading volume captures investor disagreement and mispricing captures investors expectation bias. Our empirical results not only help reconcile a number of existing studies in the literature, but also go beyond Atmaz and Basak (2018), calling for new asset pricing models that explicitly analyze the role of trading volume, mispricing, IVOL, and other economic variables, to enrich our understanding of the volume-return relation.

As for future research, as one may argue that our findings can still be a risk-return tradeoff, the challenge is to explore what model can generate our volume amplification effect in addition to explaining the associated anomalies. In addition, our methodology may also be applied to study the volume-return relation in the international equity markets, as well as in other asset classes such as bonds and currencies.

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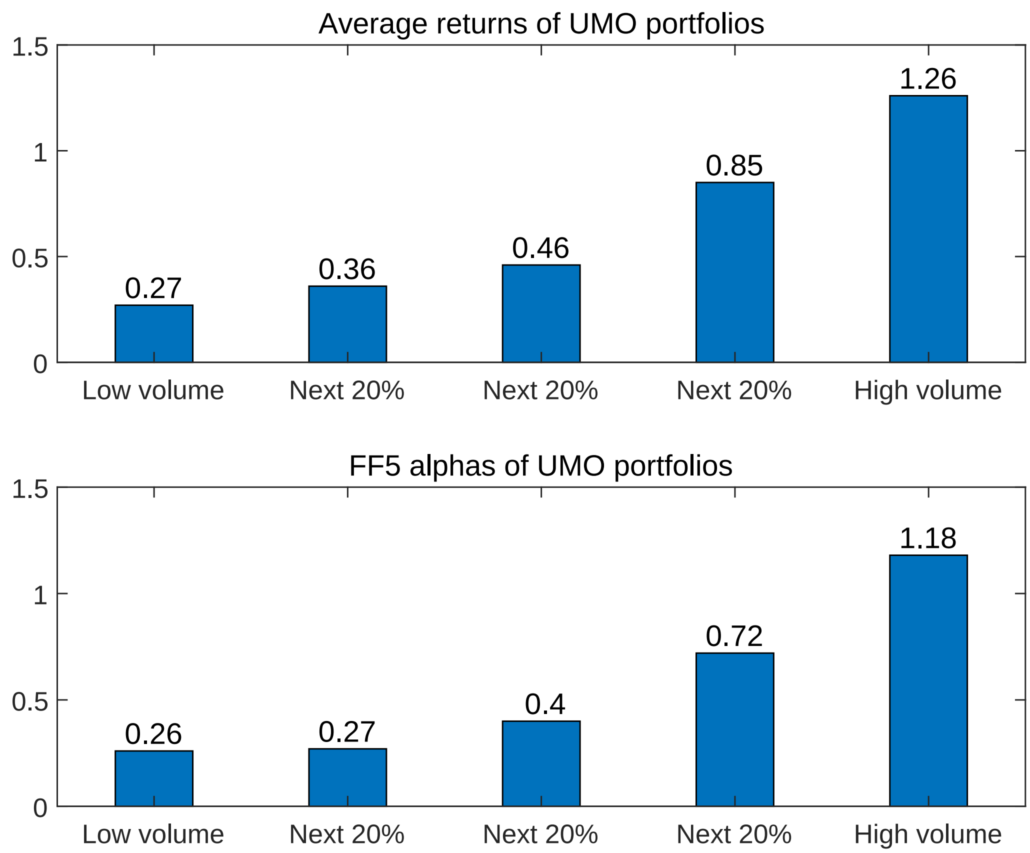

Fig. 1. This figure plots average returns and FF5 alphas of the underpriced-minus-overpriced (UMO) portfolios across volume quintiles sorted by MISP and trading volume, where trading volume is measured by the average turnover in the past three months. Portfolios are value-weighted and held for one month. Firms with market capitalization below the NYSE 20 percentile breakpoints are excluded at portfolio formation. The sample period is July 1965 to December 2019.

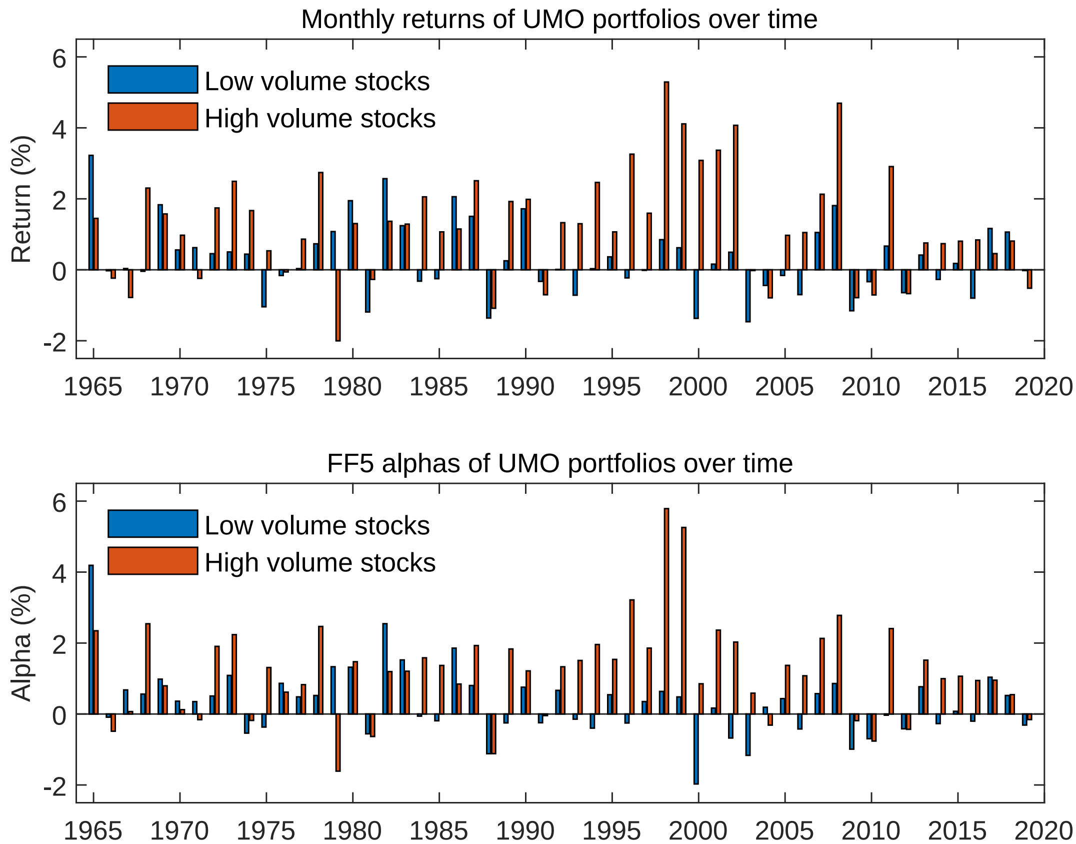

Fig. 2. This figure plots monthly returns and FF5 alphas averaged within each year (to make it easier to read) of the underpriced-minus-overpriced (UMO) portfolios sorted by MISP and trading volume, where trading volume is measured by the average turnover in the past three months. Portfolios are value-weighted and held for one month. Firms with market capitalization below the NYSE 20 percentile breakpoints are excluded at portfolio formation. The sample period is July 1965 to December 2019.

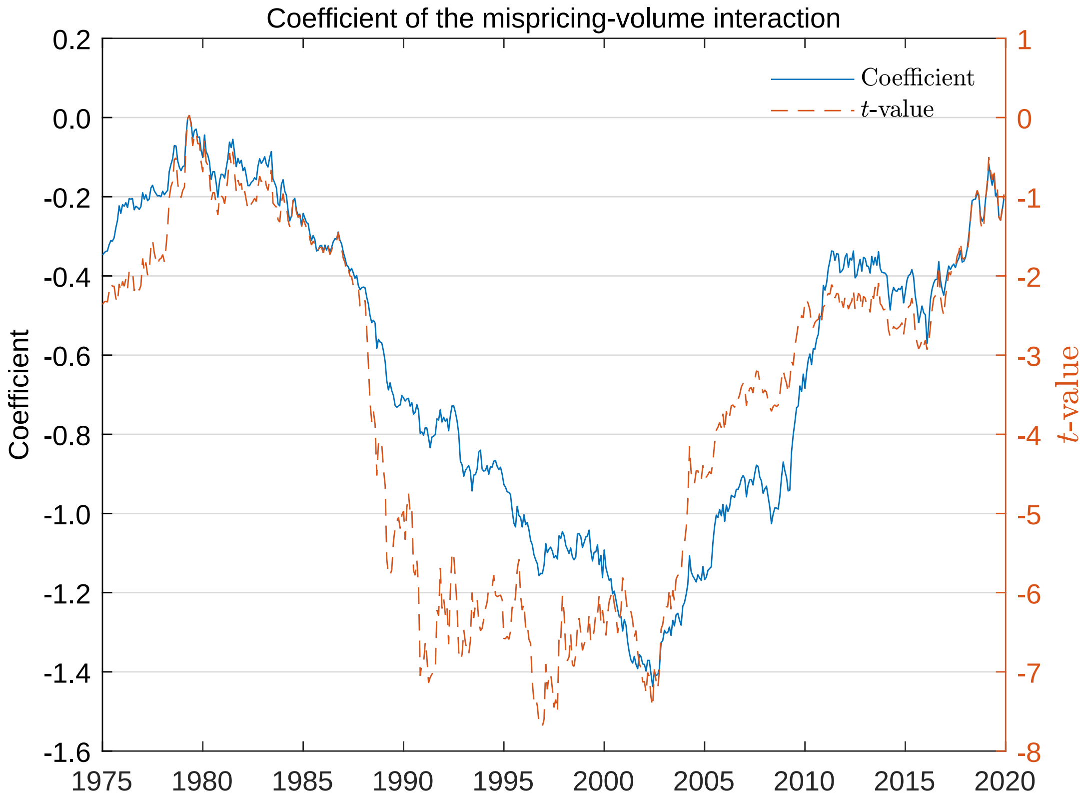

Fig. 3. This figure plots the coefficient of the interaction between MISP and volume in the Fama-MacBeth regression of one-month-ahead stock returns on MISP, trading volume, and their interaction, on a ten-year rolling window basis. The sample period is July 1965 to December 2019.

Table 1

Average returns and alphas of portfolios sorted by MISP and volume

This table reports the average returns, FF5 alphas, and Hou, Xue, and Zhang (2015) four-factor alphas of portfolios sorted by MISP and trading volume, where trading volume is measured by the average turnover in the past three months. t-values are reported in parentheses. Underpriced refers to the quintile with the lowest MISP (most underpriced), and overpriced refers to the quintile with the highest MISP (most overpriced). UMO (H-L) refers to the underpriced-minus-overpriced (high-minus-low volume) spread portfolio. Portfolios are value-weighted and held for one month. Firms with market capitalization below the NYSE 20 percentile breakpoints are excluded at portfolio formation. The sample period is July 1965 to December 2019 for Panels A and B, and January 1967 to December 2019 for Panel C.

	Low volume	2	3	4	High volume	H-L	
Panel A: Average return							
Underpriced	0.61	0.66	0.75	0.96	1.01	0.40	(1.89)
2	0.61	0.59	0.58	0.60	0.88	0.27	(1.23)
3	0.46	0.53	0.54	0.68	0.76	0.30	(1.34)
4	0.59	0.43	0.60	0.37	0.63	0.03	(0.14)
Overpriced	0.35	0.30	0.29	0.11	−0.25	−0.59	(−2.36)
UMO	0.27	0.36	0.46	0.85	1.26	0.99	(4.60)
	(1.92)	(2.57)	(3.57)	(5.50)	(6.58)		
Panel B: FF5 alpha							
Underpriced	−0.02	−0.01	0.12	0.34	0.51	0.53	(3.16)
2	−0.03	−0.10	−0.10	−0.03	0.43	0.46	(2.68)
3	−0.11	−0.16	−0.12	0.06	0.31	0.43	(2.56)
4	−0.01	−0.19	−0.04	−0.23	0.12	0.14	(0.75)
Overpriced	−0.28	−0.28	−0.28	−0.38	−0.68	−0.39	(−2.16)
UMO	0.26	0.27	0.40	0.72	1.18	0.93	(4.24)
	(1.95)	(2.04)	(3.17)	(5.02)	(6.45)		
Panel C: Hou, Xue, and Zhang (2015) alpha							
Underpriced	−0.06	−0.04	0.06	0.24	0.34	0.40	(2.17)
2	−0.03	−0.08	−0.07	−0.09	0.29	0.32	(1.71)
3	−0.10	−0.16	−0.15	0.09	0.21	0.32	(1.74)
4	0.06	−0.18	−0.04	−0.17	0.17	0.11	(0.55)
Overpriced	−0.18	−0.21	−0.20	−0.34	−0.63	−0.44	(−2.18)
UMO	0.12	0.17	0.27	0.58	0.97	0.84	(3.65)
	(0.87)	(1.18)	(1.97)	(3.78)	(5.17)		

Table 2

Alphas of portfolios sorted by CAPM (or composite) alpha and volume

This table reports the FF5 alphas of portfolios sorted by CAPM (or composite) alpha and trading volume, where composite alpha is the average alpha of the CAPM, Fama-French three-, four- (augmented with momentum), and five-factor models, and Hou, Xue, and Zhang (2015) four-factor model. t-values are reported in parentheses. Trading volume is measured by the average turnover in the past three months. Portfolios are value-weighted and held for one month. PMN (H-L) refers to the positive-minus-negative alpha (high-minus-low volume) spread portfolio. The sample period is July 1965 to December 2019.

	Low volume	2	3	4	High volume	H-L	
Panel A: Double sort on CAPM alpha and trading volume							
Positive alpha	0.16	0.27	0.29	0.60	0.62	0.46	(2.41)
2	−0.03	−0.05	−0.02	0.07	0.18	0.21	(1.22)
3	−0.08	−0.10	−0.06	−0.06	−0.25	−0.16	(−1.00)
4	−0.19	−0.21	−0.11	−0.29	−0.26	−0.07	(−0.39)
Negative alpha	−0.19	−0.22	−0.29	−0.47	−0.60	−0.41	(−2.35)
PMN	0.34	0.49	0.58	1.07	1.22	0.87	(3.71)
	(1.55)	(2.33)	(2.83)	(5.15)	(5.58)		
Panel B: Double sort on composite alpha and trading volume							
Positive alpha	0.16	0.22	0.26	0.51	0.56	0.40	(2.10)
2	−0.05	−0.04	0.01	0.09	0.02	0.07	(0.38)
3	−0.07	−0.21	−0.16	−0.15	−0.11	−0.04	(−0.26)
4	−0.09	−0.11	−0.05	−0.28	−0.46	−0.37	(−2.31)
Negative alpha	−0.10	−0.21	−0.24	−0.45	−0.55	−0.45	(−2.69)
PMN	0.26	0.43	0.49	0.95	1.11	0.85	(3.83)
	(1.32)	(2.35)	(2.74)	(5.21)	(5.60)		

Table 3

Alphas of portfolios sorted by MISP and adjusted volume

This table reports the FF5 alphas of portfolios sorted by MISP and adjusted volume, where adjusted volume is the residual from the cross-sectional regression of trading volume on IVOL in Panel A, on IVOL and size in Panel B, on IVOL, size, bid-ask spread (SPD), and institutional ownership (IO) (Nagel, 2005) in Panel C, and on IVOL, size, SPD, skewness, and capital gain overhang (CGO) (Grinblatt and Han, 2005) in Panel D. t-values are reported in parentheses. Underpriced refers to the quintile with the lowest MISP (most underpriced), and overpriced refers to the quintile with the highest MISP (most overpriced). UMO (H-L) refers to the underpriced-minus-overpriced (high-minus-low volume) spread portfolio. Portfolios are value-weighted and held for one month. The sample period is July 1965 to December 2019 for Panels A and B, and March 1980 to December 2019 for Panels C and D.

	Low volume	2	3	4	High volume	H-L	
Panel A: Adjusted by IVOL							
Underpriced	0.00	−0.04	0.12	0.21	0.41	0.41	(2.50)
2	−0.02	−0.12	−0.07	−0.05	0.32	0.34	(2.15)
3	−0.07	−0.05	−0.16	0.01	0.20	0.27	(1.77)
4	−0.07	−0.17	−0.08	−0.16	0.18	0.25	(1.47)
Overpriced	−0.40	−0.26	−0.37	−0.45	−0.46	−0.06	(−0.32)
UMO	0.40	0.22	0.49	0.66	0.87	0.46	(2.24)
	(2.96)	(1.68)	(3.63)	(4.73)	(5.05)		
Panel B: Adjusted by IVOL and size							
Underpriced	0.02	0.19	0.19	0.10	0.49	0.47	(3.00)
2	−0.04	−0.08	0.04	0.03	0.44	0.49	(2.90)
3	−0.17	−0.09	−0.03	0.13	0.32	0.48	(3.10)
4	−0.07	−0.17	−0.10	−0.05	0.21	0.28	(1.59)
Overpriced	−0.44	−0.24	−0.28	−0.44	−0.42	0.02	(0.11)
UMO	0.46	0.43	0.46	0.54	0.91	0.45	(2.20)
	(3.43)	(3.02)	(3.43)	(3.72)	(5.33)		
Panel C: Adjusted by IVOL, size, SPD, and IO							
Underpriced	−0.06	0.10	0.17	0.34	0.46	0.53	(2.12)
2	−0.06	0.09	−0.02	0.09	0.30	0.38	(1.82)
3	−0.04	−0.02	−0.11	−0.11	0.23	0.26	(1.19)
4	0.01	−0.28	−0.10	0.02	0.06	0.05	(0.21)
Overpriced	−0.39	−0.23	−0.47	−0.51	−0.61	−0.22	(−0.78)
UMO	0.32	0.33	0.59	0.85	1.07	0.75	(2.20)
	(1.52)	(1.76)	(2.94)	(3.91)	(3.82)		
Panel D: Adjusted by IVOL, size, SPD, IO, skewness, and CGO							
Underpriced	−0.06	0.22	0.42	0.37	0.45	0.47	(2.10)
2	−0.23	0.05	−0.01	0.25	0.58	0.81	(3.52)
3	−0.07	0.02	0.05	0.15	0.15	0.23	(1.14)
4	−0.25	−0.06	0.01	0.05	0.00	0.14	(0.68)
Overpriced	−0.17	−0.41	−0.31	−0.22	−0.45	−0.23	(−0.95)
UMO	0.11	0.63	0.76	0.61	0.89	0.70	(2.21)
	(0.61)	(3.15)	(3.90)	(2.58)	(3.33)		

Table 4

Alphas in month $t+h$ of portfolios sorted by MISP and volume

This table reports the FF5 alphas in month $t+h$ ($h = 6, 12, 24, 36, 48$, and 60) after portfolio formation. At the end of each month, we independently form 5×5 portfolios based on MISP and trading volume, where trading volume is measured by the average turnover in the past three months. t-values are reported in parentheses. Underpriced refers to the quintile with the lowest MISP (most underpriced), and overpriced refers to the quintile with the highest MISP (most overpriced). UMO (H-L) refers to the underpriced-minus-overpriced (high-minus-low volume) spread portfolio. Portfolios are value-weighted and held for 60 months. The sample period is August 1965 to December 2019.

	Low volume	2	3	4	High volume	H-L	
Panel A: Month $t+6$							
Underpriced	−0.04	0.01	0.07	0.22	0.40	0.44	(2.67)
Overpriced	−0.19	−0.13	−0.30	−0.40	−0.57	−0.38	(−2.15)
UMO	0.15	0.15	0.36	0.62	0.97	0.82	(3.86)
	(1.11)	(1.04)	(2.84)	(3.64)	(5.63)		
Panel D: Month $t+12$							
Underpriced	−0.10	−0.01	−0.03	0.16	0.37	0.47	(2.68)
Overpriced	−0.11	−0.27	−0.26	−0.20	−0.19	−0.08	(−0.43)
UMO	0.02	0.26	0.23	0.36	0.56	0.55	(2.43)
	(0.11)	(1.72)	(1.61)	(2.20)	(3.19)		
Panel B: Month $t+24$							
Underpriced	0.03	0.06	0.02	0.18	0.20	0.17	(0.96)
Overpriced	0.00	−0.25	−0.26	−0.43	−0.25	−0.25	(−1.24)
UMO	0.04	0.31	0.28	0.61	0.45	0.41	(1.87)
	(0.29)	(1.92)	(1.98)	(4.08)	(2.37)		
Panel C: Month $t+36$							
Underpriced	0.04	−0.07	−0.04	0.03	0.29	0.25	(1.34)
Overpriced	−0.19	−0.10	−0.13	−0.19	−0.27	−0.09	(−0.44)
UMO	0.23	0.04	0.09	0.22	0.56	0.33	(1.41)
	(1.68)	(0.26)	(0.62)	(1.48)	(3.02)		
Panel E: Month $t+48$							
Underpriced	−0.03	−0.17	−0.15	0.07	−0.01	0.02	(0.09)
Overpriced	−0.09	−0.31	−0.23	−0.15	−0.09	0.00	(0.01)
UMO	0.06	0.14	0.09	0.22	0.08	0.01	(0.07)
	(0.45)	(0.91)	(0.63)	(1.46)	(0.44)		
Panel F: Month $t+60$							
Underpriced	−0.07	−0.10	−0.02	−0.02	0.17	0.24	(1.27)
Overpriced	−0.13	−0.13	−0.11	−0.09	0.00	0.13	(0.64)
UMO	0.06	0.03	0.09	0.07	0.17	0.11	(0.46)
	(0.40)	(0.19)	(0.51)	(0.48)	(0.93)		

Table 5

Alphas of portfolios sorted by MISP and alternative volume measures

This table reports the FF5 alphas of portfolios sorted by MISP and alternative volume measures. In Panel A, volume is measured by the growth in number of monthly transactions using TAQ data (Conrad, Hameed, and Niden, 1994). In Panel B, the three-day volume around earnings announcements are excluded when calculating the volume. In Panel C, volume is estimated as the average turnover in the past six months instead of three months. In Panel D, we follow Gervais, Kaniel, and Mingelgrin (2001) and use the weekly abnormal trading volume at the end of each month as the volume sorting variable. In Panel E, we use dollar volume instead of turnover (Brennan, Chordia, and Subrahmanyam, 1998). Underpriced refers to the quintile with the lowest MISP (most underpriced), and overpriced refers to the quintile with the highest MISP (most overpriced). UMO (H-L) refers to the underpriced-minus-overpriced (high-minus-low volume) spread portfolio. The sample period is January 1993 to 2019 for Panel A, January 1972 to December 2019 for Panel B, and July 1965 to December 2019 for Panels C, D, and E.

	Low volume	2	3	4	High volume	H-L	
Panel A: Growth in number of transactions							
Underpriced	−0.05	−0.07	−0.15	−0.03	0.38	0.43	(2.88)
Overpriced	−0.43	−0.34	−0.54	−0.52	−0.46	−0.03	(−0.14)
UMO	0.38	0.27	0.39	0.49	0.84	0.46	(1.90)
	(1.79)	(1.70)	(2.12)	(2.51)	(3.98)		
Panel B: Excluding three-day volume around earnings announcements							
Underpriced	−0.16	0.05	0.17	0.38	0.49	0.65	(3.99)
Overpriced	−0.38	−0.36	−0.19	−0.42	−0.57	−0.19	(−1.05)
UMO	0.22	0.41	0.36	0.80	1.06	0.84	(4.00)
	(1.69)	(3.12)	(2.80)	(5.30)	(6.07)		
Panel C: Six-month volume							
Underpriced	0.00	−0.01	0.14	0.33	0.52	0.52	(3.07)
Overpriced	−0.30	−0.20	−0.31	−0.37	−0.73	−0.44	(−2.38)
UMO	0.29	0.19	0.45	0.70	1.25	0.96	(4.39)
	(2.20)	(1.42)	(3.54)	(4.74)	(6.71)		
Panel D: Abnormal volume							
Underpriced	0.03	0.01	0.17	0.16	0.29	0.27	(1.96)
Overpriced	−0.56	−0.55	−0.36	−0.52	−0.13	0.43	(2.70)
UMO	0.59	0.56	0.53	0.68	0.43	−0.17	(−0.84)
	(3.40)	(3.47)	(3.40)	(4.33)	(3.03)		
Panel E: Dollar volume							
Underpriced	0.04	0.06	0.07	0.06	0.12	0.09	(1.02)
Overpriced	−0.54	−0.48	−0.32	−0.37	−0.39	0.15	(1.29)
UMO	0.58	0.54	0.40	0.43	0.52	−0.07	(−0.47)
	(5.88)	(4.99)	(3.81)	(3.67)	(4.24)		

Table 6

The relation between trading volume and investor disagreement

Panel A reports investor disagreement of portfolios sorted by MISP and trading volume at portfolio formation, and Panel B reports the results from the Fama-MacBeth regression of one-month ahead stock returns on MISP, volume, IVOL, and the interactions of mispricing with volume, IVOL, and disagreement, respectively, controlling for firm size and book-to-market. Investor disagreement is measured by analysts' return and earnings forecast dispersions, respectively. Intercept and coefficients on controls are unreported for brevity. Newey-West robust t-values with four lags are reported in parentheses. The sample period is April 1999 to December 2019 for return forecast dispersion and May 1982 to December 2019 for earnings forecast dispersion.

Panel A: Investor disagreement at portfolio formation

	Disagreement: return forecast dispersion							Disagreement: earnings forecast dispersion						
	Low volume	2	3	4	High volume	H-L		Low volume	2	3	4	High volume	H-L	
Underpriced	8.48	9.21	10.91	11.48	13.70	5.18	(16.38)	0.27	0.27	0.31	0.41	0.58	0.31	(13.69)
2	8.52	9.35	11.13	12.10	14.52	6.00	(17.50)	0.31	0.41	0.49	0.55	0.66	0.35	(14.27)
3	8.67	9.36	11.57	12.70	15.95	7.29	(21.05)	0.35	0.42	0.53	0.62	0.78	0.43	(19.26)
4	9.55	9.43	11.57	13.79	17.48	7.93	(12.01)	0.37	0.40	0.59	0.76	0.95	0.57	(25.28)
Overpriced	9.29	10.11	12.48	15.08	20.50	11.10	(22.70)	0.45	0.47	0.74	0.83	1.21	0.74	(25.14)
UMO	−0.90	−0.87	−1.57	−3.58	−6.80	−5.77	(−10.43)	−0.19	−0.21	−0.42	−0.43	−0.63	−0.45	(−13.66)
	(−2.01)	(−3.10)	(−4.68)	(−8.36)	(−15.28)			(−10.05)	(−15.13)	(−11.03)	(−20.52)	(−19.62)		

Panel B: Predict stock returns with volume, IVOL, and investor disagreement

	Disagreement: return forecast dispersion				Disagreement: earnings forecast dispersion			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MISP	−0.09	0.02	−0.08	0.11	−0.07	0.04	−0.23***	0.10
	(−0.96)	(0.18)	(−1.07)	(1.07)	(−1.17)	(0.73)	(−4.50)	(1.55)
Volume	0.33			0.03	0.57***			0.38**
	(1.49)			(0.15)	(3.79)			(2.58)
MISP*Volume	−0.43**			−0.12	−0.68***			−0.43***
	(−2.21)			(−0.54)	(−5.21)			(−3.19)
IVOL		0.55***		0.35*		0.63***		0.34***
		(2.78)		(1.84)		(4.50)		(2.73)
MISP*IVOL		−0.63***		−0.38		−0.85***		−0.49***
		(−2.65)		(−1.57)		(−5.88)		(−3.32)
Disagreement			0.73***	0.60**			0.31**	0.20*
			(2.78)	(2.53)			(2.55)	(1.72)
MISP*Disagreement			−0.79***	−0.63**			−0.46***	−0.32***
			(−2.89)	(−2.53)			(−3.67)	(−2.60)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
adj. R^2	0.06	0.05	0.05	0.07	0.06	0.05	0.05	0.07

Table 7

The relation between MISP and analyst forecast error

This table reports ex post analyst forecast error in the double sort on MISP and trading volume, where the analyst forecast error (in %) of a stock is defined as the realized earnings minus the median of analyst earnings forecasts, divided by stock price, following Livnat and Mendenhall (2006). Underpriced refers to the quintile with the lowest MISP (most underpriced), and overpriced refers to the quintile with the highest MISP (most overpriced). UMO (H-L) refers to the underpriced-minus-overpriced (high-minus-low volume) spread portfolio. The sample period is January 1981 to December 2019.

	Low volume	2	3	4	High volume	H-L	
Underpriced	0.02	0.04	0.03	0.05	0.06	0.04	(3.97)
2	0.02	0.01	0.02	0.03	0.03	0.01	(1.24)
3	0.02	0.00	0.02	0.00	0.02	0.01	(0.52)
4	0.00	0.00	0.02	−0.02	−0.01	−0.01	(−0.60)
Overpriced	−0.05	−0.05	−0.01	−0.04	−0.09	−0.04	(−2.42)
UMO	0.07	0.08	0.04	0.09	0.15	0.08	(4.40)
	(4.78)	(6.69)	(4.20)	(7.75)	(10.48)		

Table 8

The volume amplification effect in high and low sentiment periods

This table reports the FF5 alphas of portfolios sorted by MISP and trading volume in high and low sentiment periods, as well as their differences. Trading volume is measured by the average turnover in the past three months. Underpriced refers to the quintile with the lowest MISP (most underpriced), and overpriced refers to the quintile with the highest MISP (most overpriced). UMO (H-L) refers to the underpriced-minus-overpriced (high-minus-low volume) spread portfolio. Portfolios are value-weighted and held for one month. Alphas are estimates of a_H and a_L in the regression of

$$R_{i,t} = a_H d_{H,t} + a_L d_{L,t} + b\mathrm{MKT}_t + c\mathrm{SMB}_t + d\mathrm{HML}_t + e\mathrm{RMW}_t + f\mathrm{CMA}_t + \varepsilon_{i,t},$$

where $R_{i,t}$ is the excess return of portfolio i in month t, $d_{H,t}$ and $d_{L,t}$ are dummy variables indicating high and low sentiment periods, respectively. A high (low) sentiment month is one in which the value of the Baker and Wurgler (2006) orthogonalized sentiment index at the end of the previous month is above (below) the median value over the July 1965 to December 2018 sample period.

	Low volume	2	3	4	High volume	H-L	
Panel A: High sentiment periods							
Underpriced	0.03	0.08	−0.04	0.40	0.70	0.67	(2.34)
2	−0.08	−0.17	−0.06	−0.16	0.51	0.59	(2.24)
3	−0.13	−0.13	−0.08	0.10	0.33	0.46	(1.97)
4	0.13	−0.15	0.07	−0.10	0.02	−0.11	(−0.43)
Overpriced	−0.14	−0.17	−0.42	−0.44	−0.93	−0.79	(−3.17)
UMO	0.17	0.25	0.38	0.84	1.63	1.45	(4.40)
	(1.00)	(1.25)	(2.07)	(3.79)	(5.55)		
Panel B: Low sentiment periods							
Underpriced	−0.07	−0.07	0.25	0.30	0.39	0.46	(2.14)
2	−0.01	−0.05	−0.12	0.09	0.42	0.44	(1.73)
3	−0.11	−0.20	−0.14	0.02	0.27	0.39	(1.64)
4	−0.18	−0.25	−0.13	−0.32	0.23	0.41	(1.58)
Overpriced	−0.43	−0.42	−0.18	−0.34	−0.42	−0.01	(−0.04)
UMO	0.36	0.35	0.43	0.64	0.81	0.45	(1.44)
	(1.90)	(1.82)	(2.26)	(3.18)	(3.19)		
Panel C: Difference between high and low sentiment periods							
Underpriced	0.10	0.15	−0.29	0.09	0.31	0.21	(0.64)
2	−0.06	−0.12	0.06	−0.25	0.09	0.15	(0.45)
3	−0.01	0.07	0.06	0.07	0.06	0.07	(0.22)
4	0.32	0.10	0.20	0.22	−0.21	−0.53	(−1.48)
Overpriced	0.29	0.25	−0.25	−0.10	−0.51	−0.80	(−2.26)
UMO	−0.19	−0.10	−0.04	0.19	0.82	1.00	(2.38)
	(−0.74)	(−0.37)	(−0.18)	(0.69)	(2.30)		

Table 9

The impacts of Reg FD and 9/11

This table evaluates the impacts of Reg FD and 9/11 on investor disagreement, trading volume, and stock returns, respectively. In Panel A, Reg FD is a time dummy that equals one after October 2000 and zero before October 2000. The sample period is October 1999 to October 2001. We choose March 1981 as the pseudo-event in the placebo test because the market and value (book-to-market spread) portfolios perform in the subsequent one year the most similarly to the post Reg FD period (November 2000 to October 2011). We control for firm and time fixed effects in columns 4 and 5, and only firm fixed effects in columns 1 to 3 because the dummy Reg FD is collinear with the time fixed effects. t-values are reported in parentheses and double clustered by firm and time. In Panel B, Post is a time dummy that equals one after September 2001 and zero before that, and Treat is a firm dummy that equals one for firms experiencing analyst casualties. The control firms are matched with the treatment firms in terms of industry, size, and pre-9/11 analyst coverage. We control for firm and time fixed effects in all regressions, except for the disagreement column, where we control for industry and time fixed effects because of small sample size. t-values are reported in parentheses and double clustered by firm and time (except for the disagreement column). The sample period is September 2000 to September 2002. In both panels, intercept and coefficients on controls are unreported for brevity. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Reg FD

	Volume	Disagreement	Volume (Placebo)	Return$_{+1}$ (%)	Return$_{+1}$ (%) (Placebo)
	(1)	(2)	(3)	(4)	(5)
Reg FD	0.010**	0.037***			
	(2.40)	(4.28)			
PseudoReg FD			−0.002		
			(−0.92)		
MISP				−0.073	−0.022
				(−1.25)	(−0.526)
Volume				−23.110	−29.452***
				(−1.46)	(2.99)
MISP*Volume				0.274*	0.282*
				(1.94)	(1.83)
MISP*Volume*Reg FD				−0.314***	
				(−5.91)	
MISP*Volume*Pseudo-Reg FD					0.078
					(0.469)
IVOL				−23.187	−2.936
				(−1.03)	(−0.16)
MISP*IVOL				0.693***	0.158
				(7.773)	(0.531)
MISP*IVOL*Reg FD				−0.002	
				(−0.01)	
MISP*IVOL*Pseudo-Reg FD					−0.126
					(−0.36)
Controls	yes	yes	yes	yes	yes
adj. R^2	0.65	0.27	0.52	0.04	0.04

Table 9 continued

Panel B: Impacts of 911

	Volume (1)	Disagreement (2)	Return_{+1} (%) (3)
Post*Treat	-0.020^{***}	-0.010^{***}	0.917
	(-4.98)	(-2.63)	(0.64)
MISP			0.056
			(1.45)
Volume			3.417
			(0.40)
MISP*Volume			-0.314
			(-1.23)
MISP*Volume*Post			-0.074
			(-0.44)
MISP*Volume*Treat			-0.079
			(-0.33)
MISP*Volume*Post*Treat			0.402^{**}
			(2.35)
IVOL			-28.29
			(-1.10)
MISP*IVOL			0.955^{*}
			(1.75)
MISP*IVOL*Post			0.368
			(1.12)
MISP*IVOL*Treat			-0.439^{**}
			(-2.37)
MISP*IVOL*Post*Treat			-0.555^{**}
			(-2.04)
Controls	yes	yes	yes
adj. R^2	0.74	0.15	0.18

Table 10

Results from regressing stock returns on MISP and volume with controls

This table reports the results of Fama-MacBeth regressions of one-month-ahead stock returns on MISP, trading volume, their interactions, and other control variables (firm size and book-to-market). Abnormal volume is defined at the monthly frequency following Gervais, Kaniel, and Mingelgrin (2001). Net arbitrage trading is the difference between quarterly abnormal hedge fund holdings and abnormal short interest and measures trading driven by private information (Chen, Da, and Huang, 2019). Newey-West t-values with four lags are reported in parentheses. Intercepts and coefficients on controls are not reported for brevity. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: one-month-ahead excess returns (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
MISP	-0.16^{***}	0.03	0.08	-0.19^{***}	-0.06	0.09
	(-4.43)	(0.78)	(1.32)	(-4.25)	(-1.00)	(1.06)
Volume	0.38^{***}	0.24^{**}	0.77^{***}	0.40^{***}	0.57^{***}	0.33^{**}
	(3.74)	(2.53)	(4.91)	(3.92)	(3.40)	(2.19)
MISP*Volume	-0.47^{***}	-0.26^{***}	-0.92^{***}	-0.48^{***}	-0.62^{***}	-0.33^{***}
	(-5.34)	(-3.12)	(-6.52)	(-5.45)	(-4.83)	(-2.61)
IVOL		0.34^{***}				0.40^{***}
		(4.75)				(3.64)
MISP*IVOL		-0.58^{***}				-0.57^{***}
		(-6.33)				(-3.92)
Bid-ask spread			0.28^{**}			0.04
			(2.35)			(0.31)
MISP*bid-ask spread			-0.34^{***}			-0.04
			(-3.32)			(-0.37)
Abnormal volume				0.11^{**}		0.01
				(2.30)		(0.17)
MISP*Abnormal volume				0.05		0.01
				(0.92)		(1.02)
Net arbitrage trading					0.02	0.12
					(0.28)	(1.15)
MISP*Net arbitrage trading					0.14^{*}	0.07
					(1.79)	(0.83)
Controls	yes	yes	yes	yes	yes	yes
adj. R^2	0.06	0.06	0.06	0.06	0.06	0.07
Start	1965:07	1965:07	1982:12	1965:07	1990:01	1990:01
End	2019:12	2019:12	2019:12	2019:12	2015:12	2015:12

Table 11

SY4 alphas of portfolios sorted by MISP (SY4 alpha) and (adjusted) volume

This table reports the Stambaugh and Yuan (SY4, 2017) four-factor alphas of portfolios sorted by MISP (SY4 alpha) and (adjusted) volume. The firm-level SY4 alpha is calculate for each firm at each point in time with the past two-year observations, and adjusted volume is the residual from the cross-sectional regression of trading volume on IVOL and size. The sample period is July 1965 to December 2019.

	Low volume	2	3	4	High volume	H-L	
Panel A: Sorted by MISP and volume							
Underpriced	−0.13	−0.12	−0.05	0.07	0.13	0.25	(1.36)
2	−0.06	−0.05	−0.09	−0.11	0.23	0.29	(1.53)
3	−0.08	−0.09	−0.05	0.07	0.30	0.38	(2.08)
4	0.08	−0.02	0.11	0.00	0.22	0.14	(0.70)
Overpriced	−0.08	−0.01	0.02	−0.04	−0.28	−0.19	(−0.98)
UMO	−0.04	−0.11	−0.06	0.11	0.41	0.45	(1.99)
	(−0.31)	(−0.83)	(−0.52)	(0.83)	(2.48)		
Panel B: Sorted by firm-level SY4 alpha and volume							
Positive alpha	0.16	0.45	0.27	0.45	0.51	0.34	(1.65)
2	−0.08	−0.13	0.05	0.09	0.10	0.18	(0.98)
3	−0.11	−0.08	−0.11	−0.09	0.03	0.15	(0.83)
4	−0.02	−0.11	−0.01	−0.14	−0.15	−0.13	(−0.78)
Negative alpha	−0.08	−0.01	−0.14	−0.28	−0.38	−0.29	(−1.72)
PMN	0.25	0.46	0.41	0.73	0.89	0.64	(2.72)
	(1.18)	(2.38)	(2.13)	(3.84)	(4.44)		
Panel C: Sorted by firm-level SY4 alpha and adjusted volume							
Positive alpha	0.14	0.47	0.49	0.52	0.57	0.43	(2.21)
2	−0.04	0.01	−0.04	0.21	0.15	0.18	(1.10)
3	−0.08	0.01	0.02	−0.21	−0.05	0.03	(0.21)
4	0.02	0.03	−0.03	−0.21	0.00	−0.02	(−0.15)
Negative alpha	−0.09	−0.10	−0.02	−0.18	−0.38	−0.29	(−1.82)
PMN	0.23	0.58	0.51	0.71	0.95	0.72	(3.17)
	(1.04)	(2.77)	(2.51)	(3.47)	(4.72)		

Online Appendix

Expected Return, Volume, and Mispricing

This appendix provides additional tests and discussions.

A1 Single sort on trading volume

This section shows that a single sort on trading volume produces an insignificant volume-return relation. At the end of each month, we form value-weighted quintile portfolios based on trading volume, and hold them for one month. A long-short spread portfolio that buys stocks with the highest trading volume and sells stocks with the lowest trading volume is denoted as H-L. Table A1 reports the average returns and FF5 alphas. Over the 1965:07–2019:12 sample period, the average returns of the extreme quintile portfolios are very similar (0.53% vs. 0.56%), making the average return of the H-L portfolio as small as 0.03% (t-value $= 0.15$). The FF5 alpha of the H-L portfolio is 0.19% (t-value $= 1.47$). This result is consistent with Hou, Xue, and Zhang (2020), who define trading volume as the average daily share turnover over the prior six months and find that the H-L portfolio (including microcaps) earns a monthly average return of -0.15% (t-value $= 0.54$).

A2 Volume and number of firms at portfolio formation

Table A2 reports the summary statistics of portfolios independently sorted by MISP and trading volume.

Panel A reports the average trading volumes at portfolio formation. We calculate the value-weighted trading volume within each portfolio each month and then average them across the sample period. Although trading volume monotonically increases in MISP, from 9.95% for underpriced stocks to 10.44% for overpriced stocks, the cross-sectional variation is so small that it is unlikely to be a good mispricing measure.

Panel B reports the average mispricing scores. In the MISP-volume double sort, the mispricing scores are flat with respect to volume among underpriced stocks (31.97 for low volume stocks and 31.44 for high volume stocks), and slightly increase in volume among overpriced stocks (66.64 for low volume stocks and 68.42 for high volume stocks). The MISP difference between the low and high volume stocks is so small that it is negligible compared to the MISP difference between the underpriced and overpriced stocks.

Panel C reports the average number of stocks within each portfolio. On average, each portfolio contains at least 50 individual stocks and can be viewed as well diversified. Over the 1965–2019 sample period, we cover 1,530 individual stocks on average within each month, close to the 1,532 stocks in Hou, Xue, and Zhang (2020) over the 1967–2016 period.

A3 Microcap stocks

Recent studies, such as Hou, Xue, and Zhang (2020), suggest that arbitrage costs are a dominant factor in driving mispricing among microcap stocks. This is the reason why our main analyses focus on all-but-microcap stocks. However, since microcap stocks have greater mispricing than others, it will be of interest to see if our conclusion holds for this subsample.

We apply the same MISP-volume double sort procedure to the microcap stocks, and report the FF5 alphas in Table A3. As expected, the magnitude of mispricing is larger among the microcap stocks than that among the non-microcap stocks. More importantly, the volume-return relation remains the same as Table 1: the FF5 alpha increases in trading volume among the underpriced stocks and decrease among the overpriced stocks. As a result, the FF5 alpha is 0.98% for the low volume UMO portfolio and 1.65% for the high volume UMO portfolio, with the volume amplification effect equal to 0.67% (t-value $= 2.71$). Thus, the main finding that volume amplifies mispricing is robust to microcap stocks.

A4 Alternative portfolio formations

In complementarity with the earlier portfolio formation, we consider two alternatives. The first is to form portfolios using breakpoints of the NYSE stocks, and the second is to use a sequential sort. Panel A of Table A4 considers the MISP-volume double sort with NYSE breakpoints. The results are similar to those without using NYSE breakpoints. For example, the FF5 alpha increases from 0.25% for the low volume UMO portfolio to 0.94% for the high volume UMO portfolio, making the volume amplification effect as large as 0.69% (t-value $= 3.38$).

Panel B of Table A4 considers a sequential double sort on MISP and trading volume. Specifically, we first sort stocks into five groups based on MISP, and then within each MISP group, we sort stocks into five subgroups based on trading volume. All portfolios are value-weighted and rebalanced monthly. Among the underpriced stocks, the FF5 alpha increases from -0.03% for the low volume portfolio to 0.54% for the high volume portfolio. Among the overpriced stocks, the FF5 alpha decreases from -0.24% for the low volume portfolio to -0.80% for the high volume portfolio. As a result, the FF5 alpha of the UMO portfolio monotonically increases from 0.20% for the low volume portfolio to 1.34% for the high volume portfolio. It should be mentioned that we use value-weighting throughout. As in most studies, results with equal-weighting are stronger and they are omitted here for brevity. As such, the volume amplification is 1.13%, with a t-value of 5.26. In summary, Table A4 shows that our results are not affected by the alternative portfolio formation methods.

A5 Additional analyses on CAPM alpha

This section explores 1) whether CAPM alpha is robust to an estimate with five-year rolling windows and 2) whether the predictive information in CAPM alpha is subsumed by, or subsumes, MISP.

In calculating CAPM alpha, we follow Amihud and Goyenko (2013) and use a two-year rolling window approach. In the literature, Grundy and Martin (2001) also use five-year windows to calculate alpha for constructing the alpha (stock-specific return) momentum strategies. For robustness, in Table A5, we consider five-year rolling windows and find qualitatively similar results. For example, in the double sort on CAPM alpha and trading volume, the FF5 alpha increases from 0.23% for the low volume UMO portfolio to 0.81% for the high volume UMO portfolio, with the difference (i.e., the amplification effect) equal to 0.58% (t-value = 2.64). In a concurrent paper, Horenstein (2020) shows a CAPM alpha reversal pattern, which is opposite to ours. One possible reason is that he forms portfolios annually, at the end of each December, and holds them for the next one year. In contrast, we form portfolios monthly and hold them only for one month. Hence, alpha may be persistent in a short horizon and reverting in a medium horizon.

If CAPM alpha is a qualified mispricing measure, what is its relation to MISP? That is, does it provide incremental mispricing information? To address this question, we perform a double sort on MISP and CAPM alpha and report the average returns in Table A6. The results show that the predictive power of CAPM alpha is weaker than that in MISP in terms of excess returns. The average returns of the positive-minus-negative CAPM alpha spread portfolios are about 0.3% and not significant, less then the average of

0.64% of the UMO portfolios. Nevertheless, untabulated results show that their FF5 alphas are similar, and similar result are found for both two- and five-year rolling windows in calculating the CAPM alpha, as well as the composite alpha.

A6 Size and IVOL effect

The subsection performs a triple sort on size (IVOL), MISP, and volume to examine if the volume amplification effect is driven by firm size or IVOL. The results in Table A7 show that the volume amplification effect is not affected by firm size, but IVOL. One possible explanation is that IVOL is also a measure of investor disagreement (Diether, Malloy, and Scherbina, 2002), and therefore, contains some information in trading volume.

A7 Non-proportional thinking

In a concurrent paper, Shue and Townsend (2020) show that investors partially think about stock price changes in dollar rather than percentage changes and are more likely to overreact to news for low price stocks. They conclude that this non-proportional thinking can be an alternative explanation to both the IVOL and size effects. To assess whether the volume amplification effect can be also explained by this behavioral bias, Table A8 presents the FF5 alphas of portfolios sorted by stock price, MISP, and volume. The results show that the non-proportional thinking is unlikely to be an explanation, because the volume amplification effect exists among both the low and high price stocks.

A8 Alternative portfolio formation and holding periods

Table A9 shows that the amplification effect is robust to alternative portfolio formation and holding periods. For example, when the formation and holding periods are both six months, the FF5 alpha increases from 0.19% for the low volume UMO portfolio to 1.08% for the high volume UMO portfolio, and in this case, the amplification effect is 0.89% (t-value $= 4.64$).

A9 Raw investor sentiment and the volume amplification effect

This section examines whether the result that the volume amplification is stronger in the high orthogonalized sentiment periods is robust to the raw sentiment index of Baker and Wurgler (2006). Specifically, we define a high (low) sentiment dummy that equals one if the value of the raw sentiment index at the end of the prior month is above (below) the median value and zero otherwise, rerun regression (2), and report the results in Table A10. Consistent with Table 8, the volume amplification effect is 1.25% (t-value = 3.71) in high sentiment periods and 0.65% (t-value = 2.12) in low sentiment periods, with the difference equal to 0.60% (t-value = 1.41). Although this value is only statistically significant at the 10% level with a one-sided test, it is economically sizeable. Thus, we conclude that the volume amplification effect is stronger in the high raw sentiment periods.

A10 Aggregate disagreement and the volume amplification effect

This section examines how aggregate disagreement, measured by aggregate trading volume, affects the cross-sectional volume amplification effect. We define aggregate trading volume in month t as the value-weighted trading volume minus its previous four-year moving average, so that the potential time-series trend is removed. A month is defined as a high (low) disagreement period if the aggregate trading volume of the prior month is above the median value. We run regression (2) by replacing the high (low) investor sentiment dummy with the high (low) disagreement dummy, and report the FF5 alphas in Table A11. The result shows that the volume amplification effect is 1.48% (t-value = 3.67) in high disagreement periods and 0.59% (t-value = 0.59) in low disagreement periods, with the difference equal to 0.89% (t-value = 2.05). Therefore, the volume amplification effect is stronger in the high disagreement periods.

A11 Other possible explanations: robustness

In Section 4.3, we consider four alternative explanations (i.e., arbitrate cost, illiquidity, investor attention, and private information) to trading volume and proxy them by using IVOL, bid-ask spread, abnormal trading volume, and net arbitrage trading, respectively. In this section, we show that the results are robust to alternative proxies. In particular, we proxy (residual) institutional ownership for arbitrage cost, Amihud measure for illiquidity, analyst coverage for attention, and institutional sell and PIN for private information.

Table A12 reports the results from the Fama-MacBeth regressions of one-month-ahead stock returns on MISP, volume, and their interaction, as well as controlling for the alternative explanation proxies one by one. Four observations stand out. First, the coefficient on the interaction between MISP and institutional ownership is positive and significant, which is consistent with Nagel (2005) that high institutional ownership indicates low arbitrage cost. However, this effect does not weaken the volume amplification effect. The coefficient on the interaction between MISP and volume becomes even larger in magnitude. Hence, trading volume is different from institutional ownership and seems unlikely capturing arbitrage cost.

Second, analyst coverage loses power in predicting future stock returns once controlling for the volume amplification effect. Third, the interaction between Amihud measure and MISP is significant but does not affect our result. Finally, institutional sell is unable to predict future stock returns, and PIN has a wrong forecasting sign if it is viewed as a private information measure.

Collectively, Table A12 confirms Table 10 that the four alternative explanations are unlikely to be the drivers of trading volume, which in turn suggests that investor disagreement seems a sensible explanation.

A12 Portfolio rebalance effect

As an additional check, we examine whether liquidity needs or portfolio rebalancing can explain our results. In a concurrent paper, Hrdlicka (2020) show that if investors maintain a target beta for their portfolio, any change in beta will lead to a trade, which seems a common feature among individual investors (Calvet, Campbell, and Sodini, 2009). On the other hand, Etula, Rinne, Suominen, and Vaittinen (2019) show that because of monthly repeated payments such as pensions and dividends, the excess demand for cash raises trading volume dramatically at the end of each month. They find that a subset of institutions are systematically selling on days $T-8$ to $T-4$ and buying on days $T-3$ to T. This is perhaps due to the 3-day settlement requirement in the U.S. stock market, and thus an institution that needs cash on the morning of the last day of the month (T) must sell securities at least 4 business days before the month end.

We perform two tests. First, we explore the volume amplification effect by filtering out the target beta-induced trading. Specifically, each month, we run a cross-sectional regression of trading volume on the absolute value of change in market beta, and use the residual and MISP to perform a double sort as in Table

1, where the market beta of a stock is estimated using the past one-year daily returns, with a requirement of at least 100 observations. Second, motivated by Etula, Rinne, Suominen, and Vaittinen (2019), we calculate trading volume by excluding the last eight-day trading volume and perform a double sort with MISP. We report the results in Table A13, and find that the volume amplification effect is robust to these adjustments.

A13 Additional results on composite alpha

In this subsection, we provide additional results on the composite alpha. First, we show that the volume amplification effect remains strong when using the composite alpha to measure mispricing and using the SY4 model to assess the performance. Panel A of Table A14 reports the abnormal returns of portfolios sorted by the composite alpha and volume. The volume amplification effect is 0.88% (t-value = 3.80), which is remarkably close to the FF5 alpha in Table 2 (0.85% with t-value = 3.83). Panel B reports a similar result when volume is replaced by the IVOL and size adjusted volume. The volume amplification effect is now 0.92% (t-value = 3.88).

Second, we show that the composite alpha is robust to our economic interpretation that trading volume is largely a measure of investor disagreement. Specifically, by using the composite alpha as a mispricing measure, we examine whether the volume amplification effect is subsumed by the interaction of the composite alpha with arbitrage costs, liquidity, investor attention, information asymmetry, or investor disagreement. We measure them with IVOL, bid-ask spread, abnormal volume, net arbitrage trading, and analysts' return forecast dispersion, respectively. To make our interpretation consistent with MISP, we follow Stambaugh, Yu, and Yuan (2015) and transform the composite alpha into a score measure (α_Score) so that a high score refers to overpricing and a low score refers to underpricing. To be consistent, the other five competing variables are also transformed into percentiles. All explanatory variables are normalized in the cross-section.

Table A15 presents the Fama-MacBeth regression results in predicting future returns. The coefficient of primary interest is the one on α_Score*Volume, which captures the volume amplification effect. The first regression includes α_Score, volume, and their interaction, but not other competing variables. The coefficient is significant at the 1% level, thereby suggesting that the volume amplification effect is robust to this composite alpha measure. The second regression controls for the IVOL effect. Interestingly, the coefficient on the interaction of α_Score with IVOL is close to zero in this case, whereas the volume amplification effect remains significant at the 5% level and the coefficient on α_Score*Volume decreases slightly in magnitude from -0.14 to -0.11. This result suggests that the volume amplification effect is not dramatically affected by the IVOL effect documented in Stambaugh, Yu, and Yuan (2015).

The third regression shows that the volume amplification effect is not affected by liquidity, because the bid-ask spread and its interaction with α_Score have insignificant coefficients in the regression. The fourth regression presents an interesting result when we control for investor attention. The volume amplification effect remains the same, although the interaction between α_Score and abnormal volume—the measure of investor attention—has a significant and positive coefficient. The fifth regression shows that net arbitrage trading predicts future stock returns, and its interaction with α_Score has an insignificant coefficient.

The last column of Table A15—the sixth regression—confirms Table 6 that the volume amplification effect is subsumed by the disagreement effect. Specifically, once controlling for analysts' return forecast dispersion, the volume amplification effect becomes insignificant. The slope coefficient on the interaction of volume and α_Score is now 0.02 (t-value = 0.17), whereas the slope coefficient on the interaction of disagreement and α_Score is -0.30 (t-value = -2.97). Hence, the volume amplification effect is largely driven by disagreement. Overall, the results consistently suggest the existence of the significant amplification effect.

A14 A Placebo Test

To examine whether trading volume contains incremental information about future stock returns beyond MISP, we run a placebo test. In the MISP-volume double sort, we replace volume with each of the 11 anomalies in Stambaugh, Yu, and Yuan (2015) and explore the resulting amplification effect. The results in Table A16 show that none of the 11 anomaly variables can generate am amplification effect. Thus, the interaction of MISP with volume is special: only trading volume can have the amplification effect, not any of the 11 anomalies.

Table A1 Average returns and FF5 alphas of portfolios sorted by trading volume

This table reports the average (excess) returns and FF5 alphas of quintile portfolios sorted by trading volume, where trading volume is measured by the average turnover in the past three months. Portfolios are value-weighted and held for one month. Firms with market capitalization below the NYSE 20 percentile breakpoints are excluded. H-L refers to the high-minus-low volume spread portfolio. The sample period is 1965:07–2019:12.

Portfolio	Return	t-value	FF5 alpha	t-value
Low volume	0.53	3.73	−0.05	−1.00
2	0.54	3.36	−0.12	−2.71
3	0.58	3.29	−0.05	−1.27
4	0.57	2.74	0.00	0.00
High volume	0.56	2.01	0.14	1.47
H-L	0.03	0.15	0.19	1.47

Table A2 Summary statistics in the double sort on MISP and trading volume

This table reports the value-weighted trading volumes, mispricing scores, and the average numbers of stocks of portfolios sorted by MISP and trading volume, where trading volume is measured by the average turnover in the past three months. Firms with market capitalization below the NYSE 20 percentile breakpoints are excluded throughout the paper. The sample period is 1965:07–2019:12.

Panel A: Trading volume						
	Low volume	2	3	4	High volume	Average
Underpriced	3.53	5.61	8.02	11.47	21.13	9.95
2	3.44	5.63	8.03	11.54	21.42	10.01
3	3.19	5.67	8.03	11.63	21.83	10.07
4	3.30	5.65	8.07	11.72	22.28	10.20
Overpriced	3.39	5.69	8.10	11.78	23.26	10.44
Panel B: MISP						
	Low volume	2	3	4	High volume	H-L
Underpriced	31.97	31.76	31.56	31.48	31.44	-0.53
2	41.38	41.45	41.58	41.61	41.63	0.26
3	48.46	48.38	48.44	48.41	48.61	0.16
4	55.73	55.70	55.74	55.76	55.91	0.18
Overpriced	66.64	66.68	67.14	67.53	68.42	1.78
UMO	-34.67	-34.92	-35.58	-36.05	-36.97	-2.31
Panel C: Number of stocks						
	Low volume	2	3	4	High volume	Total
Underpriced	65	68	65	58	50	306
2	66	67	64	59	50	306
3	65	64	63	61	55	306
4	61	58	60	62	65	306
Overpriced	50	50	54	66	86	306
Total	306	306	306	306	306	1,530

Table A3 Alphas of portfolios sorted by MISP and volume: Among microcap stocks

This table reports the FF5 alphas of portfolios sorted by MISP and trading volume, where trading volume is measured by the average turnover in the past three months. Firms with market capitalization above the NYSE 20 percentile breakpoints are excluded at portfolio formation. t-values are reported in parentheses. Underpriced refers to the quintile with the lowest MISP (most underpriced), and overpriced refers to the quintile with the highest MISP (most overpriced). UMO (H-L) refers to the underpriced-minus-overpriced (high-minus-low volume) spread portfolio. Portfolios are value-weighted and held for one month. The sample period is 1965:07–2019:12.

	Low volume	2	3	4	High volume	H-L	
Underpriced	0.38	0.46	0.56	0.56	0.66	0.28	(1.42)
2	0.08	0.10	0.13	0.15	0.11	0.02	(0.12)
3	0.01	−0.01	0.03	0.02	0.09	0.08	(0.46)
4	−0.16	−0.34	−0.13	−0.33	−0.08	0.08	(0.40)
Overpriced	−0.60	−0.69	−0.96	−0.78	−0.99	−0.39	(−1.98)
UMO	0.98	1.16	1.52	1.35	1.65	0.67	(2.71)
	(6.87)	(8.45)	(10.29)	(7.79)	(8.00)		

Table A4 Alphas of portfolios with alternative sorting methods

This table reports the FF5 alphas of portfolios sorted by MISP and trading volume with NYSE-breakpoints in Panel A and with sequential sort in Panel B, respectively. t-values are reported in parentheses. Trading volume is measured by the average turnover in the past three months. Underpriced refers to the quintile with the lowest MISP (most underpriced), and overpriced refers to the quintile with the highest MISP (most overpriced). UMO (H-L) refers to the underpriced-minus-overpriced (high-minus-low volume) spread portfolio. Portfolios are value-weighted and held for one month. The sample period is 1965:07–2019:12.

	Low volume	2	3	4	High volume	H-L	
Panel A: Sort with NYSE breakpoints							
Underpriced	−0.05	0.04	0.14	0.25	0.45	0.50	(3.09)
2	−0.04	−0.08	−0.15	0.07	0.38	0.42	(2.59)
3	−0.07	−0.25	−0.04	−0.07	0.24	0.30	(1.87)
4	−0.08	−0.20	−0.02	−0.14	−0.08	0.00	(−0.01)
Overpriced	−0.31	−0.19	−0.28	−0.50	−0.49	−0.19	(−1.11)
UMO	0.25	0.23	0.42	0.75	0.94	0.69	(3.38)
	(2.03)	(1.75)	(3.27)	(5.22)	(5.49)		
Panel B: Sequential sort with mispricing first							
Underpriced	−0.03	−0.02	0.11	0.32	0.54	0.57	(3.52)
2	0.02	−0.06	−0.09	0.02	0.37	0.35	(2.21)
3	−0.05	−0.23	−0.13	0.02	0.14	0.18	(1.09)
4	−0.08	−0.18	−0.07	−0.20	−0.16	−0.08	(−0.42)
Overpriced	−0.24	−0.19	−0.17	−0.40	−0.80	−0.56	(−2.97)
UMO	0.20	0.18	0.29	0.72	1.34	1.13	(5.26)
	(1.61)	(1.37)	(2.28)	(4.91)	(7.31)		

Table A5 Double sort on CAPM alpha and trading volume: five-year rolling windows

This table reports the FF5 alphas of portfolios sorted by CAPM alpha and trading volume, where CAPM alpha is calculated with the past five-year observations. Portfolios are value-weighted and held for one month. PMN (H-L) refers to the positive-minus-negative (high-minus-low) spread portfolio. The sample period is 1968:07–2019:12.

	Low volume	2	3	4	High volume	H-L	
Positive	0.01	0.24	0.19	0.34	0.41	0.40	(2.22)
2	−0.02	−0.18	−0.06	0.07	−0.01	0.01	(0.07)
3	−0.04	−0.15	−0.11	0.13	0.19	0.23	(1.43)
4	−0.07	−0.16	−0.15	−0.26	0.00	0.07	(0.42)
Negative	−0.23	−0.04	−0.11	−0.37	−0.40	−0.18	(−1.05)
PMN	0.23	0.29	0.31	0.71	0.81	0.58	(2.64)
	(1.34)	(1.58)	(1.77)	(4.25)	(4.19)		

Table A6 Double sort on MISP and CAPM alpha

This table reports average returns of portfolios sorted by MISP and CAPM alpha, where CAPM alpha is calculated with the past two-year observations. Portfolios are value-weighted and held for one month. UMO (PMN) refers to the underpriced-minus-overpriced (positive-minus-negative) spread portfolio. The sample period is 1968:07–2019:12.

	Negative alpha	2	3	4	Positive alpha	PMN	
Underpriced	0.70	0.70	0.75	0.75	1.03	0.33	(1.58)
2	0.59	0.65	0.59	0.66	0.87	0.28	(1.24)
3	0.56	0.39	0.55	0.57	0.85	0.29	(1.23)
4	0.31	0.49	0.44	0.51	0.75	0.44	(1.86)
Overpriced	0.01	0.25	0.16	0.10	0.17	0.17	(0.68)
UMO	0.69	0.44	0.58	0.65	0.85	0.16	(0.79)
	(3.75)	(3.21)	(4.32)	(4.11)	(4.68)		

Table A7 The IVOL and size effects

This table reports the FF5 alphas of portfolios in the $2 \times 5 \times 5$ triple sort on IVOL (size), MISP, and volume. t-values are reported in parentheses. Underpriced refers to the quintile with the lowest MISP (most underpriced), and overpriced refers to the quintile with the highest MISP (most overpriced). UMO (H-L) refers to the underpriced-minus-overpriced (high-minus-low volume) spread portfolio. Portfolios are value-weighted and held for one month. The sample period is 1965:07–2019:12.

	Low volume	2	3	4	High volume	H-L	
Panel A: Triple sort on IVOL, MISP, and volume							
	Low IVOL stocks						
Underpriced	−0.07	−0.02	0.07	0.21	0.23	0.30	(1.85)
2	−0.03	0.00	−0.12	0.00	0.14	0.18	(1.16)
3	0.01	−0.05	−0.16	−0.01	0.07	0.06	(0.34)
4	−0.08	−0.12	−0.22	−0.05	−0.01	0.06	(0.37)
Overpriced	−0.12	−0.14	−0.11	−0.24	−0.32	−0.20	(−1.15)
UMO	0.05	0.12	0.18	0.45	0.56	0.50	(2.35)
	(0.36)	(0.89)	(1.25)	(3.04)	(3.40)		
	High IVOL stocks						
Underpriced	−0.06	0.08	0.48	0.51	0.77	0.83	(3.54)
2	−0.03	−0.21	−0.06	0.34	0.20	0.23	(1.00)
3	−0.08	−0.26	0.14	−0.02	0.13	0.21	(1.02)
4	−0.30	−0.08	−0.40	0.07	−0.02	0.28	(1.27)
Overpriced	−0.58	−0.53	−0.55	−0.55	−1.04	−0.46	(−1.93)
UMO	0.53	0.61	1.03	1.06	1.81	1.29	(4.26)
	(2.77)	(3.10)	(5.28)	(5.38)	(7.43)		
Panel B: Triple sort on size, MISP, and volume							
	Small stocks						
Underpriced	0.16	0.03	0.11	0.30	0.56	0.40	(2.09)
2	0.14	0.09	0.14	0.15	0.50	0.36	(1.93)
3	−0.07	0.15	0.07	0.04	0.34	0.41	(2.15)
4	−0.21	−0.05	0.03	0.10	−0.05	0.16	(0.85)
Overpriced	−0.65	−0.39	−0.32	−0.44	−0.81	−0.16	(−0.80)
UMO	0.81	0.42	0.43	0.74	1.37	0.55	(2.35)
	(6.55)	(3.3)	(3.11)	(4.92)	(6.61)		
	Large stocks						
Underpriced	−0.05	0.08	0.17	0.31	0.47	0.53	(2.97)
2	−0.05	−0.12	−0.06	0.09	0.59	0.64	(3.61)
3	−0.08	−0.17	0.01	0.03	0.25	0.33	(1.86)
4	−0.15	−0.09	−0.17	0.02	0.14	0.29	(1.57)
Overpriced	−0.14	−0.23	−0.17	−0.33	−0.46	−0.31	(−1.63)
UMO	0.09	0.31	0.34	0.64	0.93	0.84	(3.58)
	(0.63)	(2.30)	(2.30)	(4.01)	(4.82)		

Table A8 Test the non-proportional thinking effect

This table reports the FF5 alphas of $2 \times 5 \times 5$ portfolios sorted by stock price, MISP, and trading volume, where trading volume is measured by the average turnover in the past three months. Underpriced refers to the quintile with the lowest MISP (most underpriced), and overpriced refers to the quintile with the highest MISP (most overpriced). UMO (H-L) refers to the underpriced-minus-overpriced (high-minus-low volume) spread portfolio. Portfolios are value-weighted and held for one month. The sample period is 1965:07–2019:12.

	Low volume	2	3	4	High volume	H-L	
Panel A: Low price stocks							
Underpriced	0.11	0.27	0.12	0.45	0.47	0.36	(1.69)
2	0.03	0.06	0.02	0.22	0.18	0.16	(0.79)
3	0.01	0.01	0.08	0.20	−0.14	−0.16	(−0.79)
4	−0.06	0.02	−0.04	−0.07	−0.17	−0.11	(−0.53)
Overpriced	−0.39	−0.20	−0.18	−0.45	−1.04	−0.65	(−3.28)
UMO	0.51	0.46	0.30	0.90	1.51	1.01	(3.66)
	(3.16)	(2.55)	(1.60)	(4.61)	(6.14)		
Panel B: High price stocks							
Underpriced	−0.03	−0.05	0.10	0.40	0.66	0.69	(3.56)
2	−0.07	−0.09	−0.04	−0.05	0.54	0.61	(2.99)
3	−0.10	−0.21	−0.01	0.13	0.43	0.53	(2.62)
4	−0.06	−0.26	−0.01	−0.23	0.28	0.34	(1.56)
Overpriced	−0.28	−0.41	−0.33	−0.29	−0.36	−0.08	(−0.35)
UMO	0.25	0.36	0.43	0.69	1.02	0.77	(2.76)
	(1.44)	(2.34)	(2.72)	(4.11)	(4.69)		

Table A9 Double sort on MISP and volume: Alternative portfolio formation and holding periods

This table reports the FF5 alphas of portfolios sorted by MISP and trading volume. Similar as Jegadeesh and Titman (1993), (i, j) indicates that trading volume is measured by the average turnover in the past i months and the portfolio holding period is j months. Underpriced refers to the quintile with the lowest MISP (most underpriced), and overpriced refers to the quintile with the highest MISP (most overpriced). UMO (H-L) refers to the underpriced-minus-overpriced (high-minus-low) spread portfolio. The sample period is 1965:07–2019:12.

	Low volume	2	3	4	High volume	H-L	
Panel A: Volume formation and portfolio holding periods are $(1,1)$							
Underpriced	−0.02	−0.01	0.08	0.29	0.51	0.52	(3.30)
2	0.03	−0.10	−0.14	0.03	0.38	0.36	(2.26)
3	−0.05	−0.14	−0.09	0.01	0.17	0.22	(1.41)
4	−0.04	−0.18	−0.10	−0.12	0.07	0.11	(0.63)
Overpriced	−0.23	−0.21	−0.27	−0.50	−0.61	−0.38	(−2.26)
UMO	0.21	0.20	0.36	0.78	1.11	0.90	(4.65)
	(1.75)	(1.64)	(3.19)	(5.94)	(6.78)		
Panel B: Volume formation and portfolio holding periods are $(3,6)$							
Underpriced	−0.04	−0.01	0.07	0.27	0.50	0.55	(3.58)
2	−0.03	−0.11	−0.12	0.06	0.41	0.44	(2.92)
3	−0.02	−0.11	−0.10	−0.01	0.16	0.18	(1.19)
4	−0.10	−0.21	−0.10	−0.12	0.05	0.15	(0.92)
Overpriced	−0.22	−0.18	−0.30	−0.48	−0.56	−0.33	(−2.09)
UMO	0.18	0.18	0.36	0.75	1.06	0.88	(4.78)
	(1.58)	(1.56)	(3.55)	(6.10)	(6.95)		
Panel C: Volume formation and portfolio holding periods are $(6,6)$							
Underpriced	−0.04	−0.01	0.08	0.30	0.49	0.52	(3.31)
2	−0.06	−0.13	−0.08	0.04	0.44	0.50	(3.19)
3	−0.01	−0.13	−0.06	−0.05	0.18	0.19	(1.21)
4	−0.09	−0.22	−0.11	−0.12	0.05	0.14	(0.88)
Overpriced	−0.22	−0.16	−0.30	−0.46	−0.59	−0.37	(−2.26)
UMO	0.19	0.15	0.39	0.77	1.08	0.89	(4.64)
	(1.57)	(1.25)	(3.66)	(5.98)	(6.87)		

Table A10 The volume amplification effect in high and low sentiment periods: robustness

At the end of each month, we independently form 5×5 portfolios based on MISP and trading volume, where trading volume is measured by the average turnover in the past three months. Portfolios are value-weighted and held for one month. UMO (H-L) refers to the underpriced-minus-overpriced (high-minus-low) spread portfolio. Alphas are estimates of a_H and a_L in the regression

$$R_{i,t} = a_H d_{H,t} + a_L d_{L,t} + b\text{MKT}_t + c\text{SMB}_t + d\text{HML}_t + e\text{RMW}_t + f\text{CMA}_t + \varepsilon_{i,t},$$

where $d_{H,t}$ and $d_{L,t}$ are dummy variables indicating high and low sentiment periods, and $R_{i,t}$ is the excess return of portfolio i in month t. A high (low) sentiment month is one in which the value of the Baker and Wurgler (2006) raw sentiment index at the end of the previous month is above (below) the median value for the 1965:07–2018:12 sample period. Panels A, B, and C report a_H, a_L, and their difference, respectively.

	Low volume	2	3	4	High volume	H-L	
Panel A: High sentiment periods							
Underpriced	0.05	0.10	0.03	0.48	0.64	0.59	(2.02)
2	−0.05	−0.14	−0.05	−0.18	0.58	0.63	(2.22)
3	−0.10	−0.11	−0.14	0.15	0.26	0.35	(1.47)
4	0.08	−0.29	0.13	−0.21	−0.02	−0.10	(−0.37)
Overpriced	−0.33	−0.28	−0.38	−0.45	−0.99	−0.66	(−2.57)
UMO	0.38	0.38	0.41	0.93	1.63	1.25	(3.71)
	(2.05)	(1.81)	(2.12)	(3.89)	(5.35)		
Panel B: Low sentiment periods							
Underpriced	−0.09	−0.09	0.18	0.23	0.45	0.54	(2.56)
2	−0.03	−0.07	−0.13	0.10	0.36	0.39	(1.67)
3	−0.14	−0.22	−0.07	−0.03	0.34	0.49	(2.09)
4	−0.13	−0.12	−0.18	−0.21	0.27	0.40	(1.58)
Overpriced	−0.26	−0.31	−0.22	−0.33	−0.37	−0.11	(−0.44)
UMO	0.17	0.22	0.40	0.56	0.82	0.65	(2.12)
	(0.92)	(1.22)	(2.20)	(2.93)	(3.31)		
Panel C: Difference between high and low sentiment periods							
Underpriced	0.14	0.18	−0.15	0.25	0.19	0.05	(0.15)
2	−0.02	−0.07	0.08	−0.28	0.22	0.24	(0.72)
3	0.05	0.11	−0.07	0.18	−0.08	−0.13	(−0.41)
4	0.21	−0.17	0.31	0.00	−0.29	−0.50	(−1.41)
Overpriced	−0.07	0.03	−0.16	−0.12	−0.62	−0.55	(−1.55)
UMO	0.21	0.16	0.01	0.37	0.81	0.60	(1.41)
	(0.83)	(0.60)	(0.03)	(1.31)	(2.28)		

Table A11 The volume amplification effect in high and low disagreement periods

At the end of each month, we independently form 5×5 portfolios based on MISP and trading volume, where trading volume is measured by the average turnover in the past three months. Portfolios are value-weighted and held for one month. UMO (H-L) refers to the underpriced-minus-overpriced (high-minus-low) spread portfolio. Alphas are estimates of a_H and a_L in the regression

$$R_{i,t} = a_H d_{H,t} + a_L d_{L,t} + b\text{MKT}_t + c\text{SMB}_t + d\text{HML}_t + e\text{RMW}_t + f\text{CMA}_t + \varepsilon_{i,t},$$

where $d_{H,t}$ and $d_{L,t}$ are dummy variables indicating high and low aggregate disagreement periods, and $R_{i,t}$ is the excess return of portfolio i in month t. A high (low) aggregate disagreement month is one in which the value of the value-weighted aggregate trading volume index at the end of the previous month is above (below) the median value. To remove the potential trend, the aggregate trading volume in month t is defined as its realization minus its previous four-year moving average. The sample period is 1965:07–2019:12.

	Low volume	2	3	4	High volume	H-L	
Panel A: High disagreement periods							
Underpriced	−0.01	−0.12	0.02	0.42	0.75	0.76	(2.42)
2	−0.02	−0.11	0.02	−0.08	0.73	0.75	(2.50)
3	−0.13	−0.11	−0.19	0.19	0.30	0.43	(1.62)
4	0.00	−0.21	−0.08	−0.14	0.27	0.27	(0.95)
Overpriced	−0.13	−0.25	−0.28	−0.44	−0.85	−0.72	(−2.40)
UMO	−0.12	−0.13	−0.30	−0.86	−1.60	1.48	(3.67)
	(−0.56)	(−0.54)	(−1.42)	(−3.37)	(−4.55)		
Panel B: Low disagreement periods							
Underpriced	−0.05	0.07	0.17	0.18	0.29	0.34	(1.75)
2	−0.03	−0.12	−0.14	−0.11	0.11	0.14	(0.63)
3	−0.05	−0.21	−0.07	−0.08	0.27	0.31	(1.48)
4	0.10	−0.15	−0.11	−0.30	−0.09	−0.19	(−0.83)
Overpriced	−0.36	−0.29	−0.25	−0.32	−0.61	−0.25	(−1.16)
UMO	−0.32	−0.37	−0.42	−0.50	−0.90	0.59	(2.35)
	(−1.94)	(−2.21)	(−2.39)	(−2.71)	(−4.43)		
Panel C: Difference between high and low disagreement periods							
Underpriced	0.04	−0.20	−0.14	0.24	0.46	0.42	(1.25)
2	0.01	0.01	0.17	0.03	0.62	0.61	(1.77)
3	−0.09	0.10	−0.12	0.27	0.03	0.12	(0.36)
4	−0.10	−0.06	0.03	0.16	0.37	0.47	(1.31)
Overpriced	0.24	0.05	−0.03	−0.12	−0.23	−0.47	(−1.32)
UMO	−0.20	−0.24	−0.11	0.37	0.69	0.89	(2.05)
	(−0.76)	(−0.90)	(−0.45)	(1.28)	(1.90)		

Table A12 Results from regressing returns on MISP and volume with controls: Robustness

This table reports the results from the Fama-MacBeth regressions of one-month-ahead stock returns on MISP, trading volume, their interactions, and other controls. Newey-West robust t-statistics with four lags are reported in parentheses. Intercepts and coefficients on firm controls (firm size and book-to-market) are not reported for brevity. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: one-month-ahead excess returns (%)				
	(1)	(2)	(3)	(4)	(5)
MISP	-0.33^{***}	-0.14^{***}	-0.12^{***}	-0.14	-0.12^{*}
	(-4.88)	(-3.21)	(-3.02)	(-1.40)	(-1.73)
Volume	0.62^{***}	0.51^{***}	0.39^{***}	0.64^{**}	0.68^{***}
	(4.93)	(4.02)	(3.73)	(2.13)	(2.98)
MISP*Volume	-0.78^{***}	-0.63^{***}	-0.51^{***}	-0.80^{***}	-0.63^{***}
	(-7.03)	(-5.89)	(-5.55)	(-3.24)	(-2.86)
Institutional ownership	-0.34^{***}				
	(-4.62)				
MISP*institutional ownership	0.45^{***}				
	(4.75)				
Analyst coverage		0.00			
		(0.06)			
MISP*Analyst coverage		0.07			
		(0.97)			
Amihud			0.01		
			(1.38)		
MISP*Amihud			-0.25^{***}		
			(-3.59)		
Institutional sell				0.11	
				(0.46)	
MISP*Institutional sell				-0.34	
				(-1.24)	
PIN					-0.55^{***}
					(-3.80)
MISP*PIN					0.31^{**}
					(2.43)
Controls	yes	yes	yes	yes	yes
adj. R^2	0.05	0.05	0.05	0.07	0.06
Start	1980:04	1976:03	1965:08	1997:02	1993:01
End	2019:12	2016:12	2019:12	2011:03	2012:12

Table A13 Alphas of portfolios sorted by MISP and adjusted volume: Mitigating the portfolio rebalancing concern

This table reports the FF5 alphas of portfolios sorted by MISP and adjusted trading volume. To mitigate the portfolio rebalancing concern, in Panel A volume is the residual from the cross-sectional regression of trading volume on absolute value of change in market beta, and in Panel B volume is constructed by excluding the last eight-day trading volume of each month. Market beta is estimated with the past one-year daily returns with a requirement of at least 100 observations. Portfolios are value-weighted and held for one month. The sample period is 1965:07–2019:12.

	Low volume	2	3	4	High volume	H-L	
Panel A: Adjusted by the absolute value of change in market beta							
Underpriced	0.08	−0.00	0.07	0.26	0.49	0.41	(2.45)
2	0.02	−0.07	−0.13	−0.18	0.38	0.37	(1.96)
3	0.12	−0.19	−0.16	−0.03	0.10	−0.01	(−0.07)
4	−0.09	−0.21	−0.23	−0.06	−0.15	−0.07	(−0.37)
Overpriced	−0.33	−0.29	−0.30	−0.54	−0.78	−0.44	(−2.36)
UMO	0.42	0.29	0.37	0.79	1.27	0.85	(3.58)
	(2.42)	(1.84)	(2.44)	(5.24)	(6.54)		
Panel B: Excluding month-end volume							
Underpriced	−0.04	0.03	0.08	0.32	0.51	0.55	(3.22)
2	−0.07	−0.06	−0.07	−0.02	0.41	0.48	(2.78)
3	−0.12	−0.17	−0.07	−0.01	0.36	0.48	(2.85)
4	−0.04	−0.18	−0.07	−0.17	0.05	0.09	(0.51)
Overpriced	−0.34	−0.20	−0.30	−0.41	−0.60	−0.26	(−1.43)
UMO	0.29	0.22	0.38	0.73	1.11	0.81	(3.70)
	(2.22)	(1.69)	(2.92)	(5.13)	(5.97)		

Table A14 SY4 alphas of portfolios sorted by composite alpha and (adjusted) volume

This table reports the Stambaugh and Yuan (SY4, 2017) four-factor alphas of portfolios sorted by composite alpha and volume or adjusted volume, where adjusted volume is the residual from the cross-sectional regression of trading volume on IVOL and size. Portfolios are value-weighted and held for one month. The sample period is 1965:07–2019:12.

	Low volume	2	3	4	High volume	H-L	
Panel A: Sorted by composite alpha and volume							
Positive alpha	−0.03	0.14	0.15	0.41	0.50	0.53	(2.63)
2	−0.11	−0.09	−0.03	0.07	0.00	0.11	(0.59)
3	−0.13	−0.11	−0.13	−0.14	−0.11	0.02	(0.09)
4	−0.01	−0.07	0.05	−0.15	−0.30	−0.29	(−1.72)
Negative alpha	0.13	0.05	0.08	−0.09	−0.22	−0.35	(−1.93)
PMN	−0.17	0.09	0.08	0.50	0.72	0.88	(3.80)
	(−0.82)	(0.49)	(0.40)	(2.62)	(3.56)		
Panel B: Sorted by composite alpha and adjusted volume							
Positive alpha	0.02	0.43	0.31	0.43	0.56	0.54	(2.72)
2	0.03	−0.02	0.05	0.14	−0.05	−0.08	(−0.51)
3	−0.13	−0.06	−0.17	−0.02	−0.14	0.00	(−0.02)
4	−0.02	−0.04	0.15	−0.23	0.08	0.10	(0.66)
Negative alpha	0.20	0.16	0.18	−0.10	−0.18	−0.38	(−2.29)
PMN	−0.18	0.27	0.13	0.54	0.74	0.92	(3.88)
	(−0.81)	(1.27)	(0.60)	(2.68)	(3.58)		

Table A15 Results from regressing stock returns on composite alpha and volume with controls

This table reports the results of Fama-MacBeth regressions of one-month-ahead stock returns on composite alpha, trading volume, disagreement, their interactions, and other control variables (firm size and book-to-market). Abnormal volume is defined at the monthly frequency following Gervais, Kaniel, and Mingelgrin (2001). Net arbitrage trading is the difference between quarterly abnormal hedge fund holdings and abnormal short interest and measures trading driven by private information (Chen, Da, and Huang, 2019). Disagreement is analyst's return forecast dispersion. To make the interpretation consistent with MISP, following Stambaugh, Yu, and Yuan (2015) we transform composite alpha into a score measure (α_Score) so that a high α_Score refers to overpricing and a low α_Score refers to underpricing. Newey-West t-values with four lags are reported in parentheses. Intercepts and coefficients on controls are not reported for brevity. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: one-month-ahead excess returns (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
α_Score	0.03	0.05	0.07	−0.05	0.05	0.08
	(0.54)	(0.90)	(0.85)	(−1.09)	(0.64)	(0.79)
Volume	0.06	0.09	−0.03	0.06	0.17	−0.07
	(0.75)	(1.34)	(0.30)	(0.77)	(1.25)	(0.47)
α_Score*Volume	−0.14***	−0.11**	−0.15**	−0.14***	−0.20**	0.02
	(−2.65)	(−2.21)	(−2.52)	(−2.59)	(−2.31)	(0.17)
IVOL		−0.08				
		(−1.18)				
α_Score*IVOL		−0.07				
		(−1.28)				
Bid-ask spread			−0.19			
			(−1.56)			
α_Score*bid-ask spread			−0.05			
			(−0.79)			
Abnormal volume				0.06*		
				(1.74)		
α_Score*Abnormal volume				0.12***		
				(3.12)		
Net arbitrage trading					0.18***	
					(3.64)	
α_Score*Net arbitrage trading					0.06	
					(0.98)	
Disagreement						0.22**
						(2.12)
α_Score*Disagreement						−0.30***
						(−2.97)
Controls	yes	yes	yes	yes	yes	yes
adj. R^2	0.05	0.06	0.06	0.06	0.05	0.07
Start	1965:07	1965:07	1982:12	1965:07	1990:01	1999:04
End	2019:12	2019:12	2019:12	2019:12	2015:12	2019:12

Table A16 Average returns of UMO portfolios across each MISP component variable quintiles

Each month, we perform a 5×5 double sort on MISP and X, where X is one of the 11 anomaly variables in constructing MISP. This table reports the average returns of the underpriced-minus-overpriced (UMO) portfolios across the X quintiles. Underpriced refers to the quintile with the lowest MISP score (most underpriced), and overpriced refers to the quintile with the highest MISP score (most overpriced).

Anomaly variable	Low X	2	3	4	High X	H-L
ACC	0.61	0.68	0.28	0.41	0.27	−0.34
	(2.57)	(3.54)	(1.51)	(1.93)	(1.18)	(−1.20)
AG	0.48	0.47	0.42	0.77	0.89	0.41
	(1.79)	(2.34)	(2.63)	(4.07)	(4.37)	(1.24)
CEI	0.51	0.21	0.46	1.10	0.79	0.28
	(2.36)	(1.17)	(2.47)	(5.47)	(3.29)	(0.94)
Distress	0.78	0.67	0.72	0.56	1.15	0.36
	(4.32)	(3.92)	(4.31)	(3.09)	(4.47)	(1.19)
GP	0.87	0.49	0.77	0.47	0.70	−0.16
	(4.22)	(3.01)	(4.29)	(2.36)	(2.78)	(−0.57)
ITA	0.60	0.46	0.42	0.58	0.54	−0.06
	(2.49)	(1.86)	(1.86)	(3.15)	(2.12)	(−0.19)
MOM	1.03	0.52	0.43	0.48	0.50	−0.53
	(5.13)	(3.59)	(3.00)	(3.27)	(2.86)	(−2.27)
NOA	0.59	0.50	0.34	0.59	0.99	0.41
	(2.63)	(2.11)	(1.47)	(3.15)	(3.86)	(1.31)
NSI	0.55	0.19	0.61	0.78	0.96	0.41
	(1.83)	(0.91)	(3.10)	(3.92)	(3.46)	(1.03)
O-Score	0.87	0.82	0.72	0.91	1.09	0.22
	(3.29)	(4.36)	(4.46)	(5.23)	(3.88)	(0.60)
ROA	0.88	0.59	0.61	0.61	0.43	−0.44
	(3.68)	(3.49)	(3.31)	(2.94)	(1.52)	(−1.42)

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