News disagreement, trading volume, and equity prices

Fariborz Moshirian, Hang Wang, and Bohui Zhang*

Current version: March 2021

* Fariborz Moshirian is the School of Banking and Finance, UNSW Business School, UNSW Australia, Sydney, NSW, Australia, 2052, f.moshirian@unsw.edu.au; Hang Wang is from the School of Banking and Finance, UNSW Business School, UNSW Australia, Sydney, NSW, Australia, 2052, hang.wang1@unsw.edu.au; and Bohui Zhang is from Shenzhen Finance Institute and School of Management and Economics, The Chinese University of Hong Kong, Shenzhen (CUHK-Shenzhen), 2001 Longxiang Road, Longgang District, Shenzhen China, 518172, bohuizhang@cuhk.edu.cn.

News disagreement, trading volume, and equity prices

Abstract

This paper investigates whether firm-specific news increases investor disagreement. First, we find that stock prices are convex in relation to news, confirming that prices on news days reflect the risk compensation of opinion divergence. Second, using unexplained trading volume as a proxy for investor disagreement, we confirm that investor disagreement is significantly increased on news days. Third, we find that news-day unexplained trading volume is positively priced in the cross-section, confirming that disagreement is associated with a positive risk premium. Such positive prices are related to higher return volatility and greater price convexity. Finally, we distinguish empirically between two competing channels regarding how trading volume gets incorporated into asset prices when trading volume is a proxy for disagreement. We find that news-day unexplained trading volume is associated with high liquidity and low average bias, which reduces the effect of optimistic views.

Keywords: News; Disagreement; Trading volume; Price convexity; Return predictability.
JEL classification: G12, G17

1. Introduction

The disagreement literature provides mixed results in relation to the role of news on investor disagreement. Some studies find that the magnitude of the spikes in investors' disagreement is reduced for price shocks with accompanying news (e.g., Healy and Palepu 2001). They argue that news can reduce information uncertainty and asymmetry, which should mitigate opinion divergence. Other studies show that price shocks associated with news are useful indicators of intertemporal spikes in investor disagreement as investors use different forecasting models to interpret the same news (e.g., Varian, 1985; Harris and Raviv, 1993; Kim and Verrecchia, 1994; Hong and Stein, 2007). In this study, we directly examine whether firm-specific news increases investor disagreement.

Extensive theoretical literature shows that stock prices are convex in firm-specific news in the presence of belief dispersion. Specifically, opinion divergence may be treated as an additional risk factor affecting asset prices (e.g., Varian, 1985, 1989; Abel, 1989; David, 2008; Atmaz and Basak, 2018), which results in higher asset prices around news events. Reflecting this risk compensation, stock prices thus overreact to good news and underreact to bad news. In a future period, the post-news divergence (convergence) is expected to lead to upward (downward) drifts in stock prices following both good and bad news events. As future news disclosures following a news event amplify the disagreement (and hence price convexity), we should observe post-event divergence on news days following a news event. Likewise, we should observe post-event convergence on non-news days following a news event.

As a proxy for the presence of public information, we use a comprehensive news data set collected by RavenPack. Our methodology is simple. We calculate a firm's abnormal return, defined as its daily return in excess of its return predicted by the Carhart (1997) four-factor model. A news-event day is defined as any firm-date observation with at least one news coverage. Our news events include the most important disclosures a corporation makes, a powerful setting to test theories about investor disagreement because important disclosures can lead investors to revise their beliefs (Tetlock, 2014). We next decompose post-event returns into news-day and non-news-day returns. We examine post-event returns in the news days and non-news days of the two groups of events associated with good and bad news.

Our findings are consistent with the idea that news increases investor disagreement. First, we find post-shock convergence on non-news days following both positive and negative news events. We find non-news-day return reversals following positive news events and non-news-day return continuations following negative news events, suggesting that investors overreact to good news and underreact to bad news. Second, we find that both good and bad news events are followed by higher abnormal news-day returns, confirming that investors require risk compensations when disagreement is high. These results are robust to the inclusion of various controls, different post-event horizons, and various methods of measuring abnormal returns. We call our findings as "news disagreement."

Our baseline results suggest that investor disagreement should persist in the post-event news day and converge in the post-event non-news day. To further confirm this conjecture, we explore unexplained (abnormal) trading volume changes in the post-event news day and non-news day. We use abnormal trading volume since disagreement is associated with high trading volume (Garfinkel and Sokobin, 2006).[1] Consistent with our conjecture, we find that the abnormal trading volume increases over the post-shock news-day period following the shocks and gradually decreases over the post-shock non-news-day period following the news events. To summarize our results, we demonstrate that news events tend to simultaneously increase investors' disagreement and stocks' trading volume, which is consistent with the disagreement literature that posits that disagreement and trading volume should be positively correlated (e.g., Varian, 1989; Shalen, 1993; Cao and Ou-Yang, 2008; Banerjee and Kremer, 2010; Atmaz and Basak, 2018).

To further confirm that news increases disagreement, we now test the effect of news disagreement on expected stock returns. Theories suggest that disagreement is associated with a positive risk premium (e.g., Varian, 1985, 1989; Abel, 1989; Anderson, Ghysels, and Juergens, 2005; David, 2008; Banerjee and Kremer, 2010; Atmaz and Basak, 2018). Therefore, if news increases disagreement, we should expect such news disagreement to be positively priced in the cross-section. We use abnormal trading volume on news days to proxy for news disagreement. We construct a monthly news disagreement variable using a daily average value of news-day abnormal trading volume in a firm-month. In the portfolio analysis, the strategy that buys the high news-day abnormal trading volume portfolio and short sells the low news-day abnormal trading volume portfolio generates a return of 11.29% per year.

To see whether the above finding is consistent with the disagreement view of return predictability, we perform the following tests. First, we show that news disagreement is associated with temporary increases in analyst disagreement (Diether, Malloy, and Scherbina 2002). Second, the news disagreement driven-return predictably is much stronger among stocks

[1] Garfinkel and Sokobin (2006) suggest that trading volume is increasing in three factors: investor liquidity demands, the information content of the fundamental, and the opinion divergence. They interpret "unexplained volume as an indicator of opinion divergence and conclude that post-event returns are increasing in opinion divergence.

with a high level of investor disagreements, such as those with high price volatility (Scheinkman and Xiong, 2003; Buraschi and Jiltsov, 2006; Li, 2007), a high correlation between trading volume and price volatility (Banerjee and Kremer, 2010; Banerjee, 2011), and great price convexity (Atmaz and Basak, 2018). Third, for time-series variation, we reveal that the pricing of news disagreements is significantly stronger during bad economic states, confirming that the risk premium of disagreement is concentrated in bad times (Cujean and Hasler, 2017). Overall, our results are consistent with the views that the price of news disagreement is associated with a positive risk premium.

There is a concern that our news disagreement variable captures the high-volume return premium effect documented by Gervais, Kaniel, and Mingelgrin (2001). We follow Gervais, Kaniel, and Mingelgrin (2001) to control for the high-volume return premium and classify stocks into low-, normal-, and high-volume portfolios. Our results remain robust after controlling for the high-volume return premium effect, suggesting that the return predictability of news disagreement is distinct from the positive volume shock of Gervais, Kaniel, and Mingelgrin (2001).

In robustness tests, we control for other risk factors and stock characteristics that have been shown to predict cross-sectional returns: size and book-to-market (Fama and French 1992, 1993), price momentum (Jegadeesh and Titman, 1993), idiosyncratic volatility (Ang, Hodrick, Xing, and Zhang, 2006), illiquidity shock (Bali, Peng, Shen, and Tang, 2013), and news momentum (Wang, Zhang, and Zhu, 2018). After controlling for a large set of stock return predictors, the positive relationship between news disagreement and future returns remains highly significant, suggesting that our news disagreement's return predictability cannot be explained by factors proposed in the existing literature.

Our paper contributes to the literature in several ways. First, we offer direct evidence on opinion divergence at news events. We complement the theories by providing empirical evidence that stock price is convex in cash-flow news when news increases disagreement (Xu, 2007; Atmaz and Basak, 2018). In contrast to other empirical studies of price convexity (Basu, 1997; Lu, Wang, and Wang, 2014; Wang, 2019), we find that opinion divergence is persistent in the news days following the initial news event, but opinion convergence appears in the non-news days following the initial news event. Our results are in sharp contrast to the general findings of post-news drifts in event studies of investor disagreement (e.g., Beaver, 1968; Bamber, 1987; Kandel and Pearson, 1995; Garfinkel and Sokobin, 2006).

Second, we provide new evidence that investor disagreement is positively priced. Our evidence is consistent with the theories that investors should be compensated for bearing trading risk or the risk due to modeling uncertainty when a disagreement arises (e.g., Varian, 1985, 1989; Abel, 1989; Anderson, Ghysels, and Juergens, 2005; David, 2008; Banerjee and Kremer, 2010; Atmaz and Basak, 2018). Early empirical studies also find a positive disagreement-return relationship (e.g., Qu, Starks, and Yan, 2003; Doukas, Kim, and Pantzalis, 2006; Avramov, Chordia, Jostova, and Philipov, 2009; Beber, Breedon, and Buraschi, 2010; Carlin, Longstaff, and Matoba, 2014). We complement these studies by showing that when investor disagreement is positively priced, it is also positively related to price volatility, the correlation between price volatility and trading volume, and price convexity. All these effects are driven by news, highlighting the importance of news on investor disagreement. Overall, these results are consistent with the theoretical predictions (e.g., Harris and Raviv, 1993; Shalen, 1993; Kandel and Pearson, 1995; Zapatero, 1998; Banerjee and Kremer, 2010; Banerjee, 2011).

Third, our paper is also related to the vast and mixed empirical evidence on the effects of investors' dispersion of beliefs on asset expected returns. For example, others, in fact, find a negative relationship between belief dispersion and a stock's mean return (e.g., Diether, Malloy, and Scherbina, 2002; Chen, Hong, and Stein, 2002; Goetzmann and Massa, 2005; Park, 2005; Berkman, Dimitrov, Jain, Koch, and Tice, 2009; Yu, 2011). These findings are valid only for stocks with certain characteristics (e.g., illiquid or short-sale constrained), consistent with Miller (1977). Therefore, knowing whether disagreement matters when short-selling is less constrained is important to improve our understanding of the link between disagreement and stock expected returns. On news days, the stock should be liquid and hence less short-sale constrained (e.g., Kyle, 1985; Campbell, Grossman, and Wang, 1993; Llorente, Michaely, Saar, and Wang 2002; Tetlock, 2010; Ben-David, Franzoni, and Moussawi, 2012; Cao, Chen, Liang, and Lo 2013; Beschwitz, Bastian, Chuprinin, and Massa, 2018).[2] Indeed, we find that news disagreement is correlated with increases in the level of stock liquidity. Therefore, the disagreement is accompanied by increases in liquidity that result in high future returns. This characteristic helps us resolve the controversy of existing studies.

Fourth, our paper is able to distinguish between two competing channels regarding how trading volume is incorporated into asset prices when trading volume is a measurement of investor disagreement. News captures the shocks to investors' disagreements rather than the average level of investors' disagreements. The latter is the bias of the representative investor, while the former most likely represents the extra uncertainty investors face (Atmaz and Basak,

[2] Disagreement itself has a potentially positive effect on trade by creating scope for transactions between agents with different views (Naes and Skjeltorp, 2006; Hong and Sraer, 2016).

2018). As Atmaz and Basak (2018) suggest, investor disagreement, such as trading volume, can affect the stock returns in two ways: the average bias (optimistic view) has negative effects on returns and the dispersion in beliefs (extra uncertainty) has positive effect on returns. According to Atmaz and Basak (2018), trading volume (abnormal trading volume) is negatively (positively) priced because it is dominated by the optimistic view (extra uncertainty). They predict that when trading volume on the stock is relatively high, the optimistic effect increases, and the abnormal trading volume-mean return relationship becomes less positive. As predicted, we find that our abnormal trading volume's positive price is much weaker among stocks with the higher trading volume, which directly supports the theory of Atmaz and Basak (2018). This result helps us understand why our abnormal trading volume is positively priced, but the trading volume itself is negatively priced (e.g., Lee and Swaminathan, 2000; Hong and Stein, 2007).

Finally, we contribute to the literature on the role of media in return anomalies. First, this paper underscores the relevance of content to return predictability by showing that news-based price changes are different from noise-based price changes (e.g., Chan, 2003; Savor, 2012; Savor and Wilson, 2014; Tetlock, 2014). Second, we provide additional evidence that misreaction to news plays a central role in the mechanism of return anomalies (e.g., Hillert, Jacobs, and Muller, 2014; Wang, Zhang, and Zhu, 2018; Bail, Bodmaruk, Scherbina, and Tang, 2017; Engelberg, McLean, and Pontiff, 2018).

The remainder of this paper is organized as follows. Section 2 describes the data and variables. Section 3 presents formal event studies to examine the price convexity in news. Section 4 presents formal asset pricing tests and shows that the disagreement about news is priced. Section 5 distinguishes our disagreement on news from other explanations. The last section concludes.

2. Data

Our sample period covers January 2000 to December 2016. The stock data is from the Center for Research in Security Prices (CRSP), and the firm accounting data is from CRSP/Compustat merged. We only include stocks with share codes equal to 10 or 11 and listed on the New York Stock Exchange (NYSE), American Stock Exchange (Amex), and National Association of Securities Dealers Automated Quotations (Nasdaq).

We obtain news data from RavenPack News Analytics, a leading global news database used in quantitative and algorithmic trading. RavenPack collects and analyzes real-time, firm-level business news from leading news providers (e.g., Dow Jones Newswire, The Wall Street

Journal, and Barron's) and other major publishers and web aggregators, including industry and business publications, regional and local newspapers, government and regulatory updates, and trustworthy financial websites. We only include the newest and most relevant news by setting the event-novelty score (ENS) and the news-relevance score (NRS) equal to 100 from RavanPack. This setting can reduce the measurement error for the firm-specific information.[3] We adjust the news date to the next trading day if a news event is made after 4:00 pm. A news day is a trading day with at least one news release.

The next step is to identify major price movements to perform an event study. We calculate a firm's abnormal return, defined as its daily return in excess of its return predicted by the Carhart (1997) four-factor model. For each firm-news day observation, we use pre-event returns to estimate the following regression model:

$$R_{i,t} - R_{f,t} = \alpha + \beta_{i,m}\left(R_{m,t} - R_{f,t}\right) + \beta_{i,smb}SMB_t + \beta_{i,hml}HML_t + \beta_{i,umd}UMD_t + \varepsilon_{i,t}$$

where $R_{i,t}$ is the firm's daily return, $R_{m,t}$ is the market return, $R_{f,t}$ is the risk-free rate, *SMB* is the size factor, *HML* is the value factor, and *UMD* is the momentum factor. We collected the factor returns from Kenneth French's Web site. We estimate this equation by ordinary least squares (OLS) regressions for a 255 trading day-period starting three trading days before the event day (e.g., [−257, −3]). Before we use the estimated coefficients, we require at least 30 data points.[4] With the coefficients obtained from the above equation, we then compute post-event abnormal returns (AR) as follows:

$$AR_{i,t} = R_{i,t} - R_{f,t} - [\beta_{i,m}\left(R_{m,t} - R_{f,t}\right) + \beta_{i,smb}SMB_t + \beta_{i,hml}HML_t + \beta_{i,umd}UMD_t]$$

Following Frank and Sanati (2018), we set positive news events as those with positive abnormal returns ($AR_{i,t}$) over the news-day event window [-1, +1] and set negative news events as those with negative $AR_{i,t}$ over the news-day event window [-1, +1]. Throughout the paper, we refer to the news event date as "day 0." Next, we decompose post-event returns into news-day and non-news-day returns. We examine abnormal returns on news day with

[3] The event-novelty score, which represents how novel a news article is, and the news-relevance score, which indicates how relevant a news article is to a given firm. Both ENS and NRS variables have a range of values between zero and one hundred, with a high value indicating the more recent release of a given news event or the greater relevance of a news article to a firm, respectively. Hafez (2009) finds that 80% of all news stories simply add noise.

[4] Our results are robust using different market models and estimation windows.

cumulative (average) abnormal returns ($CAR_{t,t+n}$) over the subsequent trading days with and without news.

To proxy for investor disagreement, we use abnormal trading volume. We calculate abnormal volume in two ways. First, we calculate the abnormal trading volume as the average trading volume over the post-event window (e.g., three months after a news event [+3, +60]), scaled by the average trading volume over the estimation window [−257, −3], with trading volume defined as the number of shares of firm i traded on day t divided by the total number of shares outstanding of firm i on day t ($\Delta Turn_{i,t} = \frac{Average\ Volume_{i,t,t+n}}{Average\ Volume_{i,t-257,t-3}}$). Second, we construct an unexplained volume (SUV) measure following the methodology of Garfinkel and Sokobin (2006):

$$SUV_{i,t} = UV_{i,t}/S_{i,t}\ ,$$

$$UV_{i,t} = Volume_{i,t} - E[Volume_{i,t}],$$

$$E\left[Volume_{i,t}\right] = \hat{\alpha}_i + \hat{\beta}_{i,1} \times \left|ret_{i,t}\right|^{+} + \hat{\beta}_{i,2} \times \left|ret_{i,t}\right|^{-}$$

where $ret_{i,t}$ and $Volume_{i,t}$ are return and turnover for stock i on day t, $\left|ret_{i,t}\right|^{+}$ is non-negative returns, and $\left|ret_{i,t}\right|^{-}$ is non-positive returns. Parameter estimates $\hat{\alpha}_i$; $\hat{\beta}_{i,1}$; $\hat{\beta}_{i,2}$ are obtained from the regression using daily data over the [-257, -3] estimation window. $S_{i,t}$ is the standard deviation of the residuals from the regression over the estimation window. We calculate the average daily $SUV_{i,t}$ in the event window as well as in the post-event windows.

3. Event studies

In this section, we perform an event study analysis. An extensive theoretical literature implies that opinion divergence may be treated as an additional risk factor affecting asset prices (e.g., Varian, 1985, 1989; Abel, 1989; and David, 2008), which results in a higher *ex post* return around news events. Therefore, if news increases investor disagreement, investors could treat news as a risk proxy requiring *ex post* compensation. Reflecting the high *ex post* return of the risk compensation, stock prices thus overreact to good news and underreact to bad news. In the future time, the post-news divergence (convergence) is expected to lead to upward (downward) drifts in stock prices following both good and bad news events.

3.1. News and price convexity

We test the post-event non-news-day returns in Table 1. We cluster the standard errors at the firm and event-date level. If news events increase investor disagreement, the disagreement theory predicts that non-news-day is related to opinion convergence, which is associated with negative price moves. Table 1 illustrates that news increases investor disagreement in our sample. Negative day abnormal returns are followed by significant positive reversals in returns over the next 60 non-news days under positive news events. This result suggests that investors, on average, overreact to good news. On the other hand, for negative news events, positive day abnormal returns are followed by significant drifts in returns over the next 60 non-news days. This result suggests that investors, on average, underreact to bad news. Overall, these results confirm that stock prices are convex in news, which resulted from divergent opinions on news events. After the initial positive and negative news events, opinions converge on future non-news days, and hence, we observe lower returns on those days.

[Table 1 here]

Post-event abnormal returns are greater (more negative) after bad news. For negative news events, on average, there is a -1.16% abnormal return on day 0. This news event is then followed by a negative price drift as large as 15.82% ($-0.023 \times 8 \div [-1.162]$) of the initial shock size, over the subsequent 20 days. The negative drift continues to decrease the price by as much as 28.92% of the size of the initial shock during the 60 days after the shock. For positive news shocks, the stock market responds with an average +1.29% abnormal return on news days. However, 9.93% of the initial shock is reversed in the following 20 days, and a total of 19.56% is reversed over the 60 days following the news event. On average, the magnitude of the post-event returns relative to the day 0 returns for negative news is larger than that for positive news.

To further understand the post-event returns, Panel B of Table 1 sorts news events of each sign into quintiles based on their day 0 abnormal returns. The reversal patterns are observed across all quintiles. Notably, the post-event patterns after the news events are both statistically and economically more significant for large to small shock sizes (absolute returns) of both signs, controlling for the size of day 0 news shocks. This result confirms the predictions of investor disagreement. First, extreme news shocks are useful indicators of intertemporal spikes in investor disagreement because market participants usually disagree more with the most important news, such as earnings news (e.g., Harris and Raviv, 1993; Kandel and Pearson, 1995). Second, temporarily increased investor disagreement can also be a potential cause of extreme returns on news shocks. Hence, extreme returns on news shocks are useful to identify and isolate periods of acute opinion divergence.

We then test the post-event news day returns in Table 2. As future news disclosures following news events amplify the disagreement, the stock becomes relatively riskier, which leads to a further increase in the *ex post* return and, consequently, in the stock price. Thus, we should observe post-shock divergence on news days following a news event.

As predicted, positive day 0 abnormal returns are followed by significant drifts in returns in the next 60 news days for positive news events. Negative day 0 abnormal returns are followed by significant reversals in returns in the next 60 news days for negative news events. These results further confirm that investors, on average, overreact to good news and underreact to bad news.

[Table 2 here]

Panel B of Table 2 sorts news events of each sign into quintiles based on their day 0 abnormal returns. We find that the reversal patterns exist across all quintiles. Consistently, the post-event patterns after the news events are statistically and economically more significant for large to small shock sizes of both signs, controlling for day 0 shocks. Again, this result confirms that extreme returns on news shocks indicate a high level of investor disagreement.

Furthermore, the post-event patterns after the news events are stronger among large news shock sizes, indicating our results are probably not driven by the confounding effect of overlapping news. For example, it is unlikely that more than one large piece of news can be released within a 60-trading-day interval.

3.2. Trading volume

This subsection provides direct evidence of opinion divergence on news days and the convergence on non-news days following news events by investigating the variations of disagreement proxy.

We use abnormal trading volume to proxy for investor disagreement. The earlier literature, both theoretical and empirical, suggests that a component of trading volume may be attributed to opinion divergence. For example, Kandel and Pearson (1995) predict that volume will increase in the diversity of investor opinions around earnings events because investors possess different likelihood functions. Harris and Raviv (1993) study the effect of news announcements on trading prices and volume by assuming that traders receive common information but differ in the way they interpret the same information. Commonly, these studies suggest that trading volume is higher on news days that are more likely associated with more divergent investor opinions.

[Table 3 here]

Table 3 provides evidence that investor disagreement increases on news days. Table 3, Panel A, reports post-event variations in $\Delta Turn$ for stocks with positive and negative news events. For each stock in the positive and negative news events, we calculate the average daily $\Delta Turn$ in post-event windows following these news events. Row 1 of Panel A presents the average daily $\Delta Turn$ in the post-event news days over [3, 20] following the positive news events. The estimates are well above one, confirming the findings in Tables 1 and 2 that investor disagreement increases on news days. A similar effect is confirmed in Row 2 of Panel A when we investigate the average daily $\Delta Turn$ in the post-event news days over [3, 60]. For the negative news events, the average daily $\Delta Turn$ in the post-event news days over [3, 20] and [3, 60] are 1.251 and 1.302, respectively.

The remainder of the panel indicates that changes in disagreement are significantly lower in the post-event non-news days following both negative and positive news events. For example, after negative news events, the average daily $\Delta Turn$ in post-event non-news days over [3, 60] is 0.981, suggesting that investor disagreement decreases gradually in the post-event non-news days. The differences between the average daily $\Delta Turn_{i,t}$ in the post-event news days and the average daily $\Delta Turn$ in the post-event non-news days are significantly different from zero, confirming that investor disagreements increase on news days.

We use unexplained volume to proxy for disagreement in Table 4, Panel B, and find similar results. For example, Row 4 of Panel B (e.g., [3, 60]) presents the average daily SUV in the post-event news and non-news days following the negative news events. The estimates for post-event news days are about 0.283, while the estimates for post-event non-news days are about -0.010. The differences between them are significantly different from zero. Overall, these results confirm that opinions diverge on news days, but converge on non-news days.

4. The price of news disagreement

Thus far, we have shown that news indeed increases investor disagreement since stock prices are convex in news. In this section, we investigate the relationship between news disagreement and expected stock returns. We use monthly $\Delta Turn$ and SUV to capture investor disagreement on news in each firm-month. The monthly $\Delta Turn$ (SUV) is calculated as the daily average of news days' abnormal trading volume (unexplained trading volume) in each firm-month.

The last section has presented evidence that investors treat news as a risk proxy requiring *ex post* compensation. Therefore, we should expect to see a significant positive relationship between news disagreement and future stock returns. Table 4 reports the results of univariate portfolio sorting. Specifically, in each month, we sort all stocks into five portfolios based on $\Delta Turn$ or *SUV* measured over the last month. We then compute the monthly holding period equal-weighted average returns for the future month t+1 across all firms in each portfolio. Stocks in the first quintile portfolio have the lowest $\Delta Turn$ (*SUV*), while stocks in the fifth quintile portfolio have the highest $\Delta Turn$ (*SUV*). We exclude stocks with prices lower than $1 at the end of the formation date.

In Panel A, Table 4, we report evidence that is consistent with our predictions. This panel shows that mean returns increase from the first $\Delta Turn$ quintile (0.44%) to the fifth $\Delta Turn$ quintile (1.38%). The average raw return difference between quintile five and quintile one is 0.94% per month with a corresponding Newey-West (1987) t-statistic of 4.97.

[Table 4 here]

We then assess the empirical relationship between news disagreement and stock returns by adjusting for standard measures of risk (CAPM model, the Fama-French (1993) three-factor model, the Carhart (1997) four-factor model, and a five-factor model that includes the Pastor-Stambaugh (2003) liquidity factor). Specifically, we regress the excess returns of zero-cost hedge portfolios against the respective factors and calculate the regression intercepts representing risk-adjusted returns, namely, risk-adjusted alpha. The risk-adjusted alphas for the zero-cost hedge portfolio in Columns 2 to 5 of Table 4 range from 0.83% to 0.93% per month with Newey-West t-statistics of 4.65 to 5.04. Thus, we find no evidence that the returns of portfolios sorted by news disagreement can be attributed to their co-movement with common risk factors.

Panel B of Table 4 presents results using *SUV*. The equal-weighted raw return on the *SUV* portfolios increases with *SUV* as well: from 0.58% per month for the lowest *SUV* quintile portfolio to 1.27% per month for the highest *SUV* quintile portfolio. The equal-weighted return differences and the corresponding alphas range from 0.64% to 0.76% per month between the high- and low-*SUV* portfolios. These return differentials are strongly statistically significant as well.

Overall, these results indicate that, regardless of the news disagreement proxies, a portfolio that buys stocks in the highest news disagreement quintile and shorts stocks in the lowest news disagreement quintile yields both economically and statistically significant returns ranging between 0.67% and 1.23% in the next month. Combined with the previous result that stock prices are convex in news, our findings suggest that news increases investor disagreement.

We now investigate the relationship between disagreement on news and other return predictors. Table 5 presents the summary statistics for the stocks in the quintiles. Quintile portfolios are formed at the beginning of every month t+1 by sorting stocks based on $\Delta Turn$ (Panel A) or *SUV* (Panel B) realized in month t. Specifically, the table reports the average across the months in the sample of the mean values within each month of various characteristics for the stocks in each quintile.

[Table 5 here]

In Panel A, as we move from the low $\Delta Turn$ to the high $\Delta Turn$ quintile, the average across months of mean $\Delta Turn$ increases from 0.436 to 3.496. As $\Delta Turn$ increases across the quintiles, market capitalization (*Size*), book-to-market (*BM*) ratio, and market beta (*Beta*) do not vary much. We find that the return of momentum (*MOM*) and reversal (*REV*) increases from 6.10% (-0.41%) to 27.67% (3.02%) if we move from the lowest $\Delta Turn$ to the highest $\Delta Turn$ quintile. These results are consistent with the hypothesis that news increases disagreement—the disagreement on news causes price convexity and hence increases the contemporaneous stock prices (e.g., see Tables 2.1 and 2.2). Moreover, illiquidity shock (*ILLIQ*) increases from -2.047 to 2.470 if we move from the lowest $\Delta Turn$ to the highest $\Delta Turn$ quintile. This finding is consistent with the views that news increases the level of liquidity (Kyle, 1985). The return volatility (*IVOL*) also increases from the first $\Delta Turn$ quintile (2.47%) to the fifth $\Delta Turn$ quintile (3.58%), confirming that investor disagreement is associated with high return volatility.

In Panel B, as we move from the low *SUV* to the high *SUV* quintile, the average across months of mean *SUV* increases from 0.436 to 3.496. Similarly, we find that *MOM, REV, IVOL,* and *ILLIQ* increase from the first *SUV* quintile to the fifth *SUV* quintile, and other variables do not vary much.

Panel C of Table 5 reports the time-series averages of the cross-sectional correlation coefficients for the variables, revealing two disagreement measures on news are highly correlated, with an average correlation coefficient of 88% (between $\Delta Turn$ and *SUV*). Hence, $\Delta Turn$ and *SUV* capture the same information. The average correlation coefficients between the contemporaneous stock return (*REV*) and $\Delta Turn$ and *SUV* are, respectively, 12% and 11%. This result is consistent with the findings in Panels A and B. The two measures of disagreement on news are also correlated with many known return predictors, such as illiquidity shock, size, momentum, and return volatility. These variables serve as our controls in the following analysis.

To confirm that the pricing of news disagreement in our sample period is not driven by firm characteristics that plausibly relate to stock future returns, we now examine the relationship between news disagreement and returns using the following standard Fama-MacBeth (1973) cross-sectional regressions:

$$R_{i,t} = \alpha + \beta_1 \times \Delta Turn_{i,t-1} (or\ SUV_{i,t-1}) + \theta' \times Z_{i,t-1} + \varepsilon_{i,t}$$

where $R_{i,t}$ is the monthly return for firm *i* observed at the end of month t. $Z_{i,t-1}$ is the control variables, which include the following: previous year-end log market capitalization ($Size_{t-1}$), previous year-end book-to-market ratio (BM_{t-1}), idiosyncratic volatility ($IVOL_{t-1}$) computed over the last month, illiquidity shock computed over the previous month ($ILLIQ_{t-1}$), the past two-month stock returns ($R_{t-2,t-3}$), the past three-month stock returns $\left(R_{t-4,t-6}\right)$, the past six-month returns ($R_{t-7,t-12}$), the last month market beta ($Beta_{t-1}$), and the last month news sentiment (ESS_{t-1}).

Table 6 presents the time-series averages of the slope coefficients from the stock-level Fama and MacBeth (1973) cross-sectional regressions of one-month-ahead stock returns on $\Delta Turn$ or SUV with all cross-sectional predictors controlled for simultaneously. The t-statistics computed with Newey-West standard errors are provided in parentheses.

Table 6 illustrates that the predictive ability of the abnormal trading volume variable is not subsumed by any of the other return predictors. The average slope β_1 of $\Delta Turn$ in Column (1) is 0.126 and significant at the 1% level. To interpret the economic meaning of β_1, we multiply the average β_1 with the difference in mean $\Delta Turn$ between quintile five and one (3.06). This economic magnitude is equal to 0.39% expected return difference per month. In Column (2), we find that the average slope β_1 of SUV is 0.156 with a t-statistic of 5.26. The corresponding economic magnitude is equal to 0.42% expected return difference per month.[5]

[Table 6 here]

In general, the average slope coefficients on the control variables are in line with the earlier studies. For example, the size effect is negative and significant, the value effect is positive, and idiosyncratic volatility is negatively priced. The sign and significant levels of other control variables are consistent with prior empirical studies that also focus on RavenPack data (e.g., Wang, Zhang, and Zhu, 2018; Wang, 2019).

Overall, the Fama-MacBeth regression results confirm that, even after jointly controlling for a large set of variables, our news disagreement variables have economically and statistically significant predictive power for future stock returns.

[5] The benefit of firm-level regressions is a richer cross-section that captures the information potentially lost at the portfolio level and makes the standard errors smaller. The downside is that the firm-level regressions are likely to suffer from errors in variables, which will make slopes on disagreement measures biased toward zero. These issues can be the potential reason for why the prices (t-statistics) of news disagreement in regressions are lower (higher) than those in portfolio analysis.

5. The price of news disagreement: additional evidence

The results in section 4 above suggest that abnormal trading volume is positively priced. In this section, we conduct additional tests to confirm whether this positive price is consistent with investor disagreement on news. The tests in this section are based on $\Delta Turn$. For brevity, we relegate the discussion of a similar test with SUV to Appendix IA2: the conclusions are the same.

5.1. Disagreement: news-day trading volume, price volatility, and price convexity

Studies suggest a positive relationship among disagreement, trading volume, and price volatility. For example, based on a two-period noisy rational expectations model, Shalen (1993) finds that higher dispersion causes higher price volatility, has higher trade volume, and increases the correlation between price volatility and trading volume. Harris and Raviv (1993) find that absolute price changes and trading volume around news events are positively correlated and that absolute changes in the mean forecast of the final payoff and volume are positively correlated. Banerjee and Kremer (2010) reveal that disagreement leads to a positive correlation between volatility and trading volume because investors differ in their interpretation of public signals in a dynamics of trade model. Atmaz and Basak (2018) develop a dynamic model of belief dispersion with a continuum of investors differing in beliefs and show that stock volatility and trading volume are positively correlated due to the positive effect of dispersion on both quantities. Overall, if news increases investor disagreement, we should observe a positive correlation between trading volume and return volatility. Therefore, a direct prediction is that news disagreement pricing should be stronger among stocks with greater news-day volume–volatility correlations.

We construct a monthly news-day volume–volatility correlation variable ($Corr$). $Corr$ is the correlation between news-day trading volume and return volatility within a firm-month. The daily news-day return volatility is the absolute value of abnormal return that we used in Tables 1 and 2. We then perform independent portfolio sorting. We sort all stocks into five portfolios based on their $\Delta Turn$ and further independently sort all stocks into one of three terciles based on their $Corr$. Then, we calculate the monthly equal-weighted future returns for these groups.

[Table 7]

As predicted, Panel A of Table 7 indicates that the $\Delta Turn$ effect is stronger among stocks with a high level of $Corr$. The most positive $\Delta Turn$ overperforms a portfolio of stocks with the most negative $\Delta Turn$ by 0.96% per month after adjusting for the Carhart (1997) four-factor model in high $Corr$ terciles. However, the high-low $\Delta Turn$ portfolio only earns 0.26% abnormal returns annually in low $Corr$ terciles. Hence, these results confirm that the pricing of news disagreement is stronger among firms with greater news-day volume–volatility correlations.

Another prediction is that the pricing of news disagreement should be stronger among firms with greater return volatility on news days. A stock that has both high levels of news-day abnormal trading volume and return volatility is more likely to experience a positive volume–volatility relationship. We construct a monthly news-day return volatility (Vol^{news}). Vol^{news} is the daily average of absolute news-day abnormal returns in each firm-month. We then perform independent portfolio sorting based on Vol^{news} and $\Delta Turn$.

As predicted, Panel B of Table 7 reveals that the $\Delta Turn$ effect is stronger among stocks with a high level of Vol^{news}. For example, the most positive $\Delta Turn$ overperforms a portfolio of stocks with the most negative $\Delta Turn$ by 1.32% per month after adjusting for the Carhart (1997) four-factor model in high Vol^{news} terciles, but these abnormal returns reduce to 0.70% per month in low Vol^{news} terciles.

The final prediction is that the pricing of news disagreement should be stronger among firms with greater abnormal returns on news days. Stocks with higher abnormal returns on news days are more likely to experience disagreement on news. Intuitively, as we presented in Tables 2.1 and 2.2, higher abnormal returns on news days are associated with greater price convexity. Hence, the abnormal returns on news days should be positively related to investor disagreement.

We construct a monthly news-day abnormal return ($Aret^{news}$) variable. $Aret^{news}$ is the daily average of news-day abnormal returns in each firm-month.[6] We perform independent portfolio sorting based on $Aret^{news}$ and $\Delta Turn$. Panel C of Table 2.7 shows that the $\Delta Turn$ effect is stronger among stocks with a high level of $Aret^{news}$. A portfolio that is long in stocks with the most positive $\Delta Turn$ and short in stocks with the most negative $\Delta Turn$ leads to a monthly return of 1.17% for stocks in the largest $Aret^{news}$ tercile and a return of only 0.60%

[6] Since the news-day return is correlated with news sentiment, it is useful to disentangle the portion of the news-day returns driven by news size and examine the orthogonal component of news-day returns. To investigate this issue, we first run firm-level contemporaneous cross-sectional regressions of news-day returns on news sentiment, and then use the residuals of these monthly cross-sectional regressions (that are orthogonal to news sentiment) to form perform our tests.

for stocks in the smallest $Aret^{news}$ tercile. This result further confirms that the positive pricing of news disagreement is consistent with the theoretical predictions of disagreement literature.

Overall, our results suggest that the positive price of news disagreement is consistent with predictions of disagreement theory.

5.2. News-day trading volume and Change in disagreement

We now verify whether $\Delta Turn$ is correlated with increases in the level of investor disagreement in the future month. We perform two tests.

First, we examine the average one-month-ahead portfolio transition matrix for our sample firms. This method presents results regarding the cross-sectional persistence of news disagreement. Specifically, we present the average probability that a stock in quintile i (defined by the rows) in one month will be in quintile j (defined by the columns) in the subsequent month. All the probabilities in the matrix should be approximately 20% if the evolution for investor disagreement for each stock is random and the relative magnitude of disagreement in one period has no implication on the relative disagreement in the subsequent period. However, as Table 8 displays, 45% of stocks in the lowest $\Delta Turn$ quintile in a certain month continue to be in the same quintile one month later. Similarly, 37% of the stocks in the highest $\Delta Turn$ quintile in a certain month continue to be in the same quintile one month later. These results overall suggest that $\Delta Turn$ is a highly persistent equity characteristic. Hence, a high value of $\Delta Turn$ indicates a greater investor disagreement in the future month. Investors require higher future risk compensations based on the value of $\Delta Turn$ in the current month.

Second, we verify whether $\Delta Turn$ is correlated with temporary increases in the level of analyst disagreement, which we use as an additional proxy for investor disagreement about firm value. We perform our analysis for the most frequently forecasted variable, the current fiscal year's earnings per share. We use the unadjusted detail Institutional Brokers' Estimate System (I/B/E/S) files to construct analyst disagreement. As in Diether, Malloy, and Scherbina (2002), we define analyst disagreement as the standard deviation in the outstanding earnings forecasts for the closest fiscal year-end divided by the absolute value of the mean earnings forecast. We drop the observation if the mean earnings forecast is zero.[7] These extreme values could be caused by data errors or by scaling problems.

[7] We also delete earnings forecasts with the absolute value of the forecasted earnings to price ratio greater than 0.75 and observations with the scaled change in dispersion greater than 10.

We test whether the change in forecast dispersion is higher for the stocks with currently high abnormal trading volume values than for the stocks with currently low abnormal trading volume values. We examine the cross-sectional differences since the earnings forecast dispersion decreases over the fiscal year. Following Bali, Bodnaruk, and Scherbina (2018), we compute the change in the forecast dispersion as the change in the dispersion in the active earnings forecasts at the end of the current month and the dispersion two months prior.

At the end of each month, we sort stocks into quintiles based on the value of $\Delta Turn$ realized that month. We then check the change in the analyst disagreement between that month and two months prior. The results are reported in panel B of Table 8.

[Table 8 here]

In Column (1), we find that there is no difference in the change in dispersion between the high and low $\Delta Turn$ quintiles during the month t-1. In Column (2), analyst dispersion significantly decreases for the stocks in $\Delta Turn$ quintile one, and it significantly increases for the stocks in quintile five during month t. The difference in the change in dispersion between the high and low $\Delta Turn$ quintiles is significantly positive (0.035 with a t-statistic of 8.57). This difference remains positive in the future month t+1 in Column (3), confirming that the increase in the disagreement in the high-ΔTurn month is not temporary. These findings confirm our conjecture that $\Delta Turn$ is associated with the high level of investor disagreement in the current and future months.

5.3. News-day trading volume vs. trading volume

We confirm that the positive price of $\Delta Turn$ is consistent with the predictions of theories of investor disagreement. However, early studies find that higher trading volume, which is a proxy for differences of opinion, predicts lower future returns (e.g., Lee and Swaminathan, 2000; Hong and Stein, 2007). This section addresses that our abnormal trading volume's positive price does not necessarily contradict early studies that find that trading volume is negatively priced in the cross-section.

The researchers summarize the wide range of trading volume using two sufficient measures, the average bias and dispersion in beliefs, and demonstrate that these two variables drive equilibrium quantities (Atmaz and Basak, 2018). The average bias is the bias of the representative investor, for example, investors' optimism. The dispersion in beliefs is the spikes in investor disagreement (disagreement shocks), representing the extra uncertainty investors face. Atmaz and Basak (2018) suggest that if the effect of the average bias dominates, then a negative dispersion–mean return relationship is observed. However, if the effect of the dispersion in beliefs dominates, then a positive dispersion–mean return relationship is observed.

According to Atmaz and Basak (2018), trading volume is negatively priced because the effect of the average bias dominates, while our news-day abnormal trading volume is positively priced because the dispersion in beliefs dominates. To test this conjecture, we perform the independent portfolio sorting and investigate how the price of our news-day abnormal trading volume varies across different trading volume groups. Specifically, Atmaz and Basak (2018) suggest that we should expect to see a greater positive price of news-day abnormal trading volume among stocks with lower trading volume (the smaller effect of the average bias).

We measure the monthly trading volume as the stock turnover (*Turnover*) using monthly data from CRSP. As predicted, Panel A of Table 9 indicates that the $\Delta Turn$ effect is stronger among stocks with lower *Turnover* levels. For example, the most positive $\Delta Turn$ overperforms a portfolio of stocks with the most negative $\Delta Turn$ by 1.27% per month after adjusting for the Carhart (1997) four-factor model in low *Turnover* terciles, but these abnormal returns decline to 0.75% per month in high *Turnover* terciles. This result is consistent with Atmaz and Basak's (2018) theory.

[Table 9 here]

In addition to the average bias, Miller (1977) conjectures that when frictions prevent the revelation of negative opinions (e.g., short-sale constraints), an increase in optimistic views decreases expected returns. In other words, trading volume is not only positively correlated with investors' optimism but also positively correlated with short-sale constraints. Short-sale constraints are generally related to illiquidity. Early studies show that liquidity increases in the presence of news (Kyle, 1985; Campbell, Grossman, and Wang, 1993; Llorente, Michaely, Saar, and Wang 2002; Tetlock 2010), which increases the trading activity of short sellers (e.g., Ben-David, Franzoni, and Moussawi, 2012; Cao, Chen, Liang, and Lo 2013; Beschwitz, Bastian, Chuprinin, and Massa, 2018). Hence, another reason for the positive price of our news-day abnormal trading volume could be that it decreases short-sale constraints. Therefore, to further confirm the theory of Atmaz and Basak (2018), we investigate 1) whether $\Delta Turn$ is correlated with temporary increases in the level of liquidity, and 2) whether this correlation is lower among stocks with higher trading volume.

As a measure of liquidity, we compute monthly Amihud Illiquidity using daily data from CRSP. We investigate the cross-sectional differences and compute the change in the liquidity as the negative change in the Amihud Illiquidity at the end of the current month and the Amihud Illiquidity one month prior. Moreover, to demonstrate that the increase in the liquidity in the high-$\Delta Turn$ month is not temporary, we also check the change in the liquidity between the current month and the next month.

The results are reported in panel B of Table 9. Each month, we perform the independent portfolio sorting. We sort all stocks into five portfolios based on their $\Delta Turn$ and further independently sort all stocks into *Turnover* and calculate the monthly equal-weighted change in the liquidity in the current and future months. Panel B shows that liquidity significantly decreases for the stocks in $\Delta Turn$ quintile one and significantly increases for the stocks in quintile five during month t. The differences in the change in liquidity between high and low $\Delta Turn$ quintiles are significantly positive. These differences remain positive in the future month t+1. Notably, the significant increases in liquidity are stronger among stocks with low *Turnover*. For example, in month t, the differences in the change in liquidity between the high and low $\Delta Turn$ quintiles are 5.290 with a t-statistic of 4.93 among stocks with low *Turnover*, but they become 0.432 with a t-statistic of 2.09 among stocks with high *Turnover.* We obtain a similar conclusion in month t+1.

To further illustrate that disagreement shocks are accompanied by increases in liquidity that result in high future returns, we perform an additional test as follows. We have shown that $\Delta Turn$ are, on average, associated with increases in liquidity. However, this association may not be true for all stocks. For example, a higher $\Delta Turn$ may result from the greater size of news. Therefore, for each month, we sort the stocks in the highest $\Delta Turn$ quintile into further quintiles based on the change in liquidity. In Appendix IA3, we find that it is the stocks that fall in the highest increase-in-liquidity quintile that earn high future returns: they outperform the stocks in the lowest increase-in-liquidity quintile by 0.71% per month, on average (with a t-statistic of 2.38).

These findings confirm our conjecture that $\Delta Turn$ is associated with the high level of liquidity in the current and future months, especially among stocks with low *Turnover*. Therefore, our results suggest that short-selling is less constrained for stocks with higher $\Delta Turn$, and hence, $\Delta Turn$ captures less effect from the average bias, as suggested by Atmaz and Basak (2018). This evidence improves our understanding of the link between investor disagreement and asset prices, especially when disagreement is measured by trading volume.

The effects of average bias and disagreement shocks on equity prices also varies over time. On the one hand, according to Cujean and Hasler (2017), the risk premiums associated with investor disagreement and news content is countercyclical, meaning that investors require more (less) compensation for the risk of disagreement in economic downturns (upturns). Cujean and Hasler (2017) model that investors assess uncertainty differently, and as economic conditions deteriorate, uncertainty rises, and investors' opinions polarize. Thus, disagreement spikes in bad times, causing greater equity risk premiums. On the other hand, early studies indicate that investors' average bias is positively related to market states (e.g., Daniel, Hirshleifer, and Subrahmanyam, 1998; Gervais and Odean, 2001; Baker and Wurgler, 2006; Chung, Hung, and Yeh, 2012), suggesting that the effect of the average bias is lower (higher) in economic downturns (upturns). Accordingly, we expect that in bad markets, the effect of the average bias should be decreased, but the effect of the disagreement shocks should be increased. In good markets, the opposite conclusion should be observed. We perform a time-series analysis to examine how the average bias and disagreement shocks are related to the price of news disagreement.

[Table 10 here]

We split our sample into subperiods corresponding to non-recession and recession states based on the Chicago Fed National Activity Index (*CFNAI*). We take months where the three-month moving average *CFNAI* is below −0.7 to be recession states and months where the three-month moving average *CFNAI* is greater than −0.7 to be non-recession states. We then repeat our bivariate portfolio analyses using the subset of months t+1 corresponding to each of these economic states. The results of these analyses are presented in Panel A, Table 10. The price of news disagreement is more positive in bad economic states. A portfolio that is long in stocks with high $\Delta Turn$ (increases in investor disagreement) and short in stocks with low $\Delta Turn$ (decreases in investor disagreement) leads to a monthly return of 235 basis points for stocks in recession states and a return of only 69 basis points for stocks in non-recession states.

We also use volatility index options of the S&P 500 (*VIX*) from the Chicago Board Options Exchange (CBOE) to test the above predictions. *VIX* has been widely regarded as a proxy for market turmoil, or low sentiment. We split our sample into subperiods corresponding to bad and good states based on *VIX*. A high *VIX* month t+1 is one in which the value of *VIX* at the end of month t is above the median value for the sample period, and the low *VIX* month t+1 is below median values. As predicted, in Panel B, Table 10, we find that the price of news disagreement is more positive in bad economic states than in good economic states. Specifically, the return differential for the long-short portfolio based on $\Delta Turn$ is high for the periods with the low *VIX* (124 basis points per month) and lower for the periods with high *VIX* (43 basis points per month).

In Appendix IA4, we perform the same analysis for *SUV*. A portfolio that is long in stocks with high *SUV* and short in stocks with low *SUV* leads to a monthly return of 145 (94) basis points for stocks in the recession states (high *VIX* months) and a return of only 55 (48) basis points for stocks in the non-recession states (low *VIX* months).

6. Other explanations

Gervais, Kaniel, and Mingelgrin (2001) find that the shock to dollar trading volume is positively priced in the cross-section. They argue that this positive price is associated with changes in investor visibility for a stock, as predicted by Merton's (1987) investor recognition hypothesis. We argue that the return predictability of news disagreement and the positive volume shock is not the same. In this section, we distinguish the positive volume shock for our empirical findings.

We use two variables to capture positive volume shocks. First, following Gervais, Kaniel, and Mingelgrin (2001), a stock is defined as a low (high) volume stock in month t if its trading volume on the last trading day of the month is among the lowest (highest) 10% of its 50 daily volumes prior to the formation day (inclusive). Second, we construct a continuous variable for abnormal dollar volume (*VOLDU*). That is, we subtract monthly dollar volume by its past 12-month average.

We investigate this issue based on the conditional bivariate sorts on abnormal volumes after controlling for positive volume shocks. In Column (1) of Table 11, stocks are first sorted into high, medium, and low volume shock groups following Gervais, Kaniel, and Mingelgrin (2001) (*GKM*), and then into $\Delta Turn$ quintiles within each volume shock group. We report the returns of the $\Delta Turn$ portfolios, averaged across the control groups to produce quintile portfolios with dispersion in $\Delta Turn$ but with similar levels of the control variable. We find the average alpha differences between the high $\Delta Turn$ and low $\Delta Turn$ quantiles are 0.796% per month with a t-statistic of 3.56. Thus, the predictive power of $\Delta Turn$ remains intact in bivariate portfolios.

[Table 11 here]

Column (2) presents returns averaged across the *VOLDU* quintiles to produce quintile portfolios with dispersion in $\Delta Turn$ but with similar levels of *VOLDU*. Specifically, stocks are first sorted into quintile portfolios based on *VOLDU* and then into $\Delta Turn$ quintiles within each *VOLDU* quintile. The result shows that when moving from the lowest to highest $\Delta Turn$ quintile, the monthly abnormal return averaged across the *VOLDU* quintiles increases from -

0.17% to 0.57%, with an average abnormal return difference of 0.75% (t-statistic = 4.24). The corresponding alpha has a similar magnitude and is highly significant as well. This result provides additional evidence that after controlling for positive shocks to volume, the predictive power of $\Delta Turn$ remains intact in bivariate portfolios.

In summary, our news disagreement measures continue to predict future returns after controlling for positive volume shocks, suggesting that the return predictability is consistent with investors' disagreement on news, rather than Merton's (1987) investor recognition hypothesis.

7. Conclusions

The disagreement literature provides mixed results in the role of news on investor disagreement. In this paper, we provide new evidence that news increases investor disagreement. A summary of the main findings follows.

First, we find the stock prices are convex in news; that is, stock prices overreact to good news and underreact to bad news. We find non-news-day return reversals following positive news events and non-news-day return continuations following negative news events, confirming that investors overreact to good news and underreact to bad news. We also find that both good and bad news events are followed by higher abnormal news-day returns, confirming that investors require risk compensations when disagreement is high. In addition, using abnormal trading volume as a proxy for investor disagreement, we confirm that investor disagreement is significantly increased on news days.

Second, we provide new evidence that investor disagreement is positively priced. The strategy that buys the high news-day abnormal trading volume portfolio and short sells the low news-day abnormal trading volume portfolio generates a return of 11.29% per year. Consistent with disagreement theories, the news disagreement driven-return predictably is much stronger among stocks with a high level of investor disagreements, such as those with high price volatility, high correlation between trading volume and price volatility, and great price convexity. For time-series variation, we demonstrate that the pricing of news disagreement is significantly stronger during bad economic states, confirming that the risk premium of disagreement is concentrated in bad periods. Overall, our results are consistent with the views that the price of news disagreement is associated with a positive risk premium.

Third, our results distinguish between two competing channels regarding how trading volume is incorporated into asset prices when trading volume is a measurement of investor disagreement. As Atmaz and Basak (2018) suggest, investor disagreement, such as trading volume, can affect the stock returns in two ways: through the average bias and dispersion in beliefs. According to Atmaz and Basak (2018), trading volume (abnormal trading volume) is negatively (positively) priced because it is dominated by the average bias (dispersion in beliefs). We find that the positive price of our abnormal trading volume is much weaker among stocks with higher trading volume. This result directly supports the theory of Atmaz and Basak (2018): when trading volume for the stock is relatively high, the optimistic effect increases, and the abnormal trading volume-mean return relationship becomes less positive. We also find that news disagreement is correlated with increases in the level of liquidity. Hence, the disagreement is accompanied by increases in liquidity that result in high future returns. This characteristic helps us better resolve the vast and mixed empirical evidence on the effects of the dispersion of beliefs on asset expected returns.

References:

Abel, A.B., 1989. Asset prices under heterogeneous beliefs: implications for the equity premium. Rodney L. White Center for Financial Research.

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

Anderson, E.W., Ghysels, E., Juergens, J.L., 2005. Do heterogeneous beliefs matter for asset pricing? The Review of Financial Studies 18, 875-924.

Ang, A., Hodrick, R.J., Xing, Y., Zhang, X., 2006. The cross-section of volatility and expected returns. The Journal of Finance 61, 259–299.

Atmaz, A., Basak, S., 2018. Belief dispersion in the stock market. The Journal of Finance 73, 1225-1279.

Avramov, D., Chordia, T., Jostova, G., Philipov, A., 2009. Dispersion in analysts' earnings forecasts and credit rating. Journal of Financial Economics 91, 83-101.

Bali, T.G., Bodnaruk, A., Scherbina, A., Tang, Y., 2017. Unusual News Flow and the Cross Section of Stock Returns. Management Science 64, 4137-4155.

Bali, T.G., Peng, L., Shen, Y., Tang, Y., 2014. Liquidity shocks and stock market reactions. The Review of Financial Studies 27, 1434-1485.

Bamber, L.S., 1987. Unexpected earnings, firm size, and trading volume around quarterly earnings announcements. Accounting Review, 510-532.

Banerjee, S., Kremer, I., 2010. Disagreement and learning: Dynamic patterns of trade. The Journal of Finance 65, 1269-1302.

Basu, S., 1997, The conservatism principle and the asymmetric timeliness of earnings, Journal of Accounting and Economics 24, 3–37.

Beaver, W.H., 1968. The information content of annual earnings announcements. Journal of Accounting Research, 67-92.

Beber, A., Breedon, F., Buraschi, A., 2010. Differences in beliefs and currency risk premiums. Journal of Financial Economics 98, 415-438.

Ben-David, I., Franzoni, F., Moussawi, R., 2012. Hedge fund stock trading in the financial crisis of 2007–2009. The Review of Financial Studies 25, 1-54.

Berkman, H., Dimitrov, V., Jain, P.C., Koch, P.D., Tice, S., 2009. Sell on the news: Differences of opinion, short-sales constraints, and returns around earnings announcements. Journal of Financial Economics 92, 376-399.

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

Campbell, J.Y., Grossman, S.J., Wang, J., 1993. Trading volume and serial correlation in stock returns. The Quarterly Journal of Economics 108, 905-939.

Carlin, B.I., Longstaff, F.A., Matoba, K., 2014. Disagreement and asset prices. Journal of Financial Economics 114, 226-238.

Cao, C., Chen, Y., Liang, B., Lo, A.W., 2013. Can hedge funds time market liquidity? Journal of Financial Economics 109, 493-516.

Cao, H.H., Ou-Yang, H., 2008, Differences of opinion of public information and speculative trading in stocks and options, Review of Financial Studies 22, 299–335.

Chen, J., Hong, H., Stein, J.C., 2002. Breadth of ownership and stock returns. Journal of Financial Economics 66, 171-205.

David, A., 2008, Heterogeneous beliefs, speculation, and the equity premium, Journal of Finance 63, 41–83.

Dai, L., Parwada, J.T., Zhang, B., 2015. The governance effect of the media's news dissemination role: Evidence from insider trading. Journal of Accounting Research 52, 331–366.

Dang, T.L., Moshirian, F., Zhang, B., 2015. Commonality in news around the world. Journal of Financial Economics 116, 82-110.

Diether, K.B., Malloy, C.J., Scherbina, A., 2002. Differences of opinion and the cross section of stock returns. The Journal of Finance 57, 2113-2141.

Doukas, J.A., Kim, C., Pantzalis, C., 2006. Divergence of opinion and equity returns. Journal of Financial and Quantitative Analysis, 573-606.

Engelberg, J., McLean, R.D., Pontiff, J., 2018. Anomalies and news. The Journal of Finance 73, 1971-2001.

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

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

Frank, M.Z., Sanati, A., 2018. How does the stock market absorb shocks? Journal of Financial Economics 129, 136-153.

Garcia D., 2013. Sentiment during recessions. The Journal of Finance 68, 1276-1300.

Garfinkel, J.A., Sokobin, J., 2006. Volume, opinion divergence, and returns: A study of post–earnings announcement drift. Journal of Accounting Research 44, 85-112.

Gervais, S., Kaniel, R., Mingelgrin, D.H., 2001. The high-volume return premium. The Journal of Finance 56, 877-919.

Goetzmann, W.N., Massa, M., 2005. Dispersion of opinion and stock returns. Journal of Financial Markets 8, 324-349.

Hafez, P.A., 2009. Impact of news sentiment on abnormal stock returns. White paper, RavenPack.

Harris, M., Raviv, A., 1993. Differences of opinion make a horse race. The Review of Financial Studies 6, 473-506.

Healy, P.M., Palepu, K.G., 2001. Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. Journal of Accounting and Economics 31, 405-440.

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

Hong, H., Stein, J.C., 2007. Disagreement and the stock market. Journal of Economic perspectives 21, 109-128.

Jegadeesh, N.,Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. The Journal of Finance 48, 65-91.

Kandel, E., Pearson, N.D., 1995. Differential interpretation of public signals and trade in speculative markets. Journal of Political Economy 103, 831-872.

Kim, O., Verrecchia, R.E., 1994. Market liquidity and volume around earnings announcements. Journal of Accounting and Economics 17, 41-67.

Kyle, A.S., 1985. Continuous auctions and insider trading. Econometrica: Journal of the Econometric Society, 1315-1335.

Li, T., 2007, Heterogeneous beliefs, asset prices, and volatility in a pure exchange economy, Journal of Economic Dynamics and Control 31, 1697–1727.

Llorente, G., Michaely, R., Saar, G., Wang, J., 2002. Dynamic volume-return relation of individual stocks. The Review of Financial Studies 15, 1005-1047.

Lu, H., Wang, K.Q., Wang, X., 2014. Price shocks, news disclosures, and asymmetric drifts. The Accounting Review 89, 1805-1834.

Miller, E.M., 1977. Risk, uncertainty, and divergence of opinion. The Journal of Finance 32, 1151-1168.

Newey, W.K., West, K.D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.

Park, C., 2005. Stock return predictability and the dispersion in earnings forecasts. The Journal of Business 78, 2351-2376.

Pástor, Ľ., Stambaugh, R.F., 2003. Liquidity risk and expected stock returns. Journal of Political Economy 111, 642–685.

Peress, J., 2014. The media and the diffusion of information in financial markets: Evidence from newspaper strikes. The Journal of Finance 69, 2007-2043.

Qu, S., Starks, L., Yan, H., 2003. Risk, dispersion of analyst forecasts and stock returns. University of Texas at Austin Working Paper, 1-33.

Savor, P.G., 2012. Stock returns after major price shocks: The impact of information. Journal of Financial Economics, 106, 635-659.

Savor, P., and Mungo, W., 2014. Asset pricing: A tale of two days. Journal of Financial Economics, 113, 171-201.

Scheinkman, J.A., Xiong, W., 2003. Overconfidence and speculative bubbles. Journal of political Economy, 111, 1183-1220.

Shalen, C.T., 1993, Volume, volatility, and the dispersion of beliefs, Review of Financial Studies 6, 405–434.

Tetlock, P.C., 2007. Giving content to investor sentiment: the role of media in the stock market. The Journal of Finance 24, 1139-1168.

Tetlock, P.C., 2011. All the news that's fit to reprint: Do investors react to stale information? The Review of Financial Studies 24, 1481-1512.

Tetlock, P.C., 2014. Information transmission in finance. The Annual Review of Financial Economics 6, 365-384.

Tetlock, P.C., Saar-Tsechansky, M., Macskassy, S., 2008. More than words: Quantifying language to measure firms' fundamentals. The Journal of Finance 63, 1437-1467.

Varian, H.R., 1985. Divergence of opinion in complete markets: A note. The Journal of Finance 40, 309-317.

Varian, H.R., 1989. Differences of opinion in financial markets. In financial Risk: Theory, Evidence and implications, 3-37. Springer, Dordrecht.

von Beschwitz, B., Chuprinin, O., Massa, M., 2017. Why Do Short Sellers Like Qualitative News? Journal of Financial and Quantitative Analysis 52, 645-675.

Wang, H., 2019. Lottery or asymmetric response to news: Why is skewness priced? Working Paper.

Wang, Y., Zhang, B., Zhu, X., 2018. The momentum of news. Working Paper.

Williams, C. D., 2015. Asymmetric Responses to Earnings News: A Case for Ambiguity. The Accounting Review 90, 785-817.

Xu, J., 2007. Price convexity and skewness. The Journal of Finance 62, 2521-2552.

Yu, J., 2011. Disagreement and return predictability of stock portfolios. Journal of Financial Economics 99,162-183.

Table 1: Post-event drift: Non-news days abnormal return

This Table summarizes the results for the post news patterns. We set positive news events as those with positive abnormal returns (AR_t>0) over the news-day event window [-1, +1], and set negative news events as those with negative abnormal returns (AR_t<0) over the news-day event window [-1, +1]. $AR_{i,t}$ is the average of the Carhart (1997) four-factor model-adjusted daily returns for stock *i* over the news-day event window [-1, +1] where the Carhart (1997) four-factor model is estimated over the estimation window [-257, -3]. Next, I compare abnormal returns on future non-news days after the news event with average abnormal returns ($AR_{t,t+n}$) over the subsequent 10, 20, and 60 trading days. The abnormal returns are reported in percentages. Standard errors are clustered at the firm and date levels. t-statistics are reported in the parentheses.

Panel A: All news event				
Shock level	$AR_{-1,1}$	$AR_{3,10}^{no-news}$	$AR_{3,20}^{no-news}$	$AR_{3,60}^{no-news}$
Positive	1.289	-0.016	-0.012	-0.012
(average)	(107.17)	(-6.27)	(-5.44)	(-4.28)
Negative	-1.162	-0.023	-0.023	-0.016
(average)	(-111.42)	(-7.33)	(-7.23)	(-4.22)
Number of non-news days		4	8	21
Obs		2,215,551	2,667,947	3,071,331
Panel B: Negative news event				
Shock level	$AR_{-1,1}$	$AR_{3,10}^{no-news}$	$AR_{3,20}^{no-news}$	$AR_{3,60}^{no-news}$
Q1	-3.380	-0.049	-0.056	-0.039
(Largest negative)	(-240.60)	(-5.62)	(-5.85)	(-3.06)
Q2	-1.130	-0.023	-0.023	-0.019
	(-2,039.35)	(-5.61)	(-7.14)	(-6.50)
Q3	-0.626	-0.019	-0.014	-0.008
	(-2,550.18)	(-5.82)	(-4.66)	(-2.87)
Q4	-0.331	-0.011	-0.010	-0.006
	(-2,250.45)	(-3.60)	(-4.32)	(-2.75)
Q5	-0.104	-0.005	-0.005	-0.005
(Smallest negative)	(-902.78)	(-1.53)	(-2.18)	(-2.60)
Panel C: Positive news event				
Shock level	$AR_{-1,1}$	$AR_{3,10}^{no-news}$	$AR_{3,20}^{no-news}$	$AR_{3,60}^{no-news}$
Q1	0.105	-0.001	-0.002	-0.003
(Smallest positive)	(868.38)	(-0.43)	(-0.83)	(-1.18)
Q2	0.337	-0.006	-0.004	-0.004
	(2,218.92)	(-2.05)	(-1.87)	(-1.95)
Q3	0.648	-0.010	-0.006	-0.008
	(2,561.23)	(-3.07)	(-2.35)	(-3.67)
Q4	1.195	-0.009	-0.009	-0.014
	(1,936.89)	(-2.30)	(-3.14)	(-5.35)
Q5	3.871	-0.045	-0.035	-0.028
(Largest positive)	(192.49)	(-6.88)	(-6.19)	(-3.29)

Table 2: Post-event drift: News days abnormal return

This Table summarizes the results for the post news patterns. We set positive news events as those with positive abnormal returns (AR_t>0) over the news-day event window [-1, +1], and set negative news events as those with negative abnormal returns (AR_t<0) over the news-day event window [-1, +1]. $AR_{i,t}$ is the average of the Carhart (1997) four-factor model-adjusted daily returns for stock i over the news-day event window [-1, +1] where the Carhart (1997) four-factor model is estimated over the estimation window [-257, -3]. Next, I compare abnormal returns on future news days after the news event with average abnormal returns ($AR_{t,t+n}$) over the subsequent 10, 20, and 60 trading days. The abnormal returns are reported in percentages. Standard errors are clustered at the firm and date levels. t-statistics are reported in the parentheses.

Panel A: All news event				
Shock level	$AR_{-1,1}$	$AR_{3,10}^{news}$	$AR_{3,20}^{news}$	$AR_{3,60}^{news}$
Positive	1.218	0.018	0.024	0.030
(average)	(98.88)	(8.78)	(12.63)	(17.14)
Negative	-1.105	0.030	0.032	0.030
(average)	(-102.55)	(11.29)	(13.51)	(13.68)
Number of news days		6	13	38
Obs		3,090,358	3,300,122	3,438,788
Panel B: Negative news event				
Shock level	$AR_{-1,1}$	$AR_{3,10}^{news}$	$AR_{3,20}^{news}$	$AR_{3,60}^{news}$
Q1	-3.350	0.084	0.078	0.055
(Largest negative)	(-235.88)	(8.93)	(9.63)	(7.88)
Q2	-1.128	0.020	0.026	0.027
	(-1,972.06)	(5.30)	(8.42)	(11.19)
Q3	-0.625	0.016	0.023	0.025
	(-2,435.01)	(5.69)	(8.34)	(11.73)
Q4	-0.330	0.017	0.018	0.022
	(-2,191.45)	(7.65)	(9.73)	(14.48)
Q5	-0.104	0.015	0.019	0.022
(Smallest negative)	(-949.01)	(7.42)	(10.58)	(15.61)
Panel C: Positive news event				
Shock level	$AR_{-1,1}$	$AR_{3,10}^{news}$	$AR_{3,20}^{news}$	$AR_{3,60}^{news}$
Q1	0.105	0.015	0.016	0.021
(Smallest positive)	(917.11)	(7.16)	(9.39)	(15.37)
Q2	0.337	0.014	0.019	0.024
	(2,194.55)	(6.20)	(9.86)	(15.54)
Q3	0.647	0.011	0.016	0.024
	(2,477.20)	(4.52)	(7.69)	(13.97)
Q4	1.192	0.019	0.024	0.028
	(1,876.53)	(5.68)	(8.77)	(12.79)
Q5	3.822	0.034	0.045	0.054
(Largest positive)	(192.46)	(4.70)	(7.45)	(10.71)

Table 3: Disagreement and Turnover

This Table examines variation in investor disagreement after news shocks. In Panel A, changed in turnover relative to the estimation window ($\Delta Turn$) is used as proxy for disagreement. In Panel B, standardized unexpected turnover (SUV) is used as proxy for disagreement. For example, Average daily SUV is obtained in the post-shock news days or non-news days (i.e., [2, 60]) following news shocks for each stock. For each of the post-shock windows, change in daily SUV relative to the previous window is computed. Standard errors are clustered at the firm and date levels. t-statistics are reported in the parentheses.

Panel A: Abnormal turnover				
Abnormal turnover	News (+/-)	News days	Non-news days	**Diff**
$\Delta Turn_{3,20}$	+	1.302	1.026	**0.276**
		(152.79)	(254.00)	**(43.66)**
$\Delta Turn_{3,60}$	+	1.336	1.006	**0.330**
		(168.69)	(297.38)	**(53.73)**
$\Delta Turn_{3,20}$	-	1.251	0.992	**0.258**
		(214.53)	(228.20)	**(49.08)**
$\Delta Turn_{3,60}$	-	1.302	0.981	**0.321**
		(190.02)	(317.11)	**(57.19)**

Panel B: Standardized unexpected turnover				
Abnormal turnover	News (+/-)	News days	Non-news days	**Diff**
$SUV_{3,20}$	+	0.276	0.031	**0.245**
		(50.53)	(8.49)	**(68.09)**
$SUV_{3,60}$	+	0.313	0.012	**0.301**
		(56.83)	(3.57)	**(78.67)**
$SUV_{3,20}$	-	0.236	0.002	**0.234**
		(51.29)	(0.58)	**(67.09)**
$SUV_{3,60}$	-	0.283	-0.010	**0.293**
		(57.51)	(-3.21)	**(80.91)**

Table 4: Return predictability of news day turnover

This table presents returns for stock portfolios sorted by the news day $\Delta Turn$ and SUV. In each month t, we sort all stocks into five equal-weighted portfolios based on an average of news-day $\Delta Turn$ (Panel A) and SUV (Panel B) realized in that month. Stocks in the first portfolio have the lowest $\Delta Turn$ (SUV) while stocks in the fifth portfolio have the highest $\Delta Turn$ (SUV). "High - Low" is the zero-cost portfolio that is long in the highest $\Delta Turn$ (SUV) portfolio and short in the lowest $\Delta Turn$ (SUV) portfolio. R_{t+1} shows the 1-month holding period average return of each portfolio. We also report the alpha from the CAPM model, the Fama-French (1993) three-factor model, the Carhart (1997) four-factor model, and a five-factor model that includes the Pastor-Stambaugh (2003) liquidity factor. The sample period is from January 2000 to December 2016. Newey-West adjusted t-statistics are reported in the parentheses.

Panel A: Return Predictability of $\Delta Turn$

Portfolios	R_{t+1}	*CAPM α*	*FF3 α*	*FFC4 α*	*FFC4+PS α*
$Low\ \Delta Turn$	0.436	-0.167	-0.347	-0.263	-0.291
	(0.84)	(-0.83)	(-2.22)	(-1.83)	(-1.93)
2	0.849	0.227	0.020	0.096	0.055
	(1.83)	(1.30)	(0.19)	(1.00)	(0.61)
3	0.929	0.334	0.131	0.185	0.145
	(2.18)	(1.99)	(1.32)	(2.25)	(1.93)
4	1.072	0.470	0.250	0.290	0.257
	(2.52)	(2.44)	(2.41)	(3.09)	(2.93)
$High\ \Delta Turn$	1.377	0.765	0.522	0.570	0.543
	(2.96)	(2.82)	(3.15)	(3.80)	(3.76)
High – Low	**0.941**	**0.932**	**0.869**	**0.833**	**0.834**
	(4.97)	**(4.86)**	**(5.04)**	**(4.83)**	**(4.65)**

Panel B: Return Predictability of SUV

Portfolios	R_{t+1}	*CAPM α*	*FF3 α*	*FFC4 α*	*FFC4+PS α*
$Low\ SUV$	0.576	-0.094	-0.287	-0.171	-0.211
	(1.10)	(-0.47)	(-2.00)	(-1.57)	(-2.07)
2	0.705	0.117	-0.087	-0.024	-0.057
	(1.53)	(0.65)	(-0.77)	(-0.24)	(-0.58)
3	0.923	0.346	0.134	0.181	0.144
	(2.13)	(1.89)	(1.31)	(1.96)	(1.63)
4	1.201	0.606	0.384	0.427	0.399
	(2.79)	(2.88)	(3.08)	(3.67)	(3.60)
$High\ SUV$	1.268	0.661	0.439	0.471	0.442
	(2.84)	(2.95)	(3.36)	(3.88)	(3.79)
High – Low	**0.692**	**0.755**	**0.725**	**0.643**	**0.653**
	(3.77)	**(4.90)**	**(4.90)**	**(4.60)**	**(4.67)**

Table 5: Characteristics of portfolios sorted by $\Delta Turn$ and SUV

This table reports summary statistics for quintile portfolios of stocks sorted by news-day abnormal trading volume. In panel A, quintile portfolios are formed every month from January 2000 to December 2016 by sorting stocks based on news-day abnormal trading volume ($\Delta Turn$) realized in that month. In panel B, quintile portfolios are formed every month by sorting stocks based on news-day unexplained trading volume (SUV) realized in that month. Portfolio 1 (5) is the portfolio of stocks with the lowest (highest) news-day abnormal trading volume. The table reports for each quintile the average across the months in the sample of the mean values within each month of various characteristics for the stocks — $\Delta Turn$, SUV, the liquidity shock ($ILLIQ$), the logarithm of market capitalization (*Size*), the book-to-market (*BM*) ratio, the cumulative return over the 11 months prior to portfolio formation (MOM in %), and the idiosyncratic volatility over the past one month (*IVOL*).

Panel A: Characteristics of portfolios sorted by $\Delta Turn$

Quintile	$\Delta Turn$	$Turnover$	$ILLIQ$	*BM*	*Size*	*IVOL*	*REV*	*MOM*	*Beta*
Low	0.436	0.383	-2.047	0.810	12.150	2.474	-0.416	0.061	1.179
2	0.767	0.631	0.049	0.680	13.573	2.017	0.580	0.117	1.214
3	1.002	0.766	0.166	0.660	13.973	1.974	1.097	0.148	1.172
4	1.327	0.923	0.451	0.670	13.708	2.253	1.568	0.192	1.188
$High$	3.496	1.386	2.470	0.750	12.729	3.579	3.021	0.277	1.194

Panel B: Characteristics of portfolios sorted by SUV

Quintile	SUV	$Turnover$	$ILLIQ$	*BM*	*Size*	*IVOL*	*REV*	*MOM*	*Beta*
Low	-0.589	0.560	-1.182	0.720	13.246	2.391	-0.115	0.041	1.260
2	-0.242	0.561	-0.747	0.730	13.060	2.225	0.448	0.109	1.159
3	0.005	0.665	0.266	0.720	13.181	2.218	0.994	0.162	1.148
4	0.367	0.875	1.016	0.690	13.456	2.277	1.543	0.209	1.175
$High$	2.081	1.432	1.814	0.710	13.280	3.157	2.933	0.276	1.210

Panel C: Correlation Matrix

	$\Delta Turn$	SUV	$Turnover$	$ILLIQ$	*BM*	*Size*	*IVOL*	*REV*	*MOM*
SUV	0.894								
$Turnover$	0.295	0.309							
$\Delta Illiq$	0.044	0.029	0.020						
BM	0.017	0.006	-0.070	0.063					
Size	-0.067	-0.028	0.170	-0.040	-0.249				
IVOL	0.299	0.304	0.320	0.030	0.068	-0.391			
REV	0.087	0.106	0.070	0.020	0.016	-0.017	0.117		
MOM	0.025	0.057	0.109	0.043	-0.070	0.022	-0.063	0.019	
Beta	-0.010	-0.009	0.228	-0.004	-0.047	-0.004	0.217	-0.009	-0.026

Table 6: Cross-sectional predictability of $\Delta Turn$ and SUV Fama-MacBeth regressions

Each month, we run a firm-level cross-sectional regression of the return in that month on subsets of lagged predictor variables including $\Delta Turn$ and other control variables. The other control variables include last year-end logarithm of market capitalization ($Size_{t-1}$), last year-end book-to-market ratio (BM_{t-1}), market beta ($Beta_{t-1}$), idiosyncratic volatility over last month ($IVOL_{t-1}$), past two-month stock returns ($R_{t-2,t-3}$), past three-month stock returns ($R_{t-4,t-6}$), past six-month stock returns ($R_{t-7,t-12}$), last month news scores (ESS_{t-1}), and illiquidity shock over last month ($ILLIQ_{t-1}$). In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and their associated Newey-West (1987) adjusted t-statistics (in parentheses). The sample period is from January 2000 to December 2016.

Variable	(1)	(2)
$\boldsymbol{\Delta Turn_{t-1}}$	**0.126**	
	(4.94)	
$\boldsymbol{SUV_{t-1}}$		**0.156**
		(5.26)
R_{t-1}	-0.019	-0.019
	(-4.09)	(-4.07)
$R_{t-2,t-3}$	-0.001	-0.001
	(-0.20)	(-0.18)
$R_{t-4,t-6}$	-0.000	-0.000
	(-0.09)	(-0.07)
$R_{t-7,t-12}$	0.000	0.000
	(0.07)	(0.06)
$Turnover_{t-1}$	-0.134	-0.136
	(-1.97)	(-1.92)
$ILLIQ_{t-1}$	0.009	0.010
	(1.94)	(2.07)
$Size_{t-1}$	-0.067	-0.068
	(-1.68)	(-1.72)
$IVOL_{t-1}$	-0.198	-0.187
	(-4.38)	(-4.18)
BM_{t-1}	0.195	0.196
	(1.85)	(1.85)
$Beta_{t-1}$	0.060	0.053
	(0.30)	(0.27)
ESS_{t-1}	0.622	0.618
	(6.16)	(6.16)
Adjusted R^2	0.072	0.073

Table 7: The price of $\Delta Turn_t$ and disagreement: Cross-sectional analysis

This table presents the price of $\Delta Turn$ by different levels of investor disagreement. At each formation period, we sort all stocks into five portfolios based on their $\Delta Turn$. We further independently sort all stocks into three portfolios based on the correlation between news-day trading volume and volatility over the last month (*Corr*) in Panel A, their previous month news-day return volatility (Vol^{news}) in Panel B, and their previous month news-day abnormal returns ($ARet^{news}$) in Panel C, respectively. The column labelled "FFC4 α" is the difference in four-factor alphas on the High $\Delta Turn$ and Low $\Delta Turn$ portfolios. The sample period is from January 2000 to December 2016. Newey-West adjusted t-statistics are reported in the parentheses and ***, **, * denote 1%, 5%, and 10% significant levels, respectively.

Panel A: Correlation between news day trading volume and volatility						
Portfolios	Low	2	3	4	High	H-Low
Low Corr	-0.086	0.050	0.337	0.166	0.170	**0.255**
						(1.11)
High Corr	-0.644	0.020	0.172	0.027	0.312	**0.956**
						(3.41)
Panel B: News day volatility						
Portfolios	Low	2	3	4	High	H-Low
$Low\ Vol^{news}$	0.237	0.453	0.441	0.671	0.933	**0.696**
						(4.21)
$High\ Vol^{news}$	-0.693	-0.073	0.006	0.244	0.625	**1.318**
						(4.75)
Panel C: News day return						
Portfolios	Low	2	3	4	High	H-Low
$Low\ ARet^{news}$	-0.178	0.035	0.210	0.175	0.423	**0.601**
						(2.54)
$High\ ARet^{news}$	-0.212	0.294	0.289	0.652	0.953	**1.166**
						(5.98)

Table 8: $\Delta Turn$ and Change in the disagreement

Panel A presents transition probabilities for $\Delta Turn$ at a lag of 1 month. At each month t, all stocks are sorted into quintiles based on an ascending ordering of $\Delta Turn$. The procedure is repeated in month t+1. Portfolio 1 is the portfolio of stocks with the lowest $\Delta Turn$ and Portfolio 5 is the portfolio of stocks with the highest $\Delta Turn$. For each $\Delta Turn$ quintile in month t, the percentage of stocks that fall into each of the month t+1 $\Delta Turn$ quintile is calculated. Panel A presents the time-series averages of these transition probabilities. Each row corresponds to a different month t $\Delta Turn$ portfolio and each column corresponds to a different month t+1 $\Delta Turn$ portfolio. Panel B examines whether $\Delta Turn$ is correlated with the increase in forecast dispersion. Each month t, stocks are sorted into quintiles based on $\Delta Turn$ realized in that month. Earnings forecast dispersion is calculated as the standard deviation of analysts' current fiscal year's earnings forecasts scaled by the absolute value of the mean earnings forecast (observations with the mean earnings forecast equal to zero are discarded). Changes in the forecast dispersion are calculated for each stock and then averaged across the stocks in each $\Delta Turn$ quintile. The change in month t-1 ($\Delta Disp_{t-1}$) is calculated as the difference in the forecast dispersion between the outstanding forecasts in the last month and the outstanding forecasts three months previously; the change in the current month ($\Delta Disp_t$) is calculated as the difference in dispersion between the forecasts outstanding in the current month and the outstanding forecasts two months previously; the change in the next month ($\Delta Disp_{t+1}$) is calculated as the difference in dispersion between the forecasts outstanding in the next month and the outstanding forecasts one month previously. The last row represents the differential between the high and low $\Delta Turn$ quintiles. The corresponding Newey and West (1987) adjusted t-statistics are in parentheses. The sample period is January 2000–December 2016.

Panel A: Transition matrix of $\Delta Turn$

Portfolios	$Low\ \Delta Turn_{t+1}$	2	3	4	$High\ \Delta Turn_{t+1}$
$Low\ \Delta Turn_t$	**44.68%**	19.15%	12.26%	10.67%	13.24%
2	20.94%	26.83%	21.81%	17.18%	13.24%
3	13.09%	23.45%	25.86%	22.21%	15.38%
4	10.52%	18.24%	23.95%	26.15%	21.13%
$High\ \Delta Turn_t$	10.72%	12.35%	16.15%	23.80%	**36.98%**

Panel B: $\Delta Turn$ and changes in analyst earnings forecast dispersion

Portfolios	$\Delta Disp_{t-1}$	$\Delta Disp_t$	$\Delta Disp_{t+1}$
$Low\ \Delta Turn$	-0.006	-0.016	-0.010
	(-1.30)	(-4.07)	(-3.11)
2	0.001	-0.005	-0.000
	(0.44)	(-1.48)	(-0.02)
3	-0.000	-0.001	-0.002
	(-0.01)	(-0.49)	(-0.67)
4	0.002	0.003	0.000
	(0.55)	(1.17)	(0.12)
$High\ \Delta Turn$	-0.006	0.020	0.009
	(-1.50)	(5.69)	(2.57)
High – Low	**-0.000**	**0.035**	**0.019**
	(-0.01)	**(8.57)**	**(5.74)**

Table 9: Price of $\Delta Turn$ and turnover

Panel A presents the price of $\Delta Turn$ by different levels of turnover. At each formation period, we sort all stocks into five portfolios based on their $\Delta Turn$. We further independently sort all stocks into three portfolios based on their previous month turnover (*turnover*). The column labeled "H-Low" is the difference in four-factor alphas on the High $\Delta Turn$ and Low $\Delta Turn$ portfolios. Panel B reports changes in liquidity around $\Delta Turn$. Liquidity is calculated as the Amihud Illiquidity using daily data from CRSP. We compute the change in the liquidity as the change in the Amihud Illiquidity at the end of the current month and the Amihud Illiquidity one month prior (ΔLiq_t). Moreover, to show that the increase in the liquidity in the high-ΔTurn month is not only temporary, we also check the change in the liquidity between the previous month and one month after (ΔLiq_{t+1}). ΔLiq_t and ΔLiq_{t+1} are calculated for each stock and then averaged across the stocks in each $\Delta Turn$ quintile. The last row represents the differential between the high and low $\Delta Turn$ quintiles. The corresponding Newey and West (1987) adjusted t-statistics are in parentheses. The sample period is March 2000–December 2016.

Panel A: Price of $\Delta Turn$ and Turnover

Portfolios	Low	2	3	4	High	H-Low
Low Turnover	-0.077	0.305	0.378	0.698	1.192	**1.269**
						(8.47)
High Turnover	-0.484	-0.120	-0.034	0.082	0.269	**0.754**
						(2.76)

Panel B: Price of $\Delta Turn$ and change in liquidity

	Low Turnover		*High Turnover*	
Portfolios	ΔLiq_t	ΔLiq_{t+1}	ΔLiq_t	ΔLiq_{t+1}
$Low\ \Delta Turn$	-2.475	-1.044	0.199	0.230
	(-1.96)	(-0.57)	(1.46)	(1.56)
2	1.187	-0.721	0.012	0.014
	(1.03)	(-1.44)	(1.07)	(1.68)
3	0.280	-0.457	0.088	0.073
	(0.52)	(-0.84)	(1.13)	(0.92)
4	-8.060	-1.290	0.001	0.001
	(-0.99)	(-0.99)	(0.03)	(0.10)
$High\ \Delta Turn$	2.815	2.267	0.631	0.657
	(2.27)	(2.06)	(4.46)	(3.34)
High – Low	**5.290**	**3.312**	**0.432**	**0.427**
	(3.93)	**(1.95)**	**(2.09)**	**(1.68)**

Table 10: The price of $\Delta Turn$ and disagreement: Time-series analysis

At each formation period, all stocks are sorted into ascending quintile portfolios based on values of $\Delta Turn$. The table presents the time-series means of the monthly one-month-ahead excess returns for each of the equal-weighted quintile portfolios for portfolio holding months corresponding recession and non-recession periods (Panel A); and portfolio holding months following previous month high VIX and low VIX (Panel B). The column labeled "H-Low" is the difference in four-factor alphas on the High $\Delta Turn$ and Low $\Delta Turn$ portfolios. The sample period is from January 2000 to June 2016. Newey-West adjusted t-statistics are reported in the parentheses and ***, **, * denote 1%, 5%, and 10% significant levels, respectively.

Panel A: Recession						
Portfolios	Low	2	3	4	High	H-Low
Good States	-0.172	0.150	0.142	0.258	0.519	**0.691**
						(4.17)
Bad States	-1.628	-0.630	0.067	0.104	0.723	**2.351**
						(2.52)
Panel B: VIX						
Portfolios	Low	2	3	4	High	H-Low
Low VIX	-0.109	0.069	0.003	0.104	0.317	**0.426**
						(3.03)
High VIX	-0.437	0.080	0.356	0.486	0.804	**1.241**
						(4.12)

Table 11: Price of $\Delta Turn$ after controlling for positive-volume return premium

We perform the dependent sorting that first sort on the positive volume shocks, and within each positive volume shocks' portfolio we sort stocks into quintile portfolios based on $\Delta Turn$. We then averaging of the equal-weighted returns across the lottery demand quintiles, and hence the differences between returns on portfolios that vary in $\Delta Turn$ but have approximately the same levels of the positive volume shocks. In the first column, stocks are first sorted into high, medium, and low groups following Gervais, Kaniel, and Mingelgrin (2001) (GKM), and then into $\Delta Turn$ quintiles within each control variable quintile. In the second column, stocks are first sorted into five portfolios based on abnormal dollars trading volume (*VOLDU*), and then into $\Delta Turn$ quintiles within each *VOLDU* quintile. The row labeled "Hing-Low" is the difference in four-factor alphas on the High $\Delta Turn$ and Low $\Delta Turn$ portfolios. The sample period is from January 2000 to December 2016. Newey-West adjusted t-statistics are reported in the parentheses.

Portfolios	*GMK*	*VOLDU*
$Low\ \Delta Turn$	-0.370	-0.174
	(-2.26)	(-1.40)
2	-0.078	0.094
	(-0.69)	(1.14)
3	0.081	0.132
	(0.75)	(1.48)
4	0.249	0.270
	(1.62)	(2.85)
$High\ \Delta Turn$	0.426	0.574
	(2.22)	(3.31)
High – Low	**0.796**	**0.748**
	(3.56)	**(4.24)**

Table IA1

The table examines the robustness of the $\Delta Turn$ and SUV effect by using different specifications. "NYSE" means that we only use NYSE stocks. "20% Smallest Stocks Omitted" means that we exclude stocks in the bottom 20% of firm size ranking. "NYSE breakpoints" means that we use the NYSE breakpoints following Fama and French (1992) to generate quintile portfolios with a relatively more balanced average market share. "Decile" means that all stocks are grouped into ten portfolios based on $\Delta Turn$ or SUV at each formation date. "Median returns" means that we use the equal-weighted median returns in each portfolio. "Short-term detrended" means that we use a shorter estimation window, i.e., [-52, -3], to calculate the $\Delta Turn$ and SUV. R_{t+1} shows the 1-month holding period average return of the hedge portfolio that is long in high skewness portfolio and short in low skewness portfolio. We also report the alpha from the CAPM model, the Fama-French (1993) three-factor model, the Carhart (1997) four-factor model, and a five-factor model that includes the Pastor-Stambaugh (2003) liquidity factor. The sample period is from January 2000 to December 2016. Newey-West adjusted t-statistics are reported in the parentheses and ***, **, * denote 1%, 5%, and 10% significant levels, respectively.

Panel A: Return Predictability of $\Delta Turn$

Portfolios	R_{t+1}	*CAPM α*	*FF3 α*	*FFC4 α*	*FFC4+PS α*
NYSE	0.394	0.416	0.433	0.418	0.420
	(2.66)	(2.99)	(2.82)	(2.69)	(2.61)
20% Smallest Stocks Omitted	0.652	0.680	0.650	0.613	0.629
	(3.53)	(4.00)	(3.95)	(3.75)	(3.80)
NYSE breakpoints	0.707	0.676	0.653	0.640	0.638
	(4.66)	(4.07)	(4.13)	(4.03)	(3.91)
Decile	1.205	1.167	1.066	1.025	1.026
	(4.76)	(4.35)	(4.47)	(4.32)	(4.13)
Median returns	0.827	0.812	0.780	0.753	0.750
	(5.04)	(4.62)	(4.93)	(4.67)	(4.43)
Short-term detrended	0.862	0.832	0.798	0.828	0.801
	(5.57)	(5.10)	(5.19)	(5.62)	(5.43)

Panel B: Return Predictability of SUV

Portfolios	R_{t+1}	*CAPM α*	*FF3 α*	*FFC4 α*	*FFC4+PS α*
NYSE	0.358	0.416	0.468	0.414	0.414
	(2.64)	(3.68)	(4.04)	(3.43)	(3.37)
20% Smallest Stocks Omitted	0.475	0.540	0.541	0.471	0.493
	(2.82)	(3.83)	(3.84)	(3.51)	(3.63)
NYSE breakpoints	0.638	0.629	0.624	0.590	0.583
	(4.08)	(3.99)	(4.06)	(3.81)	(3.69)
Decile	0.785	0.881	0.827	0.729	0.735
	(3.37)	(4.60)	(4.73)	(4.32)	(4.33)
Median returns	0.609	0.675	0.666	0.619	0.615
	(3.51)	(4.98)	(5.17)	(4.65)	(4.62)
Short-term detrended	0.714	0.717	0.702	0.719	0.703
	(4.67)	(4.82)	(4.92)	(5.22)	(5.06)

Appendix IA2: The price of SUV and disagreement: Cross-sectional analysis

This table presents the price of SUV by different levels of investor disagreement. At each formation period, we sort all stocks into five portfolios based on their SUV. We further independently sort all stocks into three portfolios based on the correlation between news-day trading volume and volatility over the last month (*Corr*) in Panel A, their previous month news-day return volatility (Vol^{news}) in Panel B, and their previous month news-day abnormal returns ($ARet^{news}$) in Panel C, respectively. The column labelled "FFC4 α" is the difference in four-factor alphas on the High $\Delta Turn$ and Low SUV portfolios. The sample period is from January 2000 to December 2016. Newey-West adjusted t-statistics are reported in the parentheses and ***, **, * denote 1%, 5%, and 10% significant levels, respectively.

Panel A: Correlation between news day trading volume and volatility						
Portfolios	Low	2	3	4	High	H-Low
Low Corr	0.170	-0.176	0.245	0.191	0.155	**-0.014** **(-0.07)**
High Corr	-0.563	0.008	0.085	0.151	0.256	**0.820** **(3.16)**
Panel B: News day volatility						
Portfolios	Low	2	3	4	High	H-Low
$Low\ Vol^{news}$	0.259	0.333	0.522	0.676	0.816	**0.557** **(4.66)**
$High\ Vol^{news}$	-0.399	-0.265	-0.015	0.509	0.549	**0.948** **(4.62)**
Panel C: News day return						
Portfolios	Low	2	3	4	High	H-Low
$Low\ ARet^{news}$	-0.185	-0.033	0.138	0.379	0.383	**0.568** **(2.67)**
$High\ ARet^{news}$	-0.058	0.133	0.371	0.786	0.855	**0.914** **(5.54)**

Appendix IA3: The price of $\Delta Turn$ and change in liquidity

This table illustrates that it is disagreement shocks that are accompanied by increases in liquidity that result in high future returns. For each month, we sort the stocks in the highest $\Delta Turn$ quintile into further quintiles based on the change in liquidity (ΔLiq). "High - Low" is the zero-cost portfolio that is long in the highest ΔLiq portfolio and short in the lowest ΔLiq portfolio. R_{t+1} shows the 1-month holding period average return of each portfolio. We also report the alpha from the CAPM model, the Fama-French (1993) three-factor model, the Carhart (1997) four-factor model, and a five-factor model that includes the Pastor-Stambaugh (2003) liquidity factor. The sample period is from January 2000 to December 2016. Newey-West adjusted t-statistics are reported in the parentheses.

Portfolios	R_{t+1}	*CAPM α*	*FF3 α*	*FFC4 α*	*FFC4+PS α*
$Low\ \Delta Liq$	1.419	0.819	0.546	0.665	0.582
	(2.95)	(2.45)	(2.23)	(2.91)	(2.65)
2	0.918	0.231	0.046	0.136	0.138
	(1.97)	(0.88)	(0.22)	(0.75)	(0.75)
3	1.062	0.439	0.183	0.208	0.219
	(2.31)	(1.89)	(1.42)	(1.73)	(1.77)
4	1.628	1.011	0.771	0.765	0.731
	(3.07)	(3.19)	(3.72)	(3.64)	(3.60)
$High\ \Delta Liq$	1.936	1.407	1.157	1.179	1.134
	(3.63)	(3.45)	(3.79)	(3.94)	(3.81)
High – Low	**0.517**	**0.589**	**0.612**	**0.514**	**0.552**
	(1.93)	**(2.23)**	**(2.36)**	**(1.98)**	**(2.09)**

Appendix IA4: The price of SUV and disagreement: Time-series analysis

At each formation period, all stocks are sorted into ascending quintile portfolios based on values of SUV. The table presents the time-series means of the monthly one-month-ahead excess returns for each of the equal-weighted quintile portfolios for portfolio holding months corresponding recession and non-recession periods (Panel A); and portfolio holding months following previous month high VIX and low VIX (Panel B). The column labeled “H-Low” is the difference in four-factor alphas on the High SUV and Low SUV portfolios. The sample period is from January 2000 to June 2016. Newey-West adjusted t-statistics are reported in the parentheses and ***, **, * denote 1%, 5%, and 10% significant levels, respectively.

Panel A: Recession

Portfolios	Low	2	3	4	High	H-Low
Good States	-0.127	0.031	0.183	0.396	0.422	**0.549**
						(3.27)
Bad States	-0.709	-1.154	-0.313	0.155	0.737	**1.446**
						(2.43)

Panel B: VIX

Portfolios	Low	2	3	4	High	H-Low
Low VIX	-0.206	0.026	0.145	0.143	0.275	**0.481**
						(3.53)
High VIX	-0.254	-0.055	0.256	0.6746	0.684	**0.938**
						(3.85)