Skewness: Lottery or asymmetric response to news?

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Abstract

While recent studies argue that the pricing of skewness comes from its lottery-like payoff, they do not address an important question of whether the return skewness is an endogenous feature. To address this question, I relate the pricing of skewness to investors' inability to price news correctly. I find novel evidence that only the skewness extracted from observed news-day returns is negatively priced. This effect is stronger for stocks with greater asymmetric responses to good and bad news, and investors' lottery preferences do not explain these results. Collectively, my findings suggest that accounting for endogeneity (asymmetric response to news) in skewness rather than treating skewness as an exogenous characteristic of the return distribution is critical for understanding the negative relation between skewness and future returns. More broadly, my findings are consistent with the idea that misreaction to news plays an important role in understanding the return predictability.

Keywords: News; Skewness; Lottery preferences; Cross-sectional return predictability.

JEL Code: G10; G14; G40

1. Introduction

The negative relation between stock return skewness and expected return has been explored extensively in the literature. Recent studies argue that the pricing of the stock return skewness comes from its lottery feature - a small probability of an extreme positive payoff (lottery-like payoff). Theoretically, errors in the probability weighting of investors cause them to overvalue stocks that have a lottery-like payoff, and hence these stocks have lower future returns (Barberis and Huang, 2008). While various empirical results in previous studies are consistent with the above explanation (e.g., Kumar, Page, and Spalt, 2011; Amaya, Chrristoffersen, Jacobs, and Vasquez, 2015; Bali, Engle, and Murray, 2016), they do not address an important question of whether the return skewness is an endogenous feature: why does it arise in the first place? The goal of my paper is to address this question and provide an alternative explanation for the pricing of skewness.

My rationale is that the return skewness arises due to asymmetric responses to good and bad news (Hong and Stein, 2003; Xu, 2007; Epstein and Schneider, 2008).[1] Such asymmetric news reactions can be attributed to investors' inability to interpret information quickly and correctly, resulting in under- and over-reaction to news.[2] Since misreaction to news is also correlated with stock future returns (Engelberg, McLean, and Pontiff, 2018), relating this familiar concept to skewness can explain the well-known negative relation between stock return skewness and future returns.

My mechanism can be illustrated in the following example. If investors respond more strongly to good versus bad news (e.g., underreaction to bad news), good news increases the stock's price more than bad news of equal size decreases the stock's price. This asymmetric news reaction creates an asymmetry in returns, that is, positive returns are more extreme than negative returns in absolute value. Correspondingly,

[1] I discuss this effect in greater detail in Section 2.
[2] Investors' under- and over-reaction to news manifests in asymmetric reactions to good and bad news. For example, the stock price can react more strongly to good news than to bad news (overreaction to good news or underreaction to bad news), or it can react more strongly to bad news than to good news (overreaction to bad news or underreaction to good news) (e.g., Conrad, Cornell, and Landsman, 2002; Skinner and Sloan, 2002; Chan, 2003; Nagel, 2005; Tetlock, 2014; Frank and Sanati, 2018). Following Xu (2007), I refer to such misreaction to news as "asymmetric reaction to good and bad news".

the right tail of the return distribution is long and thin while the left tail is short and thick - the skewness is high. Likewise, low skewness can result from underreactions to good news (if investors respond more strongly to bad versus good news) which produces extreme negative returns.[3] Because under- and over-reactions create mispricing, stocks with more positive (negative) skewness should be relatively overpriced (underpriced). Consequently, subsequent stock prices will adjust to eliminate this mispricing. As a result, the relationship between the skewness and the future stock returns should be negative.[4] I refer to the above mechanism as the "news mispricing hypothesis": a stock's expected return depends on the return skewness of individual securities that arises from investors' inability to interpret information correctly.

To test this hypothesis, I develop the following methodology. Using a comprehensive news dataset from RavenPack, I decompose daily stock returns into news day and non-news day returns and compute the return skewness for both of these day types. Non-news day returns normally reflect reactions to private signals, stale and irrelevant firm news, or liquidity shocks. However, news-day returns mostly capture reactions to public news (e.g., Engelberg, Reed, and Ringgenberg, 2012; Frank and Sanati, 2018). The news-day return skewness ($Skew^{news}$) is therefore more likely to capture asymmetric responses to good and bad news.

My baseline findings confirm the negative relation between $Skew^{news}$ and future stock returns (I refer to this relationship as the "$Skew^{news}$ effect"). This pattern holds robustly in both portfolio analysis and Fama-MacBeth regressions. Specifically, a portfolio of stocks with the most positive $Skew^{news}$ underperforms a portfolio with the most negative $Skew^{news}$ by up to 4.55% per year, and this effect is statistically and economically significant. My results are robust to various risk-adjustment approaches, survive multiple stock characteristics controls, and persist under different approaches for measuring skewness.

[3] Similarly, high (low) return skewness can result from overreactions to good (bad) news if such overreactions occur.
[4] Although there are other skewness factors can affect the overall level of skewness (e.g., Black, 1976; Christie, 1982; Pindyck, 1984; French, Schwert, and Stambaugh, 1987; Campbell and Hentschel, 1992; Bekaert and Wu, 2000), my explanation for the negative relation between skewness and future returns is still valid. First, other skewness factors do not create mispricing directly. Second, they cannot affect the relative skewness conditional on the asymmetric reaction to news, as long as they do not completely counteract the effect of asymmetric reaction to news on skewness.

However, I do not find a significant negative relation between non-news day return skewness ($Skew^{no-news}$) and future stock returns (-1.69% per year, t-statistic of -0.81), suggesting that skewness which cannot be attributed to reactions to public news is not priced. Overall, my baseline findings suggest that investors' inability to interpret information correctly is at least a partial explanation for the pricing of the stock return skewness.

To further understand what drives the pricing of skewness, I consider two tests. The first test focuses on the link between the $Skew^{news}$ effect and asymmetric reaction to good and bad news. I first confirm that investors react to news asymmetrically in my sample. I then find that the $Skew^{news}$ effect is about -52.5 bps (t-statistic of -3.12) per month among stocks experiencing asymmetric reactions to good and bad news, while it drops to -13.6 bps (t-statistic of -1.19) among stocks experiencing symmetric reactions to news. A similar stronger effect is observed among firms with a high value of asymmetric reaction (*AR*) index, in which *AR* index is constructed by combining five stock characteristics that signal the asymmetric reaction to news (Xu, 2007).[5] Turning to the time variation of the $Skew^{news}$ effect, I find the premium to be higher following high market-wide ambiguity periods when the market participants typically are more sensitive to bad news (e.g., Epstein and Schneider, 2008; Williams, 2015).[6] These results confirm that differences in asymmetric reaction to news explain the variation (in the cross-section and time series) in the relation between skewness and future stock returns.

My second test shows that the $Skew^{news}$ effect is stronger among stocks with greater barriers to understanding news. Specifically, I find that the $Skew^{news}$ effect ranges from -4.9% to -7.5% per year among stocks with less routine-sounding news coverage, less analyst coverage, and more complex 10-K reports. Given investors' inability to price news correctly is positively related to the barriers to

[5] Xu (2007) predicts that optimistic investors overreact to good public signals, while pessimistic investors stay out of the market due to short-sale constraints. Consequently, this over- and under-reaction to news results in a positive return skewness followed by a price correction in the next period. Five characteristics used in Xu (2007) are: 1) institutional ownership (D'Avolio, 2002); 2) ownership breadth (Chen, Hong, and Stein, 2002); 3) turnover (Chen, Hong, and Stein, 2001); 4) market capitalization (D'Avolio, 2002); 5) past returns (Zhang, 2006).

[6] My analysis in Section 5 confirms that investors react more strongly to bad news than to good news during high market-wide ambiguity periods.

understanding news (e.g., Daniel, Hirshleifer, and Subrahmanyam, 1998; Daniel, Hirshleifer, and Subrahmanyam, 2001; Zhang, 2006), this result again confirms that investors' inability to price news correctly is likely the primary force driving the negative relation between skewness and future stock returns.

While the lottery preference theory also predicts a negative relation between skewness and future stock returns, the economic mechanism underlying my news mispricing hypothesis differs considerably from the lottery preference theory. The lottery preference theory posits that investors overweight low probability of extreme gains. Barberis and Huang (2008) suggest that one can think of this overweighting as "simply a modeling device that captures the common preference for a lottery-like, or positively skewed, wealth distribution" (p. 2066). Therefore, the lottery preference theory focuses on the unconditional demand for lottery-like payoffs, where the lottery feature is treated as an exogenous characteristic of the return distribution which is not directly related to mispricing of news (Eraker and Ready, 2015). In contrast, my news mispricing hypothesis posits that skewness is directly related to under- and over-reactions to news. In other words, a distinct feature of my hypothesis is the focus on how future price behavior varies with under- and over-reactions to news captured by the skewness measure. I perform a number of tests to distinguish my news mispricing hypothesis from the lottery preference theory of the skewness pricing.

In my first test, I focus on exogenous variation in demand for lottery-like stocks. Specifically, I use large U.S. national lottery (Powerball and Mega Millions) jackpots as a natural shock to the demand for lottery-like stocks. When a lottery jackpot exceeds the 95th percentile (210 million U.S. dollars) of all jackpots throughout the sample period, I define it as a large jackpot. Firstly, large jackpots occur randomly and are unlikely to be driven by factors that affect the stock market. Secondly, Huang, Huang, and Lin (2018) show that large lottery jackpots generate gambling attitudes among investors.[7] Finally, Bali, Brown, and Murry (2017) confirm that the negative relation between stocks' lottery features and stock future returns is stronger in months with greater gambling attitudes among investors. Thus, if the $Skew^{news}$ effect arises

[7] Recent studies confirm that the demands for lotteries and lottery-like stocks are positively correlated in the U.S., especially when gambling attitudes are strong (Kumar, 2009; Doran, Jiang, and Peterson, 2012; Chen, Kumar, and Zhang, 2017). My analysis in Section 6 confirms that large jackpots generate gambling attitudes among lottery investors, i.e., they are highly correlated with the Google search volume index for the word "lottery".

due to demands on lottery-like stocks, we would expect this effect to be stronger in months with large lottery jackpots. I find that the $Skew^{news}$ effect earns an average excess return of -4.8 bps (t-statistic of -0.44) per month in months with large lottery jackpots, while the same strategy earns an average excess return of -51.4 bps per month (t-statistic of -3.54) in other months. More importantly, this difference is mainly driven by non-lottery-like stocks (the most negative $Skew^{news}$ portfolio). It is therefore unlikely that investors' preference for lottery payoffs is the main force behind the $Skew^{news}$ effect.

My subsequent tests further suggest that the lottery preference is at least insufficient to explain the negative relation between skewness and future stock returns. First, if lottery investors overweight stocks likely to produce extreme gains, then the return premium of the long-short portfolio should primarily come from the most positive $Skew^{news}$ portfolio. In contrast, I find that the return premium comes from the negative skewness portfolios, that is, the long side (most negative $Skew^{news}$) of the trade contributes up to 68% to the long-short spread. Second, an unconditional preference for lottery-like assets implies that lottery investors might overvalue stocks with positive $Skew^{no-news}$. The intuition is that $Skew^{no-news}$ includes a small probability of an extreme positive return,[8] and hence errors in the probability weighting of investors cause them to exhibit a preference for stocks that have a positive $Skew^{no-news}$. However, as I noted earlier, $Skew^{no-news}$ is not priced in the cross-section. Finally, I document that the $Skew^{news}$ effect persists after I directly control for the lottery preference measure of Bali, Cakici, and Whitelaw (2011) and the lottery mispricing factor of Bali, Brown, and Murray (2017).

My paper contributes to the literature on the pricing of skewness. First, I draw novel evidence that investors' inability to interpret news correctly contributes to the pricing of skewness. While recent studies argue that the pricing of skewness should be attributed to its lottery feature, I find that this argument cannot explain the empirical patterns. Second, my study emphasizes that accounting for endogeneity in skewness rather than treating skewness as an exogenous characteristic of the return distribution is critical for understanding the negative relation between skewness and future returns.

[8] I confirm that $Skew^{no-news}$ includes extreme positive returns: 56% of the extreme positive return days are non-news days in my sample.

I also 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 compared to noise-based (non-news or lottery feature) price changes (e.g., Chan, 2003; Savor, 2012; Tetlock, 2014). Second, I provide additional evidence that under- and over-reaction to news plays a central role in the mechanism of mispricing (e.g., Hillert, Jacobs, and Muller, 2014; Wang, Zhang, and Zhu, 2016; Bail, Bodmaruk, Scherbina, and Tang, 2017; Engelberg, McLean, and Pontiff, 2018). Third, I add to a more recent line of research that studies the importance of asymmetric response to news (e.g., Xu, 2007; Lu, Wang, and Wang, 2014; Williams, 2015; Frank and Sanati, 2018).

The remainder of this paper is organized as follows. Section 2 provides a more detail discussion of how my paper is motivated. Section 3 describes the construction and summary statistics of my skewness measures. Section 4 presents formal asset pricing tests and shows that the news-day return skewness is priced. Section 5 further examines whether the pricing of skewness derives from investors cannot interpret news correctly. Section 6 distinguishes my news mispricing hypothesis from the lottery preference explanation. The last section concludes.

2. Literature review

Several literature streams motivate my study. The first stream relates to the pricing of skewness. Beginning with Arditti (1967, 1971) and Scott and Horvath (1980), a large body of finance research suggests that skewness is priced. Recent papers argue that the pricing of skewness comes from its lottery-like payoff. Theoretically, Barberis and Huang (2008) model that investors with cumulative prospect theory overweight probability of extreme gains and exhibit preferences for stocks with highly skewed returns. The model of optimal beliefs by Brunnermeier, Gollier, and Parker (2007) also predicts that investors will overinvest in the most positively skewed stocks.[9] Mitton and Vorkink (2007) develop a rational model that investors have heterogeneous preferences for idiosyncratic skewness. Empirically, Boyer, Mitton, and

[9] They also show that, while there is a rational expectations solution to their model, it represents a knife-edge case.

Vorkink (2009) show that the relation between expected idiosyncratic skewness and next month's stock returns is negative. Amaya, Christoffersen, Jacobs, and Vasquez (2015) demonstrate that the realized skewness, calculated based on intraday data, has a strong negative cross-sectional relation with future stock returns. Bali, Engle, and Murray (2016), Lin and Liu (2017), and Jiang, Wu, Zhou, and Zhu (2017) provide detail discussions and empirical tests to confirm the negative relation between skewness and future returns.

The above studies might explain why the pricing of skewness seems to persist, although not why skewness arises in the first place. Hence, another possible way to see how skewness is priced in the cross-section is to address the question of whether skewness is an endogenous feature. Important evidence that suggests skewness is an endogenous feature includes results for investors cannot price news correctly (investors' asymmetric responses to good and bad news) in Hong and Stein (2003), Epstein and Schneider (2008), and Xu (2007). Hong and Stein (2003) explain negative skewness through the revelation of bad news hidden by short sale constraint. They argue that when pessimistic investors reveal more bad information, the market reacts more strongly to bad news than to good news (overreactions to bad news), implying higher volatility in bad news and negatively skewed returns. Epstein and Schneider (2008) also argue that negative skewness arises from overreactions to bad news. Specifically, they argue that when an ambiguous public signal conveys bad news, the worst case is that the signal is very reliable and investors respond more strongly to bad news than to good news, and vice versa for good signals. Xu (2007) shows that optimistic investors react more strongly to good news than to bad news, and pessimistic investors stay out of the market by short-sale constraint. This misreaction to news results in a positive return skewness following by a price correction in the next period. Collectively, the above studies suggest that skewness is an endogenous characteristic of the return distribution which is directly related to misreaction to news.[10]

Interestingly, investor misreaction to news not only explains skewness but also creates mispricing. For example, Lu, Wang, and Wang (2014) find that when there is a disagreement between investors, the stock price reacts more strongly to good news than to bad news, which creates mispricing and results in a

[10] Although these models differ in their assumptions, they all predict that the return skewness arises due to asymmetric responses to good and bad news.

future price correction. Recent studies also use investor misreaction to news to explain anomalies. Chan (2003) and Savor (2012) relate momentum to mispricing of news and show that only stocks with news exhibit momentum in next periods, indicating that misreaction to news exacerbates mispricing. Similarly, Hillert, Jacobs, and Muller (2014) provide evidence that firms with greater media coverage exhibit stronger return momentum. Jiang, Li, and Wang (2015) further show that the news-driven return predictability is particularly pronounced for firms with imperfect investor reaction to news.

Furthermore, Choi and Lee (2015) show that realized daily skewness as a measure of information uncertainty is positively correlated with stock future returns in the presence of earnings announcements and analyst recommendations. Bali, Bodnaruk, Scherbina, and Tang (2017) relate idiosyncratic volatility to mispricing of news and show that the pricing of expected idiosyncratic volatility comes from investors' disagreement on unusual firm-level news flows. More broadly, Engelberg, McLean, and Pontiff (2018) use a sample of 97 stock return anomalies documented in published studies to show that anomaly returns are seven times higher on earnings announcement days and two times higher on news days. In sum, these studies evidence that investors' inability to price news correctly is identified as the key explanation for mispricing: most return anomalies are directly related to the mispricing of news.

3. Data and descriptive statistics

3.1. Data and sample

My sample period covers January 2000 to December 2016. The stock data come from the Center for Research in Security Prices (CRSP), and the firm accounting data come from CRSP/Compustat merged. I only include stocks with share code 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). I further exclude stocks with prices below $1.

I 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.[11] I 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.[12] Additionally, I only include firms with at least one news story covered by RavenPack to minimize the bias that the low news day to companies is due to RavenPack may not cover. I define the news-day (I adjust the news date to the next trading day if a news event is made after 4:00 pm) as the three-day surrounding the news release day [-1, 1] and the rest days are the non-news days. I select three days for two reasons. First, a given piece of news is highly likely to be reproduced and disseminated within one day following its initial discovery. Second, stock prices may not instantly respond to news.

A key element of my empirical work is constructing a proxy for skewness that is more likely to be related to asymmetric responses to good and bad news. Using a comprehensive news dataset from RavenPack, I decompose daily stock returns into news day and non-news day returns and compute the return skewness for both of these day types. I denote the measures of all-day skewness using $Skew^{all}$, the news-day skewness measures as $Skew^{news}$, and the non-news-day measures as $Skew^{no-news}$. Non-news-day returns normally reflect reactions to private signals, stale and irrelevant firm news, or liquidity shocks. However, news-day returns capture reactions to public news (e.g., Engelberg, Reed, and Ringgenberg, 2012; Frank and Sanati, 2018). The news-day return skewness is therefore more likely to capture asymmetric responses to good and bad news.

[11] Several accounting and finance papers use RavenPack News Analytics (e.g., Kolasinski, Reed, and Ringgenberg, 2013; Dai, Parwada, and Zhang, 2015; Dang, Moshrian, and Zhang, 2015; Wang, Zhang, and Zhu, 2016; Ben-Rephael, Da, and Israelsen, 2017).

[12] The event-novelty score, which represents how novel a news article is, and the news-relevance score (NRS), which indicates how relevant a news article is to a given firm. The ENS variable allows users to isolate and focus on only the first news article in a chain of similar articles about a given news event, whereas the NRS variable provides the opportunity to remove potentially noisy news and focus only on firm-relevant news. 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.

My baseline measure of skewness is calculated by taking the third moment of daily log residual returns from a regression of excess stock returns on the excess return of the market portfolio and the squared excess market return over the calendar quarter $q-3$ to the end of calendar quarter q (four-quarter rolling estimation window, the variable is defined in more detail in Appendix A).[13] Following Byun and Kim (2016), I update skewness quarterly. In doing so, for each stock, I have a new $Skew^{all}$, $Skew^{news}$, and $Skew^{no-news}$ every quarter. Such quarterly rebalanced variable gives us rich information to investigate the news mispricing hypothesis.[14] My choice to use a rolling four-quarter window to estimate skewness is driven more by measurement concerns. First, given skewness is strongly influenced by outliers in the data, four-quarter is selected as a compromise between data accuracy and sample size. For example, Xu (2007) and Bali, Engle, and Murray (2016) show that skewness is more accurately measured using four-quarter estimation periods. To increase the data accuracy, I require stocks to have at least 50 valid observations on daily returns for both news days and non-news days over the measurement period. Second, strategic news releases can influence both skewness and future returns (e.g., Jin and Myers, 2006). A four-quarter window can reduce the biases in skewness from such strategic news patterns in some special months. Because I calculate skewness over the past four quarters, my return prediction period is from January 2001 to December 2016.

[13] I use log returns instead of simple returns because simple returns are obviously more positively skewed (even when investors react to news symmetrically), and it induces a pronounced correlation between skewness and contemporaneously measured volatility and returns (it is also more influenced by outliers in the data). I have also redone everything with a skewness measure based instead on simple daily returns, and I find that my main results are not affected, i.e., see Appendix Table IA2.

[14] In my paper, I do not update skewness in the higher frequency (e.g., weekly or monthly) also for the following concerns. First, there are only a few news days for each firm-month observation, and hence monthly updated skewness does not give us enough new information about skewness in the cross-section. Second, the skewness theory suggests that news-day skewness is highly correlated with the contemporaneous news-day return (Xu, 2007). Given the news-day return has a positive effect on future returns in the short-term (Jiang, Li, and Wang, 2015), the coefficients of news-day skewness could be biased toward zero if we update skewness in the higher frequency. Third, the price correction process is probably very slow for the relative skewness conditional on the asymmetric reaction to news (Hong and Stein, 2003; Xu, 2007). Final, the major firm news is released in a quarterly frequency, i.e., earnings announcements. Hence, quarterly rebalanced skewness is more likely to capture investor misreaction to firm-specific news.

Insofar as news-day returns might be noisy measures of news reactions and I might misclassify news-day as non-news-day,[15] the coefficients in my analysis should be biased toward zero, understating the true importance of $Skew^{news}$.

3.2. Summary statistics

I report some descriptive statistics for my sample on Table 1 Panel A that consists of 137,931 firm-quarter observations for the period January 2001 to December 2016, with at least 50 valid news-day returns and 50 valid non-news-day returns. An important point that emerges from Table 1 Panel A is that the statistic of $Skew^{news}$ is similar to $Skew^{all}$, but $Skew^{no-news}$ is not. The distribution of $Skew^{all}$ and $Skew^{news}$ is skewed, with some stocks exhibiting very high skewness; however, the distribution of $Skew^{no-news}$ is close to normal. For example, the mean (median) of $Skew^{news}$, $Skew^{all}$, and $Skew^{no-news}$ is -0.04 (0.10), -0.02 (0.13) and 0.18 (0.15), respectively. This result provides preliminary evidence that the underlying driver of skewness is investor reaction to news. Because the average of news days (107) is lower than the average of non-news days (144), it's unlikely that the similar distribution of $Skew^{all}$ and $Skew^{news}$ arises due to the number of overlapping daily returns. However, I find that the above pattern is not presenting to the mean return and return volatility. For example, the mean (median) news volatility is 2.82% (2.44%), the mean (median) news volatility is 3.29% (2.77%), and the mean (median) non-news volatility is 2.38% (2.05%). The news-day volatility is higher than the non-news volatility, confirming that news-day returns are capturing price reactions to firm-specific news.

[Table 1 here]

To further pin down the relation between news and return moments, I do the correlations in Panel B. The most noteworthy fact is that the contemporaneous correlation between $Skew^{all}$ and $Skew^{news}$ (0.94) is much higher than the contemporaneous correlation between $Skew^{all}$ and $Skew^{no-news}$ (0.18),

[15] Similarly, misclassifying news-day as non-news-day could induce a negative relation between non-news day skewness and future returns. Hence, if mispricing of news does not contribute to the pricing of the skewness, then one might expect to see there is no pricing for both news-day skewness and non-news-day skewness.

again confirming that the underlying driver of the skewness is investors' reaction to news.[16] However, I do not find a similar conclusion for the first two moments.

Furthermore, I find that $Skew^{news}$ is highly correlated with news-day returns (Ret^{news}). This result is consistent with the positive skewness model of Xu (2007) that over- and under-reaction to public news results in a positive return skewness and high contemporaneous stock returns. I also find a negative correlation between Ret^{news} and non-news-day returns ($Ret^{no-news}$), confirming that news is mispriced. Intuitively, if news is mispriced at time t, subsequent stock prices will adjust to correctly reflect the news mispricing, and hence, we should observe a negative correlation between Ret^{news} and $Ret^{no-news}$.

[Table 2 here]

I also investigate the relation on the portfolios. Table 2 presents summary statistics for the stocks in the quantiles. Quantile portfolios are formed at the begin of every quarter by sorting stocks based on $Skew^{news}$ over the past four-quarter. Specifically, the table reports the average across the quarters in the sample of the median values within each quarter of various characteristics for the stocks in each quantile. As I move from the low $Skew^{news}$ to the high $Skew^{news}$ quantile, the average across quarters of median $Skew^{news}$ is similar to $Skew^{all}$, while $Skew^{no-news}$ is not. I do not find the portfolios exhibit some striking patterns. For instance, as $Skew^{news}$ increases across the quantiles, market capitalization (*Size*), book-to-market (*BM*) ratio, and idiosyncratic volatility (*IVOL*) do not vary too much. However, I find that the return over the 11 months prior to portfolio formation (*MOM*) increases from -11.93% to 19.26% if I move from the lowest $Skew^{news}$ to the highest $Skew^{news}$ quantile. This result is consistent with the finding in Table 1 that the correlation between $Skew^{news}$ and Ret^{news} is highly positive.

4. The pricing of skewness

In this section, I investigate the pricing of skewness. Table 3 and Table 4 report the results of univariate portfolio sorting. Specifically, in each quarter, I sort all stocks into five portfolios based on their

[16] That $Skew^{news}$ and $Skew^{no-news}$ are positively correlated might seem to confirm the view that $Skew^{no-news}$ includes misclassifying news-day as non-news-day.

skewness (news, non-news, and all days) measured over the previous four-quarter. I then compute the monthly holding period equal-weighted average returns for the future month t+1 across all firms in each portfolio. Hence, my trading strategy is effectively re-balanced each month. Stocks in the first quintile portfolio have the lowest (most negative) return skewness while stocks in the fifth quintile portfolio have the highest (most positive) return skewness. I present $Skew^{all}$ first, $Skew^{news}$ second, and $Skew^{no-news}$ last.

[Table 3 here]

Table 3 shows the time-series average of the equal-weighted $Skew^{all}$ portfolio returns. The main conclusion from Table 3 is that the observed negative relation between skewness and future stock returns is very pronounced in my sample period. I find that the average raw return difference between quintile five (high $Skew^{all}$) and quintile one (low $Skew^{all}$) is -0.41% per month with a corresponding Newey-West t-statistic of -2.62. I also find that the majority of the $Skew^{all}$ portfolios return difference comes from the lowest skewness portfolio.

In this paper, I argue that the pricing of skewness comes from mispricing of news, and hence we should expect to see a significant negative relation between $Skew^{news}$ and future returns. In Panel A of Table 4, I report evidence that is consistent with my predictions. It shows that mean returns decline from the first quintile (1.14%) to the fifth quintile (0.76%). The average raw return difference between quintile five (high $Skew^{news}$) and quintile one (low $Skew^{news}$) is -0.38% per month with a corresponding Newey-West (1987) t-statistic of -2.62. In other words, the zero-cost hedge portfolio that long in the lowest skewness portfolio and short in the highest skewness portfolio earns an economically significant return of 4.55% per year.[17] This 4.55% $Skew^{news}$ effect is about 93% of the $Skew^{all}$ effect (4.92% per year in Table 3), which is consistent with the 0.94 correlation between $Skew^{news}$ and $Skew^{all}$ in Table 1.

Another noteworthy fact in Panel A is that the return decline is far more dramatic for quintile one. Specifically, the long side (quintile one) of the trade contributes about 68% to the long-short spread, which

[17] I further examine the robustness of the $Skew^{news}$ effect by using different specifications in Appendix Table IA1.

is similar to that shown in the $Skew^{all}$ portfolios. Given lottery preference investors bid up the price for the extremely positive skewness stocks (Barberis and Huang, 2008), one might expect to see the long-short strategy return comes from quintiles five (the most positive $Skew^{news}$ stocks). Hence, my result suggests that the $Skew^{news}$ effect is unlikely to be caused by investors' preference for lottery-like stocks. I will discuss the lottery preference more in detail in Section 6 below.

[Table 4 here]

In Panel B, where I present $Skew^{no-news}$ portfolios, I find that the test statistics of the zero-cost portfolios is statistically insignificant (-0.14% per month with t-statistic of -0.81). I also find that the return patterns in $Skew^{no-news}$ portfolios are different compared to those shown in the $Skew^{news}$ and $Skew^{all}$ portfolios, indicating that $Skew^{no-news}$ contains different pricing information than $Skew^{news}$ and $Skew^{all}$. For example, the highest $Skew^{no-news}$ stocks that exhibit lower future returns, accounting for the majority of the $Skew^{no-news}$ portfolios' return difference. In other words, I do not notice any material change in returns of the highest skewness portfolio when splitting the skewness between $Skew^{news}$ and $Skew^{no-news}$, but the changes mainly reside in the lowest skewness portfolio. Overall, because $Skew^{no-news}$ is more likely to capture reactions to non-public information, the result in Panel B implies that the skewness without mispricing of news is not priced.

I then assess the empirical relation between skewness 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, I regress the excess returns of zero-cost hedge portfolio against the respective factors and calculate the regression intercepts that represent risk-adjusted returns, namely, risk-adjusted alpha. The risk-adjusted alphas for the zero-cost hedge portfolio in Column 2-5 of Table 3 (Table 4 Panel A) are in the range of -0.33% to -0.41% (-0.28% to -0.35%) per month with Newey–West t-statistics ranging from -2.14 to -3.16 (-2.07 to -3.15). Thus, I find no evidence that the returns of portfolios sorted by skewness can be attributed to their co-movement with common risk factors. I also find that on average, the risk-adjusted alphas for the zero-cost hedge portfolio of $Skew^{no-news}$ are statistically insignificant. I further examine the robustness of the above results by using different specifications in Appendix Table IA2.

Finally, to confirm that the pricing of skewness in my sample period is not driven by firm characteristics that plausibly relate to stock future returns, I examine the relation between skewness and returns using standard Fama-MacBeth (1973) cross-sectional regressions. Specifically, I run the following regressions:

$$R_{i,t} = a + \beta_1 Skew_{i,t-1} + \theta' Z_{i,t-1} + e_{i,t} \quad (1)$$

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 include: previous year end log market capitalization ($Size_{t-1}$), previous year end book-to-market ratio (BM_{t-1}), AHXZ's idiosyncratic volatility ($IVOL_{t-1}$) computed over last month, Amihud's (2002) illiquidity computed over previous year ($Illiquidity_{t-1}$), past two-month stock returns ($R_{t-2,t-3}$), past three-month stock returns $\left(R_{t-4,t-6}\right)$, past six-month returns($R_{t-7,t-12}$), previous four-quarter systematic skewness ($Coskew_{t-1}$), last month market beta ($Beta_{t-1}$), and last month news sentiment (ESS_{t-1}).

[Table 5 here]

Table 5 reports the time-series averages of the slope coefficients over the 192 months from January 2001 to December 2016. The standard errors in parentheses are robust to heteroscedasticity and autocorrelation for up to six months. Consistently, the average slope β_1 of $Skew^{news}$ ($Skew^{all}$) in Column 2 (Column 1) is -0.102 (-0.140) and significant at the 1% level. To interpret the economic meaning of β_1 for $Skew^{news}$, I multiply the average β_1 with the difference in median $Skew^{news}$ between quantile five and one (3.5 from Table 2). This economic magnitude is equal to -0.36% expected return difference per month which is similar to that shown in Table 4, Panel A. I also find that the coefficient for $Skew^{no-news}$ is insignificant at the 10% level. The sign and significant levels for $Skew^{news}$ and $Skew^{all}$ coefficients remain similar when I control for other firm characteristics, confirming that the pricing of skewness in my sample period is not driven by firm characteristics that plausibly relate to expected stock returns. In general, the coefficients on individual control variables are also as expected. For example, the size effect is negative and significant, the value effect is positive, and *IVOL* is negatively priced. The other control variables are statistically insignificant, but it is consistent with prior empirical studies that also focus on RavenPack data (e.g., Wang, Zhang, and Zhu, 2016).

In summary, I find that both $Skew^{all}$ and $Skew^{news}$ are priced in the cross-section, while $Skew^{no-news}$ is not priced. Given $Skew^{news}$ is explained by asymmetric responses to news, our results confirm that investors' inability to interpret information correctly is at least a partial explanation for the pricing of the stock return skewness.

5. The interaction of skewness and mispricing of news

In this section, I investigate the news mispricing hypothesis directly. I perform two tests. First, I focus on the link between the $Skew^{news}$ effect and asymmetric reaction to news. If the pricing of skewness comes from the asymmetric reaction to news, the negative relation between skewness and future stock returns should be stronger among stocks experiencing greater asymmetric reactions to good and bad news. Second, I test whether the $Skew^{news}$ effect is stronger among firms with greater barriers to understanding news, since investors' inability to price news correctly is likely to be positively related to the degree of barriers to understanding news (e.g., Daniel, Hirshleifer, and Subrahmanyam, 1998; Daniel, Hirshleifer, and Subrahmanyam, 2001; Zhang, 2006; Tetlock, 2011).

I present the cross-section variations in the asymmetric reaction to news first, the time-series variation in the asymmetric reaction to news second, and barriers to understanding news last.[18]

5.1. Asymmetric responses to good and bad news

To do my first test, I perform the following analysis. First, I follow the method in Conrad, Cornell, and Landsman (2002) and Williams (2015) to explore asymmetric responses to good and bad news. Specifically, I run the following regression:

[18] For brevity, I relegate discussion of a similar test with $Skew^{no-news}$ to the Online Appendix: I do not find any significant results for $Skew^{no-news}$ among above subsamples.

$$AR_{i,t} = a + \beta_g * Good\ News_{i,t} + \beta_b * Bad\ News_{i,t} + \beta * AR_{i,t-231,t-2} + e_{i,t} \quad (2)$$

where, $AR_{i,t}$ is the average of the market model-adjusted daily returns for stock *i* over the news-day event window [-1, +1] where the market model is estimated over the estimation window [-231, -2], and $AR_{i,t-231,t-2}$ is the regression intercept from the market model over the estimation window [-231, -2] which captures part of the stock-fixed effect on its returns. Although the measurement for the size of news is not straightforward, RavenPack News Analytics gives us the advantage to capture the size of news. The variable news sentiment score (ESS) from RavenPack indicates how firm-specific news events are categorized and rated as having a positive or negative effect on stock prices by experts with extensive experience and backgrounds in linguistics, finance, and economics. Hence, I calculate daily news size as a daily sum of ESS from RavenPack for each firm-day. I set $Good\ News_{i,t}$ ($Bad\ News_{i,t}$) equals to the daily sum of ESS if the sum of ESS is greater (smaller) than 0, otherwise it equals to zero. Therefore, the coefficient β_g represents the market's response to good news, while β_b represents the market's response to bad news. The difference between β_b and β_g ($\beta_b - \beta_g$) can be a proxy of asymmetric responses to good and bad news.

I first verify whether my sample is experiencing an asymmetric response to good and bad news by running a pooled OLS regression of Eq. (2) with a time-fixed effect. For brevity, the results are not reported. I find that the response to good news ($\beta_g = 1.19$) and bad news ($\beta_b = 2.45$) are both significantly different from zero, indicating that both the good and bad news include significant firm-specific information that is ultimately incorporated into the stock price. I then find that the difference in β_b and β_g is significantly at 1% level under the Wald test, confirming that price reactions are stronger for bad news than for good news of similar size. Given negative skewness comes from underreaction to good news, this result is consistent with my baseline findings in Table 3 and Table 4. That is, investors on average underreact to good news in my sample, and hence the most negative skewness portfolios earn a significant risk-adjusted alpha and account for the majority of the $Skew^{news}$ effect.

I then perform independent portfolio sorting. I sort all stocks into five portfolios based on their $Skew^{news}$ and further independently sort all stocks into one of three terciles based on their beta differences and calculate the monthly equal-weighted future stock returns for them. I estimate the beta difference from the rolling regressions of Eq. (2) over a four-quarter rolling window for each stock and require stocks to have at least 20 days of return data to run the regression. In doing so, I have a new $\beta_b - \beta_g$ every calendar quarter. I denote the negative $\beta_b - \beta_g$ tercile portfolio as "React more strongly to good- than to bad-news", the neutral $\beta_b - \beta_g$ tercile portfolio as "Symmetric reaction to good- and bad-news", and the positive $\beta_b - \beta_g$ tercile portfolio as "React more strongly to bad- than to good-news".

As predicted, Panel A of Table 6 shows that the $Skew^{news}$ effect is only statistically significant in negative and positive $\beta_b - \beta_g$ terciles. The most positive $Skew^{news}$ underperforms a portfolio of stocks with the most negative $Skew^{news}$ by 5.6% to 6.3% per year after adjusting for the Carhart (1997) four-factor in negative and positive $\beta_b - \beta_g$ terciles. However, I do not find the $Skew^{news}$ effect among stocks experiencing symmetric reactions to news (the neutral $\beta_b - \beta_g$ tercile). Hence, these results confirm that the investors' asymmetric reaction to good and bad news is the underlying source of the $Skew^{news}$ effect.

[Table 6 here]

Second, motivated by the skewness model of Hong and Stein (2003) and Xu (2007), I construct an asymmetric reaction to news (*AR*) index by combining five stock characteristics that signal the asymmetric reaction to news. Five stock characteristics are: 1) institutional ownership (D'Avolio, 2002) over the last quarter; 2) ownership breadth (Chen, Hong, and Stein, 2002) over the last quarter; 3) firm size (D'Avolio, 2002) at the end of the last quarter; 4) stock turnover (Chen, Hong, and Stein, 2001) over the last quarter; 5) past 11 months of stock returns (Zhang, 2006). I construct a quarterly *AR* index using a method similar to that in Stambaugh, Yu, and Yuan (2015). Stocks in the high *AR* index have a greater asymmetric reaction to news in the cross-section. Panel B of Table 6 reports the results for independent double sorting according to $Skew^{news}$ and *AR* index. The return predictability of $Skew^{news}$ is pronounced only in the high *AR* index tercile but not in the low *AR* index tercile. After the adjustment for risk exposures to the Carhart (1997) four-factor, the $Skew^{news}$ effect is -7.7% per year (t-statistic = -3.05) among stocks in the high *AR* index, while it drops to -2.6% per year (t-statistic = -1.57) among stocks in the low *AR* index.

Finally, I use Manela and Moreira (2017) news implied volatility (*NVIX*) to identify states in which asymmetric responses to news are more likely to occur.[19] I modify the sorting procedure somewhat due to the shift in focus from the cross-section to the time series when investigating the $Skew^{news}$ effect.

Why do I use *NVIX*? Firstly, *NVIX* is a text-based measure of market-wide ambiguity starting in 1890 from front-page articles of the Wall Street Journal. Manela and Moreira (2017) show that *NVIX* peaks during shocks to economic uncertainty, i.e., stock market crashes, times of policy-related uncertainty, world wars, and financial crises. Hence, *NVIX* is a reasonable proxy for the market-wide ambiguity. Secondly, recent studies show that investors typically are more sensitive to bad news, especially when the level of market-wide ambiguity is high. For instance, Epstein and Schneider (2008) show that market participants do not have enough experience to be comfortable with the relevance of various types of information under an ambiguity environment, and hence they are choosing the worst-case distribution by overweighting bad news. Williams (2015) provides further empirical evidence that in times of greater market-wide ambiguity, the reaction to good and bad news is more asymmetric. Therefore, I expect that investors should respond more strongly to bad news than to good news in periods with high *NVIX*.

[Figure 1 here]

I compute a quarterly *NVIX* by averaging monthly values within each quarter. I first verify whether the market reacts more strongly to bad news than to good news when *NVIX* is high. I plot the time series of *NVIX* and aggregate $Skew^{news}$ (construed by averaging of $Skew^{news}$ across all stocks in each quarter). Fig.1. shows that the aggregate $Skew^{news}$ and *NVIX* is negatively correlated, especially in periods with *NVIX* is above its median value. Moreover, *NVIX* peaks and the aggregate $Skew^{news}$ dips during shocks to economic uncertainty, i.e., the internet bubble and the global financial crisis.[20] In sum, Fig.1. suggests that

[19] I thank the authors of Manela and Moreira (2017) for making *NVIX* data available via Asaf Manela's website at http://apps.olin.wustl.edu/faculty/manela/data.html.

[20] If $Skew^{news}$ is a proxy for investors' lottery demand, then the aggregate $Skew^{news}$ should represent an aggregate lottery demand (Bali, Brown, Murray, and Tang, 2017). If so, then Fig.1. would imply that the aggregate lottery demand is weaker in states with high economic uncertainty. Given economic uncertainty can be positively correlated with bad economic states, Fig.1. is inconsistent with Kumar (2009) who shows that the aggregate lottery demand is stronger in bad economic states. Hence, it's unlikely that $Skew^{news}$ is directly related to the demand for lottery-type stocks.

when market-wide ambiguity is greater, investors indeed react more strongly to bad news than to good news, resulting in negatively skewed returns.

I then perform the portfolio sorting and compute $Skew^{news}$ effect separately for the high and low *NVIX* quarters. A high *NVIX* quarter is one in which the value of *NVIX* in the previous quarter is above the median value for the sample period, and the low *NVIX* quarter is those with below median values. As predicted, I find that the $Skew^{news}$ effect is significant only following high *NVIX*.[21] The $Skew^{news}$ quantile spread strategy delivers a significant four-factor alpha of -0.57% per month with a t-statistic of –4.38 following high *NVIX* periods, while it delivers an insignificant alpha of 0.13% per month with a t-statistic of 0.91 following low *NVIX* periods (Table 7 Panel A).[22]

[Table 7 here]

I also use changes in *VIX* to proxy the market-wide ambiguity as a robustness test. Specifically, previous studies suggest that the observed reaction in *VIX* is a result of investors using options to protect against ambiguity and indicates that the time-variation in ambiguity is strongly reflected in variation in *VIX* (e.g., Bloom, 2009). Given this potential link between ambiguity and *VIX*, I use the quarterly change in *VIX* (ΔVIX) to capture any uncertainty shocks. ΔVIX is the difference between *VIX* at the end of quarter q and *VIX* at the end of quarter $q-1$. In Table 7 Panel B, I find that the $Skew^{news}$ effect is -0.49% per month with a t-statistic of –2.71 following high ΔVIX periods, while it becomes an insignificant alpha of 0.10% per month with a t-statistic of -0.73 following low ΔVIX periods.[23]

[21] In untabulated results, I conduct an alternative analysis, using predictive regressions to investigate whether the level of *NVIX* predicts returns in ways consistent with my hypotheses. Specifically, I regress excess returns on the lagged *NVIX* as well as the contemporaneous returns on the Fama and French and Carhart (1997) four-factor. As predicted, I find that the slope coefficient for *NVIX* is -0.03 with t-statistics equals to -2.49, suggesting that my $Skew^{news}$ effect is stronger when investors react to good and bad news asymmetrically.

[22] The result in Table 7 also implies that my $Skew^{news}$ effect is unlikely from the lottery preference. Investors have information (or have a rational expectation) about the probability distribution of a large jump in the price for lottery-type stocks, while ambiguity means that investors are uncertain about the uncertainty (the probability distribution of a large jump). Hence, it’s unlikely that the demand for lottery-type stocks will be varied among different ambiguity level.

[23] One concern here is that the $Skew^{news}$ effect can capture the investor hedging demand in high market ambiguity periods. Therefore, I control for the *VIX* factor (*FVIX*) of Ang, Hodrick, Xing, and Zhang (2006). I examine if the *FVIX* factor can explain my $Skew^{news}$ effect. I find that the *five-FVIX-factor* alpha is -0.26% per month and significant at the 5% level.

Overall, my results confirm that differences in asymmetric reaction to news explain the variation (in the cross-section and time series) in the relation between skewness and future stock returns. Specifically, the negative relation between skewness and future returns is stronger among stocks (and in months) experiencing greater asymmetric reactions to good and bad news. Hence, these results provide robust evidence that a stock's expected return depends on the return skewness of individual securities that arises from investors' inability to interpret information correctly.

5.2. Barriers to understanding news

I then test whether the $Skew^{news}$ effect is stronger among firms with greater barriers to understanding news. I adopt three firm-level characteristics to proxy greater barriers to understanding news.[24]

The first characteristic to proxy for greater barriers to understanding news is the high analyst coverage. For instance, Hong, Lim, and Jeremy (2000) and Chan (2003) find that stocks with little analyst coverage experience the most barriers to understanding public information. I collect analyst coverage data from I/B/E/S summary files and measure the analyst coverage for each firm-quarter in my sample by counting the number of analysts making fiscal year-end forecasts.

The second characteristic to proxy for greater barriers to understanding news is high soft news coverage. Intuitively, soft news is less-routine-sounding news that is likely to induce larger valuation uncertainty (Neuhierl, Scherbina, and Schlusche, 2013) and is likely to include linguistic content captures otherwise hard-to-quantify information (Tetlock, Tsechansky, and Macskassy, 2008; Beschwitz, Oleg, and Massa, 2017). I divide news articles into hard news and soft news following Wang, Zhang, Zhu (2016): the hard news group consists of four categories of news: "revenues", "earnings", "analyst-ratings", and "credit-

[24] Theoretically, both the firm's underlying fundamental volatility and the quality of information can affect investors' ability to price news correctly. However, since stocks with a greater firm's underlying fundamental volatility (e.g., firm size and volatility) are often argued to be a natural habitat of lottery preferences investors (e.g., Lin and Liu, 2017; Kumar, 2009), I focus on the quality of information only (barriers to understanding news). Although it is hard to empirically disentangle one from the other as observed stock volatility and other empirical constructs capture both effects, I adopt three firm-level characteristics that are most likely to capture the quality of information.

ratings", and all other news categories are included in the soft news group. I measure the soft news coverage for each firm in my sample by counting the number of soft news articles over the same period as skewness.

The third characteristic to proxy for greater barriers to understanding news is the lower readability of 10-K reports, since recent studies suggest that the lower readability of 10-K reports is associated with greater barriers to understanding firms' news (e.g., Li 2008). I collect the readability of 10-K filings data from Li (2008).[25] Li (2008) measures the readability of 10-K filings using the Fog Index (*FOG*) that captures the written complexity of a document as a function of the number of syllables per word and the number of words per sentence. Investors therefore have greater barriers to understanding news in a given quarter if the most recent *FOG* is high.

[Table 8 here]

I sort all stocks into five equal-weighted portfolios based on their $Skew^{news}$. I further independently sort all stocks into one of three terciles based on their soft news coverage, *FOG*, and analyst coverage. I then calculate the monthly equal-weighted future stock returns for them. Panel A, B, and C of Table 8 present results by using the independent double sorting approach, respectively. Consistent with the news mispricing hypothesis, I find that the $Skew^{news}$ effect is particularly large among stocks with greater barriers to understanding news, i.e., among low routine-sounding news coverage, low analyst coverage, and high *FOG*. In these greater barriers to understanding news subsamples, the $Skew^{news}$ effect ranges from 4.2% to 7.3% per year after risk adjustments. For example, the raw return of the $Skew^{news}$ effect is -0.42% per month in the low analyst coverage tercile. After the adjustment for risk exposures to the Carhart (1997) four-factor, the next period return is -0.41% per month (t-statistic = -2.63).

Overall, the results in Table 8 suggest that the $Skew^{news}$ effect is economically significant among stocks with greater barriers to understanding news, confirming the robustness of my news mispricing hypothesis.

[25] I thank Feng Li for making Fog data available: http://webuser.bus.umich.edu/feng/.

6. The $Skew^{news}$ effect and the lottery preference theory

Is it possible that the $Skew^{news}$ effect I document here is a lottery preference phenomenon? The lottery preference theory posits that investors overweight low probability of extremely gains, and hence they exhibit the preference for lottery-like stocks (Barberis and Huang, 2008). Specifically, the lottery preference theory only focuses on an unconditional demand for lottery-like payoffs, meaning just the presence of lottery-like payoffs is sufficient for inducing the pricing of skewness (Eraker and Ready, 2015). In this section, I go on to distinguish the lottery preference theory for my empirical findings.

6.1. Large lottery jackpots

I start with the exogenous variation in the demand for lottery-like stocks. Specifically, I use large national lottery jackpots as a natural shock to the demand for lottery-like stocks.[26] I use large national lottery jackpots for three reasons. Firstly, large jackpots occur randomly and are unlikely to be driven by factors that affect the stock market. Secondly, Chen, Kumar, and Zhang (2017) and Huang, Huang, and Lin (2018) show that large lottery jackpots generate gambling attitudes among investors who may gamble in the stock market. Finally, Bali, Brown, and Murry (2017) confirm that the negative relation between stocks' lottery features and stock future returns is stronger in months with greater gambling attitudes among investors. Thus, if the $Skew^{news}$ effect arises due to demands on lottery-like stocks, we would expect this effect to be stronger in months with large lottery jackpots.

I separate the lottery jackpots into large lottery jackpot and non-large lottery jackpot. I define a lottery jackpot as a large jackpot if a cumulated lottery prize is above 210 million U.S. dollars, which is slightly higher than the 95th percentile of all jackpots throughout my sample period.[27] I then split my sample into months corresponding to high lottery demand and low lottery demand based on the value of jackpots.

[26] The national lotteries are Powerball and Mega Millions (from January 2000 to December 2016). Data source: Mega Millions and Powerball websites.

[27] I also define a lottery jackpot as a large jackpot if a cumulated lottery prize above the 99^{th} percentile of all jackpots throughout my sample period. The results are similar.

A high lottery demand month is a month with at least one large jackpot (69 months), and the low lottery month is a month without any large jackpots.

[Figure 2 here]

To verify large jackpots in my sample period directly capturing the high demand for lotteries, I compare the monthly Google search volume index with lottery jackpot size as Google search volume can be viewed as a direct measure of the demand for lotteries (Huang, Huang, and Lin, 2018). I manually collect the Google monthly search index over the sample period. [28] Fig.2. plots the monthly search volume index and the maximum value of jackpot in a given month. I find that the two series track each other very closely, especially in months with large lottery jackpots, with their correlating being 0.9.

Furthermore, I use an average of the highest five daily returns in the previous month (MAX^5) as a proxy for the demand of lottery-like stocks to verify whether the demands for lotteries and lottery-like stocks are positively correlated in my data. Following the method in Bali, Brown, and Murry (2017), I perform a bivariate portfolio analysis using the subset of months t+1 corresponding to each of these lottery demand months. I find that the *MAX* effect documented in Bali, Cakici, and Whitelaw (2011) is stronger in months with large jackpots (Appendix Table IA3), which is consistent with the findings in Bali, Brown, and Murry (2017). For example, the *MAX* effect is -0.75% per month in months without large lottery jackpot; however, it becomes -1.73% per month in months with a large lottery jackpot. Collectively, my results are consistent with the idea that months with large lottery jackpots are likely to create a greater demand for the lottery and lottery-like stocks, resulting in a stronger lottery preference effect.

I then repeat my bivariate portfolio analysis using the subset of months corresponding to each of these lottery demand months.[29] The results of my analysis, presented in Table 9, demonstrate that the abnormal returns of the positive-negative $Skew^{news}$ portfolios are much more negative in months with low

[28] Google Trends: http://www.google.com/trends/.

[29] Williams and Siegel (2013) find that investors pay attention to lotteries when jackpot prizes pass certain thresholds. Hence, the positive price impact of large jackpots on lottery-like stocks is likely to occur in month t when large jackpots happen during the month t+1. I also perform a robustness test using the subset of months t (t+1) corresponding to each of these lottery demand months if the large lottery jackpot happens within the last ten days in month t (the first ten days in month t+1). The result is similar.

lottery demand than in months with high lottery demand. Based on four-factor risk-adjusted alphas, the zero-cost strategy earns an average excess return of -5 bps per month in high lottery demand months (t-statistic: -0.44);[30] however, the same strategy earns an average excess return of -51 bps in low lottery demand months (t-statistic: -3.54). Hence, the $Skew^{news}$ effect is indeed about 90% weaker in high lottery demand months than in other months. I also find that the long leg of the zero-cost strategy earns an average excess return of -21 bps per month in high lottery demand months (t-statistic: -1.45). In contrast, the same long leg earns a positive average excess return of 46 bps in low lottery demand months (t-statistic: 3.34). Hence, the demand for lotteries has a stronger effect on the long leg (non-lottery-like stocks), which is contradict with the argument that the demand for lotteries and lottery-like stocks are positively correlated.

[Table 9 here]

In addition to identifying jackpots as the lottery demand, previous work has demonstrated that the lottery effect is stronger in January (e.g., Bailey, Kumar, and Ng, 2011; Doran, Jiang, and Peterson, 2011). Therefore, I also include January as a high lottery demand month. Table 9 Panel B reveals that the $Skew^{news}$ effect is approximately 58.9 bps weaker in high lottery demand months than in low lottery demand months.

Overall, it is unlikely that investors' preference for lottery payoffs is the main force behind the $Skew^{news}$ effect.

6.2. The lottery demand variables

Next, I examine the $Skew^{news}$ effect after controlling for the demand for lottery-like stocks. If the negative prediction power of $Skew^{news}$ comes from the investors' lotteries preference, I will have lost the significance of the cross-sectional relation between $Skew^{news}$ and future stock returns after controlling for

[30] Individual traders will be less likely to respond to firm-specific news if their attention is drawn to a big external non-financial markets event, and hence weaken the news mispricing correction process (e.g., Chan, 2003; Xu, 2007). Given the large lottery jackpots can generate great attention (Huang, Huang, and Lin, 2018), the $Skew^{news}$ effect should be weaker in the large lottery jackpot months. Indeed, in untabulated results, I find that the stock turnover (attention) of my positive-negative $Skew^{news}$ portfolio is reduced in large lottery months.

the lottery demand. Following Bali, Cakici, and Whitelaw (2011) and Boyer, Mitton, and Vorkink (2009), I use the maximum daily return during the previous month (*MAX*), MAX^5, and expected skewness (*Eskew*) as proxies for the lottery demand. As preliminary evidence, Table 10 Panel A provides the average monthly cross-sectional correlations between four variables of interest. I find that $Skew^{news}$ and the lottery demand variables are not highly correlated. Their correlations are between -0.01 and -0.03, suggesting stocks with high $Skew^{news}$ do not necessarily exhibit a lottery feature. Given *MAX* is highly correlated with volatility (Bali, Cakici, and Whitelaw, 2011), the result in Table 10 Panel A is consistent with my findings in Table 1 Panel B.

I then perform the dependent sorting that first sort on the lottery demand variable, and within each lottery demand quantile I sort stocks into quantile portfolios based on $Skew^{news}$. I then averaging of the equal-weighted returns across the lottery demand quantiles, and hence the differences between returns on portfolios that vary in $Skew^{news}$ but have approximately the same levels of the lottery demand. Table 10 Panel B reports the results for dependent double sorting according to the lottery demand and $Skew^{news}$. I find the average alpha difference between the negative $Skew^{news}$ and positive $Skew^{news}$ quantiles is between -0.28% to -0.30% per month with a range of t-statistic from -2.49 to -2.86, again suggesting my $Skew^{news}$ effect does not proxy for the lottery preference effect.

[Table 10 here]

Furthermore, I directly control for the lottery mispricing factor (*FMAX*) of Bali, Brown, and Murray (2017). Bali, Brown, and Murray (2017) show that *FMAX* captures returns that are driven by the aggregate lottery demand. Hence, I examine if the *FMAX* factor can explain my $Skew^{news}$ effect. Table 10 Panel C presents the empirical relation between skewness and stock returns by adjusting for a five-factor model that includes the *FMAX* factor.[31] The alpha in the five-*FMAX*-factor model is -27.8 basis points per month, compared to -37.3 basis points in the four-factor model, indicating that about 25% of the alpha relative to

[31] I thank the authors of Bali, Brown, and Murray (2017) for making *FMAX* data available via Scott Murray's website at http://scotttmurray16.wixsite.com/mysite.

the Carhart (1997) four-factor model is absorbed by $FMAX$.[32] This result is hardly surprising. First, I note that both news and lotteries are preferred by individual investors (Kumar, 2009; Lin and Liu, 2017; Peress, 2014; Bali, Hirshleifer, Peng, and Tang, 2019), and hence they can capture the similar individual investors' effect. Second, McLean and Pontiff (2016) show that many mispricing variables are co-movement following the time due to market arbitrage activities. As a result, after controlling for the lottery demand variables and $FMAX$, my risk-adjusted alpha is reduced.

Finally, I control for the lottery demand in the Fama-MacBeth regressions. I find that the coefficient on the $Skew^{news}$ from in Appendix Table IA4 is still significantly negative after controlling for the *MAX*, MAX^5, and *Eskew*. Specifically, the average slope β_1 of $Skew^{news}$ in Column 1 is -0.099 (t = -4.09) after control for *MAX*, in Column 2 is -0.095 (t = -4.14) after control for MAX^5, and in Column 3 is -0.105 (t = -4.21) after control for *Eskew*.

Collectively, my results suggest that the lottery preference theory is at least insufficient to explain the negative relation between skewness and future stock returns. Hence, the $Skew^{news}$ effect is unlikely driven by investors' lottery preferences.

7. Conclusion

In this paper, I provide a new explanation for the pricing of skewness. I argue that a stock's expected return depends on the return skewness of individual securities that arises from investors' inability to interpret information correctly. My rationale is that skewness is an endogenous characteristic of the return distribution which is directly related to asymmetric reactions to news. Since such misreaction to news also creates mispricing, relating this concept to skewness can explain the negative relation between skewness and future returns. I find that skewness extracted from observed news-day return has a robust negative relation to returns with up to 7.7% annual risk-adjusted returns for the zero-cost trading strategy.

[32] This magnitude is similar to the *five-FVIX-factor* alpha in Section 5, which is consistent with the findings in Barinov (2018) who argues that *FMAX* captures the investor hedging demand.

The critical difference between my news mispricing hypothesis and the lottery preference theory is that the lottery preference is an unconditional preference for lottery-like stocks, meaning just the presence of lottery-like payoffs is sufficient for inducing the pricing of skewness. In contrast, the news mispricing hypothesis predicts the pricing of skewness depends on asymmetric reactions to good and bad news being present. I design a set of tests and conduct the empirical exercise to show that the lottery preference theory is at least insufficient to explain the negative relation between skewness and future stock returns.

To enhance our understanding of the pricing of skewness, I further find that the $Skew^{news}$ effect is stronger among stocks with greater barriers to understanding news and greater asymmetric responses to good and bad news, confirming the robustness of my news mispricing hypothesis. Overall, my study suggests that accounting for endogeneity in the return skewness is important for an understanding of the negative relation between skewness and future returns. I provide additional evidence to Engelberg, McLean, and Pontiff (2018) that most return anomalies are correlated with investors' inability to price news correctly.

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Appendix A: **Variables construction**

Variable	Acronym	Definition
News-day return skewness	$Skew^{news}$	$$\text{Skew}^{\text{news}} = \frac{[n(n-1)^{\frac{3}{2}}\sum E_{i,t}^3]}{[(n-2)(n-1)(\sum E_{i,t}^2)^{\frac{3}{2}}]}$$ $$R_{i,t} - R_{f,t} = a + \beta_{i,1}MTK_t + \beta_{i,2}MTK_t^2 + e_{i,t}$$ where, $E_{i,t}^2$ represents the square of de-meaned daily log return to firm *i* during four-quarter period *t*. I use log returns instead of simple returns because simple returns are obviously more positively skewed. The log return is calculated as the log of residuals $(e_{i,t})$. To reduce the impact of infrequent return on skewness estimates, I require a minimum of 50 news-day over four-quarter for which RavenPack reports at least one news for the firm. The news-day is the three days surround the news release [-1, 1].
Non-News-day return skewness	$Skew^{no-news}$	$$\text{Skew}^{\text{no-news}} = \frac{[n(n-1)^{\frac{3}{2}}\sum E_{i,t}^3]}{[(n-2)(n-1)(\sum E_{i,t}^2)^{\frac{3}{2}}]}$$ $$R_{i,t} - R_{f,t} = a + \beta_{i,1}MTK_t + \beta_{i,2}MTK_t^2 + e_{i,t}$$ where, $E_{i,t}^2$ represents the square of de-meaned daily log return to firm *i* during four-quarter period *t*. I use log returns instead of simple returns because simple returns are obviously more positively skewed. The log return is calculated as the log of residuals $(e_{i,t})$. To reduce the impact of infrequent return on skewness estimates, I require a minimum of 50 non-news-day over four-quarter.
News-day up-down volatility	$Udvol^{news}$	$$Udvol^{news}{}_{i,t} = log\frac{(n_g - 1)\sum_{good} E_{i,t}^2}{(n_b - 1)\sum_{bad} E_{i,t}^2}$$ This variable is the log of the ratio of the standard deviation on the good news days to the standard deviation on the bad news days. I separate all news days with the return below the period mean (''bad news'' days) from those with the return above the period mean (''good news" days) and compute the standard deviation for each of these subsamples separately. I require a minimum of 15 observations in each bad and good news sub-sample. Up-down volatility is an alternative skewness measure that is less influenced by outliers in the data.
Non-News-day up-down volatility	$Udvol^{no-news}$	$$Udvol^{no-news}{}_{i,t} = log\frac{(n_g - 1)\sum_{good} E_{i,t}^2}{(n_b - 1)\sum_{bad} E_{i,t}^2}$$ This variable is the log of the ratio of the standard deviation on the good non-news days to the standard deviation on the bad non-news days. I separate all non-news days with the return below the period mean (''bad non-news days) from those with the return above the period mean (''good non-news" days) and compute the standard deviation for each of these subsamples separately. I require a minimum of 15 observations in each bad and good non-news sub-sample.

Mean of News scores	ESS	I use the ESS and adjust them fall in an interval between -1 and 1. 0 sentiment score means neutral news. I exclude repeated news by setting the event novelty score (ENS) and Relevance score provided by RavenPack to be 100, which captures only new specific-news about a firm. The mean of News scores is the average ESS in the last month.
Book-to-market ratio	BM	The logarithm of the ratio of book value of equity to the market value of equity in the previous calendar year-end.
Firm size	$Size$	Measured as the natural logarithm of the market value of the firm's equity in the previous calendar year-end.
Analyst coverage	*Analyst*	The number of analysts issuing earnings forecasts on the stock in the past quarter.
Turnover	$Turn$	The logarithm of the firm's monthly share turnover, measured as the trading volume divided by the total number of share outstanding, detrend by the previous 18 months average.
AHXZ's idiosyncratic volatility	$IVOL$	Measured as the standard deviation of the residuals $\varepsilon_i$after estimating the: $r_i = a_i + \beta_i MKT + \beta_i SMB + \beta_i HML + \varepsilon_i$ using daily excess returns over the past month. I require a minimum of 15 days non-missing return in a month.
Readability of 10-K reports	*FOG*	The Fog Index is the written complexity of a most recently 10-K report as a function of the number of syllables per word and the number of words per sentence.
Past two-month stock returns	$R_{t-3,t-2}$	Compounded return in percentage from month t-3 to t-2.
Past three-month stock returns	$R_{t-6,t-4}$	Compounded return in percentage from month t-6 to t-4.
Past six-month stock returns	$R_{t-12,t-7}$	Compounded return in percentage from month t-12 to t-7.
Amihud's (2002) illiquidity	*Illiquidity*	Illiquidity is the daily ratio of absolute stock return to its dollar volume, averaged over the previous year, which is scaled by 10,000 in the analysis.
Market beta	*Beta*	Regression of r_i=*alpha*+*beta* r_m+*e* from month t-59 to t.
Institutional ownership	*InstOwn*	Number of shares held by institutional investors divided by total shares outstanding in the previous quarter.
Breadth of ownership	*Dbreadth*	The number of funds who hold the stock at quarter t minus the number of funds who hold the stock at quarter t-1 and divide by the total number of funds in the sample at quarter t-1.
Maxing return	MAX	The maximum daily return for a firm in the previous month. I require a minimum of 15 days non-missing return in a month.

Maxing five-day returns	MAX^5	The average of the highest five daily returns for a firm in the previous month. I require a minimum of 15 days non-missing return in a month.
Expected skewness	$Eskew$	The expected skewness of Boyer, Mitton, and Vorkink (2009).
Change in VIX	ΔVIX	*VIX* at the end of quarter q minus *VIX* at the end of quarter q-1.
News implied volatility	$NVIX$	It is a text-based measure of market-wide ambiguity starting in 1890 using front-page articles of the Wall Street Journal.
Co-skewness	$Coskew$	It is $\beta_{i,2}$ from $r_{i,t} = a + \beta_{i,1} MTK_t + \beta_{i,2} MTK_t^2 + e_{i,t}$.

Table 1: Descriptive statistics

Panel A reports the return moments' statistics for news-day, non-news-day, and all-day. Return is the first moment of raw returns over four-quarter, volatility (skewness) is the second (third) moment of daily log residual returns from a regression of excess stock returns on the excess return of the market portfolio and the squared excess market return over four-quarter. Days are the number of trading days. All variables are computed over four-quarter and updated each quarter. News-day is three days around the news event day t [t-1, t+1]. Panel B reports the correlation between return moments for news-day, non-news-day, and all-day. $Skew^{all}$ is the all-day return skewness, $Skew^{news}$ is news-day return skewness, $Skew^{no-news}$ is non-news-day return skewness, Ret^{all} is the all-day mean return, Ret^{news} is the news-day mean return, $Ret^{no-news}$ is the non-news-day mean return, Std^{all} is the all-day return volatility, Std^{news} is news-day return volatility, $Std^{no-news}$ is non-news-day return volatility. The sample period is from January 2001 to December 2016.

Panel A: Statistic, Entire sample

Variable	*News days*		*Non-news days*		*All days*	
	Mean	*Median*	*Mean*	*Median*	*Mean*	*Median*
Return (%)	0.096	0.078	0.036	0.043	0.057	0.056
Volatility	3.285	2.772	2.379	2.045	2.820	2.437
Skewness	**-0.040**	**0.095**	**0.177**	**0.150**	**-0.016**	**0.126**
Days	107	98	144	153	251	252

Panel B: Correlation Matrix

	$Skew^{news}$	$Skew^{no-news}$	$Skew^{all}$	Ret^{news}	$Ret^{no-news}$	Ret^{all}	Std^{news}	$Std^{no-news}$
$Skew^{no-news}$	0.007							
$Skew^{all}$	**0.936**	**0.177**						
Ret^{news}	0.407	-0.035	0.375					
$Ret^{no-news}$	-0.025	0.183	0.001	-0.101				
Ret^{all}	0.322	0.094	0.321	0.668	0.580			
Std^{news}	-0.127	0.101	-0.135	0.118	-0.115	-0.008		
$Std^{no-news}$	-0.015	0.121	0.009	0.063	-0.083	-0.025	0.795	
Std^{all}	-0.099	0.113	-0.097	0.085	-0.110	-0.023	0.954	0.920

Table 2: Characteristics of portfolios sorted by $\mathbf{Skew}^{\mathbf{news}}$

This table reports summary statistics for quantile portfolios of stocks sorted by news-day return skewness. Quantile portfolios are formed every quarter from January 2001 to December 2016 by sorting stocks based on news-day return skewness ($Skew^{news}$) over the past four-quarter. Portfolio 1 (5) is the portfolio of stocks with the lowest (highest) $Skew^{news}$. The table reports for each quantile the average across the quarters in the sample of the median values within each quarter of various characteristics for the stocks— $Skew^{news}$, all-day return skewness ($Skew^{all}$), non-news-day return skewness ($Skew^{no-news}$), 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*). All the variables are defined in Appendix A.

Quantile	$Skew^{news}$	$Skew^{all}$	$Skew^{no-news}$	BM	$Size$	$IVOL$	MOM
$Low\ Skew^{news}$	-1.932	-1.549	0.159	0.530	13.157	1.991	-11.933
2	-0.447	-0.237	0.132	0.597	13.126	1.834	2.104
3	0.085	0.115	0.127	0.601	13.132	1.779	7.700
4	0.568	0.445	0.145	0.563	13.059	1.862	11.569
$High\ Skew^{news}$	1.568	1.245	0.161	0.517	13.089	1.919	19.259

Table 3: Return predictability of all-day skewness: Portfolio analysis

This table presents returns for stock portfolios sorted by the all-day return skewness ($Skew^{all}$). On each portfolio formation date, I sort all stocks with at least 50 valid news-day and 50 valid non-news-day into five equal-weighted portfolios based on their skewness measured over the past four-quarter. Stocks in the first portfolio have the lowest skewness while stocks in the fifth portfolio have the highest skewness. "High - Low" is the zero-cost portfolio that is long in the highest skewness portfolio and short in the lowest skewness portfolio. R_{t+1} shows the 1-month holding period average return of each portfolio. I 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 2001 to December 2016. Newey-West adjusted t-statistics are reported in the parentheses and ***, **, * denote 1%, 5%, and 10% significant levels, respectively. There is an average of 427 stocks per portfolio.

Portfolios	R_{t+1}	*CAPM α*	*FF3 α*	*FFC4 α*	*FFC4+PS α*
$Low\ Skew^{all}$	1.175**	0.394	0.149	0.274**	0.237**
	(2.24)	(1.43)	(0.93)	(2.11)	(2.02)
2	0.819*	0.095	-0.120	-0.039	-0.079
	(1.69)	(0.59)	(-1.47)	(-0.44)	(-0.85)
3	0.932**	0.237*	0.030	0.077	0.056
	(1.98)	(1.70)	(0.38)	(0.99)	(0.72)
4	0.881*	0.182	-0.021	0.020	0.005
	(1.82)	(1.11)	(-0.25)	(0.25)	(0.06)
$High\ Skew^{all}$	0.763	0.042	-0.183	-0.136	-0.141
	(1.49)	(0.21)	(-1.60)	(-1.19)	(-1.24)
High – Low	**-0.412*** **	**-0.352** **	**-0.333** **	**-0.410*** **	**-0.378*** **
	(-2.62)	**(-2.14)**	**(-2.19)**	**(-3.16)**	**(-2.99)**

Table 4: Return predictability of news-day and non-news-day skewness: Portfolio analysis

This table presents returns for stock portfolios sorted by news-day return skewness (Panel A) and non-news-day return skewness (Panel B). On each portfolio formation date, I sort all stocks with at least 50 valid news-day and 50 valid non-news-day into five equal-weighted portfolios based on their skewness measured over the past four-quarter. Stocks in the first portfolio have the lowest skewness while stocks in the fifth portfolio have the highest skewness. "High - Low" is the zero-cost portfolio that is long in the highest skewness portfolio and short in the lowest skewness portfolio. R_{t+1} shows the 1-month holding period average return of each portfolio. I 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 2001 to December 2016. Newey-West adjusted t-statistics are reported in the parentheses and ***, **, * denote 1%, 5%, and 10% significant levels, respectively. There is an average of 427 stocks per portfolio.

Panel A: Return Predictability of $\mathbf{Skew^{news}}$

Portfolios	R_{t+1}	*CAPM α*	*FF3 α*	*FFC4 α*	*FFC4+PS α*
$Low\ Skew^{news}$	1.144**	0.367	0.121	0.240**	0.205*
	(2.19)	(1.41)	(0.79)	(1.98)	(1.85)
2	0.870*	0.145	-0.075	0.004	-0.030
	(1.77)	(0.81)	(-0.85)	(0.05)	(-0.36)
3	0.826*	0.129	-0.090	-0.047	-0.076
	(1.73)	(0.92)	(-1.22)	(-0.66)	(-1.03)
4	0.966*	0.253	0.055	0.111	0.097
	(1.95)	(1.46)	(0.58)	(1.12)	(0.99)
$High\ Skew^{news}$	0.764	0.056	-0.156*	-0.113	-0.117
	(1.57)	(0.32)	(-1.69)	(-1.25)	(-1.27)
High – Low	**-0.379*** **	**-0.311** **	**-0.277** **	**-0.353*** **	**-0.322*** **
	(-2.62)	**(-2.10)**	**(-2.07)**	**(-3.15)**	**(-3.03)**

Panel B: Return Predictability of $\mathbf{Skew^{no-news}}$

Portfolios	R_{t+1}	*CAPM α*	*FF3 α*	*FFC4 α*	*FFC4+PS α*
$Low\ Skew^{no-news}$	0.946*	0.231	0.042	0.125	0.090
	(1.97)	(1.31)	(0.41)	(1.26)	(0.93)
2	0.873*	0.163	-0.028	0.030	0.004
	(1.89)	(1.11)	(-0.37)	(0.40)	(0.05)
3	0.925*	0.212	-0.015	0.039	0.008
	(1.94)	(1.20)	(-0.19)	(0.55)	(0.12)
4	1.020**	0.296	0.062	0.125	0.113
	(2.07)	(1.57)	(0.64)	(1.45)	(1.35)
$High\ Skew^{no-news}$	0.806	0.048	-0.206	-0.124	-0.136
	(1.45)	(0.20)	(-1.45)	(-0.88)	(-1.00)
High – Low	**-0.141**	**-0.183**	**-0.247***	**-0.249**	**-0.226**
	(-0.81)	**(-1.05)**	**(-1.68)**	**(-1.63)**	**(-1.61)**

Table 5: Cross-sectional predictability of skewness - Fama-MacBeth regressions

Each month, I run a firm-level cross-sectional regression of the return in that month on subsets of lagged predictor variables including $Skew^{news}$, $Skew^{all}$, and $Skew^{no-news}$ 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}), co-skewness over past four-quarter ($Coskew_{t-1}$), and Amihud's (2002) illiquidity over last year ($Illiquidity_{t-1}$). All the variables are defined in Appendix A. 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). ***, **, * denote 1%, 5%, and 10% significant levels, respectively. The sample period is from January 2001 to December 2016.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
$Skew_{t-1}^{all}$	**-0.140*** **			**-0.134*** **		
	(-3.26)			**(-4.36)**		
$Skew_{t-1}^{news}$		**-0.102*** **			**-0.104*** **	
		(-2.83)			**(-4.05)**	
$Skew_{t-1}^{no-news}$			**-0.037**			**-0.034**
			(-0.37)			**(-0.47)**
ESS_{t-1}				0.430***	0.430***	0.426***
				(4.26)	(4.25)	(4.25)
$Coskew_{t-1}$				-0.012	-0.012	-0.013
				(-1.26)	(-1.31)	(-1.30)
$R_{t-2,t-3}$				0.002	0.002	0.001
				(0.50)	(0.41)	(0.14)
$R_{t-4,t-6}$				0.000	0.000	-0.001
				(0.10)	(0.05)	(-0.25)
$R_{t-7,t-12}$				-0.000	-0.000	-0.001
				(-0.06)	(-0.13)	(-0.50)
$Illiquidity_{t-1}$				0.003	0.003	0.002
				(1.12)	(1.08)	(0.69)
$Size_{t-1}$				-0.135**	-0.131**	-0.129**
				(-2.15)	(-2.11)	(-2.09)
$IVOL_{t-1}$				-0.192***	-0.191***	-0.184***
				(-3.59)	(-3.56)	(-3.44)
BM_{t-1}				0.151*	0.150*	0.140*
				(1.93)	(1.92)	(1.78)
$Beta_{t-1}$				0.102	0.100	0.091
				(0.59)	(0.57)	(0.52)
Adjusted R^2	0.002	0.002	0.002	0.068	0.068	0.068

Table 6: The $Skew^{news}$ effect and asymmetric reaction to good and bad news, cross-sectional variation

At each formation period, I sort all stocks into five portfolios based on their $Skew^{news}$. In Panel A, I further independently sort all stocks into three portfolios based on their previous four-quarter beta difference ($\beta_b - \beta_g$). I estimate the beta difference from the firm-quarter rolling regressions of Eq. (2) over a four-quarter rolling window and require all stocks to have at least 20 days of return data to run the regression. I denote the negative $\beta_b - \beta_g$ tercile portfolio as "React more strongly to good- than to bad-news", the neutral $\beta_b - \beta_g$ tercile portfolio as "Symmetric reaction to good- and bad-news", and the positive $\beta_b - \beta_g$ tercile portfolio as "React more strongly to bad- than to good-news". In Panel B, I further independently sort all stocks into three portfolios based on their previous quarter AR index. I construct an AR index by bundling five stock characteristics that are related to investors' disagreement and short-sales constraints: 1) institutional ownership (D'Avolio, 2002) over the last quarter; 2) ownership breadth (Chen, Hong, and Stein, 2002) over the last quarter; 3) firm size (D'Avolio, 2002) at the end of the last quarter; 4) stock turnover (Chen, Hong, and Stein, 2001) over the last quarter; 5) past 11 months stock returns (Zhang, 2006). I then compute the equally weighted one-month-ahead average returns for each portfolio. The column labelled "H-Low" is the difference in average monthly raw returns between the High $Skew^{news}$ and Low $Skew^{news}$ portfolios, and "FFC4 α" is the difference in four-factor alphas on the High $Skew^{news}$ and Low $Skew^{news}$ portfolios. The sample period is from January 2001 to December 2016. Newey-West adjusted t-statistics are reported in the parentheses and ***, **, * denote 1%, 5%, and 10% significant levels, respectively.

Panel A: Asymmetric reaction to good and bad news							
Portfolios	Low	2	3	4	High	H-Low	FFC4 α
React more strongly to good- than to bad-news	1.350	1.107	0.856	0.997	0.839	**-0.511**** **(-2.49)**	**-0.464***** **(-2.63)**
Symmetric reaction to good- and bad-news	0.960	0.770	0.834	1.077	0.808	**-0.153** **(-1.00)**	**-0.136** **(-1.19)**
React more strongly to bad- than to good-news	1.147	0.760	0.854	0.673	0.608	**-0.540***** **(-2.78)**	**-0.525***** **(-3.12)**

Panel B: AR Index							
Portfolios	Low	2	3	4	High	H-Low	FFC4 α
Low AR Index	1.174	0.828	0.817	0.860	0.921	**-0.253** **(-1.17)**	**-0.216** **(-1.57)**
High AR Index	1.359	1.083	0.876	0.992	0.721	**-0.639**** **(-2.51)**	**-0.638***** **(-3.05)**

Table 7: The $Skew^{news}$ effect and asymmetric reaction to good and bad news, time-series variation

At each formation period, all stocks are sorted into ascending quantile portfolios based on values of $Skew^{news}$. The table presents the time-series means of the monthly one-month-ahead excess returns for each of the equal-weighted quantile portfolios for portfolio holding months following previous quarter high $NVIX$ and low $NVIX$ (Panel A); and portfolio holding months following previous quarter high ΔVIX and low ΔVIX (Panel B). The column labelled "H-Low" is the difference in average monthly returns between the High $Skew^{news}$ and Low $Skew^{news}$ portfolios, and "FFC4 α" is the difference in four-factor alphas on the High $Skew^{news}$ and Low $Skew^{news}$ portfolios. The sample period is from January 2001 to June 2016. Newey-West adjusted t-statistics are reported in the parentheses and ***, **, * denote 1%, 5%, and 10% significant levels, respectively.

Panel A: Time-varying uncertainty, $NVIX$

Portfolios	Low	2	3	4	High	H-Low	FFC4 α
Low NVIX	0.050	0.050	0.093	0.196	0.223	**0.173**	**0.130**
						(1.34)	**(0.91)**
High NVIX	2.361	1.828	1.653	1.770	1.467	**-0.894*** **	**-0.569*** **
						(-3.74)	**(-4.38)**

Panel B: Time-varying uncertainty, ΔVIX

Portfolios	Low	2	3	4	High	H-Low	FFC4 α
Low ΔVIX	0.536	0.587	0.597	0.709	0.424	**-0.112**	**-0.098**
						(-0.87)	**(-0.73)**
High ΔVIX	1.751	1.153	1.056	1.223	1.105	**-0.647** **	**-0.490*** **
						(-2.27)	**(-2.71)**

Table 8: The $Skew^{news}$ effect and barriers to understanding news

This table presents the $Skew^{news}$ effects by different levels of barriers to understanding news. At each formation period, I sort all stocks into five portfolios based on their $Skew^{news}$. I further independently sort all stocks into three portfolios based on their previous four-quarter soft news coverage (*Soft news*) in Panel A, readability of most recently10-K filings before portfolio formation date (*FOG*) in Panel B (sample period is from 2000-2012), and previous quarter analyst coverage (*Analyst*) in Panel C, respectively. The column labelled "H-Low" is the difference in average monthly raw returns between the High $Skew^{news}$ and Low $Skew^{news}$ portfolios, and "FFC4 α" is the difference in four-factor alphas on the High $Skew^{news}$ and Low $Skew^{news}$ portfolios. The sample period is from January 2001 to December 2016. Newey-West adjusted t-statistics are reported in the parentheses and ***, **, * denote 1%, 5%, and 10% significant levels, respectively.

Panel A: Soft news coverage

Portfolios	Low	2	3	4	High	H-Low	FFC4 α
Low Soft	1.077	1.069	0.830	1.192	0.867	**-0.210**	**-0.163**
						(-1.13)	**(-1.01)**
High Soft	1.098	0.697	0.737	0.907	0.600	**-0.498****	**-0.470*****
						(-2.57)	**(-2.64)**

Panel B: Complex report, FOG

Portfolios	Low	2	3	4	High	H-Low	FFC4 α
Low FOG	1.262	1.068	0.629	0.883	1.027	**-0.235**	**-0.183**
						(-1.29)	**(-1.17)**
High FOG	1.321	0.749	0.607	0.623	0.693	**-0.628*****	**-0.601*****
						(-2.69)	**(-2.73)**

Panel C: Analyst coverage

Portfolios	Low	2	3	4	High	H-Low	FFC4 α
Low Analyst	1.160	1.009	1.032	1.100	0.739	**-0.421****	**-0.410*****
						(-2.47)	**(-2.63)**
High Analyst	0.885	0.733	0.574	0.881	0.613	**-0.271**	**-0.235**
						(-1.27)	**(-1.34)**

Table 9: The $Skew^{news}$ effect in months with large lottery jackpots

On each portfolio formation date, all stocks are sorted into ascending decile portfolios based on values of $Skew^{news}$. The table presents the time-series means of the monthly one-month-ahead returns for each of the equal-weighted quantile portfolios for: portfolio holding periods in high lottery demand months and in low lottery demand months (Panel A); portfolio holding periods in high lottery demand months + January and in other months (Panel B). I define a lottery jackpot as a large jackpot if a cumulated lottery prize above 210 million U.S. dollars, which is slightly higher than the 95th percentile of all jackpots throughout my sample period. I then split my sample into months corresponding to high lottery demand and low lottery demand based on the value of jackpots. A high lottery demand month is a month with at least one large jackpot, and the low lottery month is a month without any large jackpots. Raw returns (R_{t+1}) and four-factor returns ($FFC4\ \alpha$) are reported in percent per month. The column labelled "H-Low" presents results for a zero-cost portfolio that is long the quantile five portfolio and short the quantile one portfolio. The sample period is from January 2001 to December 2016. Newey-West adjusted t-statistics are reported in the parentheses and ***, **, * denote 1%, 5%, and 10% significant levels, respectively.

Panel A: Large lottery jackpots

Portfolios	Value	Low	2	3	4	High	H-Low
Large lottery jackpot months	R_{t+1}	1.243**	1.285**	1.272**	1.416**	1.162**	**-0.081**
		(2.04)	(2.26)	(2.27)	(2.62)	(2.07)	**(-0.69)**
	$FFC4\ \alpha$	-0.206	-0.069	-0.084	0.083	-0.254*	**-0.048**
		(-1.45)	(-0.74)	(-0.69)	(0.87)	(-1.77)	**(-0.44)**
Other months	R_{t+1}	1.087	0.638	0.576	0.714	0.541	**-0.546*** **
		(1.61)	(1.00)	(0.94)	(1.13)	(0.86)	**(-2.68)**
	$FFC4\ \alpha$	0.463***	0.045	-0.018	0.148	-0.051	**-0.514*** **
		(3.34)	(0.42)	(-0.19)	(0.99)	(-0.48)	**(-3.54)**

Panel B: Large lottery jackpots + January

Portfolios	Value	Low	2	3	4	High	H-Low
Large lottery jackpot months + January	R_{t+1}	1.437**	1.420***	1.243**	1.486***	1.270**	**-0.168**
		(2.44)	(2.80)	(2.46)	(2.82)	(2.33)	**(-0.81)**
	$FFC4\ \alpha$	-0.068	0.099	0.002	0.176	-0.051	**0.017**
		(-0.59)	(1.19)	(0.02)	(1.59)	(-0.35)	**(0.14)**
Other months	R_{t+1}	0.929	0.469	0.522	0.587	0.395	**-0.534*** **
		(1.30)	(0.70)	(0.82)	(0.89)	(0.61)	**(-2.77)**
	$FFC4\ \alpha$	0.403***	-0.077	-0.050	0.041	-0.168*	**-0.571*** **
		(3.05)	(-0.72)	(-0.42)	(0.31)	(-1.69)	**(-3.80)**

Table 10: The $Skew^{news}$ effect after controlling for the lottery demand variables

Panel A reports the correlation between $Skew^{news}$ and the lottery demand variables (*MAX*, MAX^5, *and Eskew*). In Panel B, I perform the dependent sorting that first sort on the lottery demand variable, and within each lottery demand quantile I sort stocks into quantile portfolios based on $Skew^{news}$. I then averaging of the equal-weighted returns across the lottery demand quantiles, and hence the differences between returns on portfolios that vary in $Skew^{news}$ but have approximately the same levels of the lottery demand. I report the alpha from the Carhart (1997) four-factor model. In Panel C, I control for Carhart (1997) four-factor and *FMAX* factor (*FMAX5* α) of Bali, Brown, and Murry (2017) to test the $Skew^{news}$ effect. The column labelled "High-Low" is the difference in average monthly excess returns between the High $Skew^{news}$ and Low $Skew^{news}$ portfolios. The sample period is from January 2001 to December 2016. Newey-West adjusted t-statistics are reported in the parentheses and ***, **, * denote 1%, 5%, and 10% significant levels, respectively.

Panel A: Correlations between $\mathbf{Skew^{news}}$ and the lottery demand variables

	$Skew^{news}$	MAX	MAX^5	$Eskew$
$Skew^{news}$	1			
MAX	**-0.010**	1		
MAX^5	**-0.031**	0.889	1	
$Eskew$	**-0.025**	0.235	0.262	1

Panel B: $\mathbf{Skew^{news}}$ effect controlling for the lottery demand variables

Portfolios	MAX	MAX^5	$Eskew$
$Low\ Skew^{news}$	0.233**	0.226*	0.221*
	(1.98)	(1.82)	(1.86)
2	-0.043	-0.027	0.009
	(-0.51)	(-0.33)	(0.11)
3	-0.004	-0.044	0.029
	(-0.06)	(-0.57)	(0.39)
4	0.075	0.101	0.040
	(0.79)	(1.01)	(0.44)
$High\ Skew^{news}$	-0.064	-0.057	-0.080
	(-0.71)	(-0.64)	(-0.93)
High – Low	**-0.297*** **	**-0.283** **	**-0.301*** **
	(-2.86)	**(-2.49)**	**(-2.86)**

Panel C: $\mathbf{Skew^{news}}$ effect controlling for FMAX

	Low	2	3	4	High	High-Low
$FMAX5\ \alpha$	0.278**	0.096	0.038	0.210*	0.000	**-0.278** **
	(2.39)	(0.96)	(0.49)	(1.77)	(0.00)	**(-2.29)**

Table IA1

The table examines the robustness of the $Skew^{news}$ effect by using different specifications. "ENS≤100" means that news days include days with ENS score small than 100. "ENS≤100 and RNS≤100" means that news days include days with ENS and RNS score small than 100. "News days [0, 1]" means that news day is the 2-day window [0, 1] around the news releasing day. "2000-2008" and "2009-2016" means the sample period is from January 2000 to December 2008 and from January 2009 to December 2016, respectively. On each portfolio formation date, I sort all stocks with more than 50 news-day and 50 non-news-day into five equal-weighted portfolios based on their skewness measured over the past four-quarter. Stocks in the first portfolio have the lowest skewness while stocks in the fifth portfolio have the highest skewness. 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. I 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.

Portfolios	R_{t+1}	*CAPM α*	*FF3 α*	*FFC4 α*	*FFC4+PS α*
ENS≤100	-0.377***	-0.310**	-0.275**	-0.350***	-0.319***
	(-2.60)	(-2.08)	(-2.05)	(-3.08)	(-2.97)
ENS≤100 and RNS≤100	-0.405**	-0.362**	-0.322**	-0.370**	-0.340**
	(-2.44)	(-2.17)	(-2.01)	(-2.44)	(-2.21)
News days [0, 1]	-0.331**	-0.248*	-0.232*	-0.312***	-0.290***
	(-2.40)	(-1.73)	(-1.75)	(-2.82)	(-2.75)
2001-2008	-0.418*	-0.495*	-0.403*	-0.481**	-0.409*
	(-1.87)	(-1.77)	(-1.71)	(-2.35)	(-1.98)
2009-2016	-0.341*	-0.304*	-0.333*	-0.321**	-0.320**
	(-1.91)	(-1.68)	(-1.94)	(-2.35)	(-2.38)

Table IA2

The table examines the robustness of Table 3 and Table 4 by using different specifications. "Decile" means that all stocks are grouped into ten portfolios based on skewness at each formation date. "Skip one month" means that I skip one month between portfolio formation date and holding period date. "Half-yearly updated skewness" and "Yearly updated skewness" means that skewness is updated half-yearly and yearly, respectively. "NYSE breakpoints" means that I use the NYSE breakpoints following Fama and French (1992) to generate quintile portfolios with a relatively more balanced average market share. "Up-Down Ivol" means that all stocks are grouped into five portfolios based on up-down volatility at each formation date. "Up-Down Ivol" is an alternative skewness measure that is less influenced by outliers in the data. "40 days" and "60 days" means that I require stocks have at least 40 news and non-news days and 60 news and non-news days available over past four-quarter, respectively. "Median days" means that I require stocks have available news-day between 90 and 110 days over past four-quarter. "Non-Log returns" means that skewness is calculated based on residuals from the regression of stock returns on excess market return and its square. "Raw returns" and "FF3 returns" means that skewness is calculated based on the log of raw returns and the log of residuals from the Fama-French (1993) three-factor model. "Controlling for news-day returns" means that I perform the dependent sorting to control the effect of news-day returns. "Controlling for news-day" means that I perform the dependent sorting to control the effect of news-day. R_{t+1} shows the monthly holding equal-weighted average return of the hedge portfolio that is long in high skewness portfolio and short in low skewness portfolio. I also report the alpha from the Carhart (1997) four-factor model. The sample period is from January 2001 to December 2016. Newey-West adjusted t-statistics are reported in the parentheses and ***, **, * denote 1%, 5%, and 10% significant levels, respectively.

Portfolios	$Skew^{all}$		$Skew^{news}$		$Skew^{no-news}$	
	R_{t+1}	$FFC4\ \alpha$	R_{t+1}	$FFC4\ \alpha$	R_{t+1}	$FFC4\ \alpha$
Decile	-0.686***	-0.652***	-0.536***	-0.486***	-0.153	-0.275
	(-3.33)	(-3.82)	(-2.85)	(-3.18)	(-0.63)	(-1.24)
Skip one month	-0.314**	-0.336***	-0.322**	-0.324***	-0.073	-0.171
	(-2.11)	(-2.79)	(-2.49)	(-3.21)	(-0.40)	(-1.02)
Half-yearly updated skewness	-0.372***	-0.374***	-0.331**	-0.311***	-0.075	-0.175
	(-2.64)	(-3.45)	(-2.49)	(-3.19)	(-0.45)	(-1.15)
Yearly updated skewness	-0.298***	-0.306***	-0.277**	-0.267***	-0.016	-0.115
	(-2.65)	(-3.77)	(-2.34)	(-3.31)	(-0.11)	(-0.85)
NYSE breakpoints	-0.409**	-0.396***	-0.357**	-0.330***	-0.110	-0.218
	(-2.51)	(-2.98)	(-2.55)	(-3.04)	(-0.68)	(-1.53)
Up-Down Ivol	-0.334**	-0.361***	-0.308**	-0.295***	-0.039	-0.155
	(-2.16)	(-2.88)	(-2.28)	(-2.72)	(-0.21)	(-0.95)
Non-log returns	-0.388**	-0.406***	-0.339***	-0.344***	-0.053	-0.163
	(-2.51)	(-2.98)	(-2.68)	(-3.17)	(-0.23)	(-0.83)
40 days	-0.396***	-0.392***	-0.339**	-0.314***	-0.151	-0.255*
	(-2.58)	(-2.94)	(-2.44)	(-2.79)	(-0.95)	(-1.82)
60 days	-0.363**	-0.368***	-0.331**	-0.308***	-0.067	-0.176
	(-2.27)	(-2.82)	(-2.29)	(-2.83)	(-0.36)	(-1.06)
Median days	-0.562***	-0.524**	-0.574***	-0.512***	0.096	0.002
	(-2.61)	(-2.54)	(-2.90)	(-2.72)	(0.36)	(0.01)
Raw returns	-0.456***	-0.437***	-0.376***	-0.338***	-0.145	-0.201
	(-2.89)	(-3.36)	(-2.82)	(-3.36)	(-0.85)	(-1.25)
FF3 returns	-0.477***	-0.466***	-0.355**	-0.327***	-0.132	-0.237*
	(-3.10)	(-3.70)	(-2.51)	(-3.03)	(-0.83)	(-1.76)
Controlling for news-day	-0.416***	-0.391***	-0.363***	-0.315***	-0.114	-0.207
returns	(-3.46)	(-3.52)	(-3.79)	(-3.49)	(-0.73)	(-1.47)
Controlling for news-day	-0.399**	-0.401***	-0.362***	-0.342***	-0.119	-0.240
	(-2.59)	(-3.19)	(-2.73)	(-3.32)	(-0.72)	(-1.63)

Table IA3

At the end of each month t, all stocks are sorted into ascending quantile portfolios based on values of the average of the highest five daily returns (MAX^5). The table presents the time-series means of the monthly one-month-ahead returns for each of the equal-weighted quantile portfolios for: portfolio holding periods in high lottery demand months and in low lottery demand months. I define a lottery jackpot as a large jackpot if a cumulated lottery prize above 210 million U.S. dollars, which is slightly higher than the 95th percentile of all jackpots throughout my sample period. I then split my sample into months corresponding to high lottery demand and low lottery demand based on the value of jackpots. A high lottery demand month is a month with at least one large jackpot, and the low lottery month is a month without any large jackpots. The column labelled "H-Low" presents results for a zero-cost portfolio that is long the quantile five portfolio and short the quantile one portfolio. The sample period is from January 2001 to December 2016. Newey-West adjusted t-statistics are reported in the parentheses and ***, **, * denote 1%, 5%, and 10% significant levels, respectively.

Portfolios	Value	Low	2	3	4	High	H-Low
Large lottery jackpot months	R_{t+1}	1.669***	1.660***	1.464***	1.070	0.639	**-1.030**
		(5.44)	(3.75)	(2.71)	(1.57)	(0.75)	**(-1.52)**
	$FFC4\ \alpha$	0.811***	0.549***	0.195	-0.384***	-0.915***	**-1.726*** **
		(3.92)	(2.91)	(1.41)	(-2.71)	(-3.63)	**(-4.11)**
Other months	R_{t+1}	0.887**	0.905**	0.890*	0.842	0.352	**-0.536**
		(2.42)	(2.02)	(1.66)	(1.22)	(0.39)	**(-0.72)**
	$FFC4\ \alpha$	0.417***	0.334***	0.266**	0.213	-0.331	**-0.748** **
		(3.22)	(2.82)	(2.31)	(1.23)	(-1.08)	**(-2.12)**

Table IA4: Cross-sectional predictability of skewness - Fama-MacBeth regressions

Each month, I run a firm-level cross-sectional regression of the return in that month on subsets of lagged predictor variables including $Skew^{news}$, $Skew^{all}$, and $Skew^{no-news}$ 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}), co-skewness over past four-quarter ($Coskew_{t-1}$), Amihud's (2002) illiquidity over last year ($Illiquidity_{t-1}$), the maximum daily return in the last month (MAX_{t-1}), the average of top five daily returns in the last month (MAX^5_{t-1}), and the expected skewness in the last month ($Eskew_{t-1}$). All the variables are defined in Appendix A. 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). ***, **, * denote 1%, 5%, and 10% significant levels, respectively. The sample period is from January 2001 to December 2016.

Variable	(1)	(2)	(3)
$Skew^{news}_{t-1}$	**-0.099*** **	**-0.095*** **	**-0.105*** **
	(-4.09)	**(-4.14)**	**(-4.21)**
$Skew^{no-news}_{t-1}$	-0.028	-0.019	-0.043
	(-0.40)	(-0.27)	(-0.61)
MAX_{t-1}	-0.012		
	(-0.64)		
MAX^5_{t-1}		-0.284***	
		(-4.82)	
$ESkew_{t-1}$			-0.069
			(-0.49)
ESS_{t-1}	0.431***	0.542***	0.426***
	(4.50)	(5.44)	(4.27)
$Coskew_{t-1}$	-0.011	-0.010	-0.014
	(-1.18)	(-1.00)	(-1.33)
$R_{t-2,t-3}$	0.001	-0.000	0.002
	(0.31)	(-0.01)	(0.35)
$R_{t-4,t-6}$	-0.000	-0.000	-0.000
	(-0.00)	(-0.03)	(-0.05)
$R_{t-7,t-12}$	-0.000	0.000	-0.000
	(-0.06)	(0.01)	(-0.09)
$Illiquidity_{t-1}$	0.003	0.002	0.002
	(0.91)	(0.62)	(0.59)
$Size_{t-1}$	-0.125**	-0.119*	-0.146**
	(-2.06)	(-1.87)	(-2.37)
$IVOL_{t-1}$	-0.166*	0.132	-0.187***
	(-1.71)	(1.54)	(-3.69)
BM_{t-1}	0.141*	0.148*	0.147*
	(1.78)	(1.90)	(1.93)
$Beta_{t-1}$	0.121	0.204	0.093
	(0.69)	(1.10)	(0.55)
Adjusted R^2	0.071	0.073	0.072

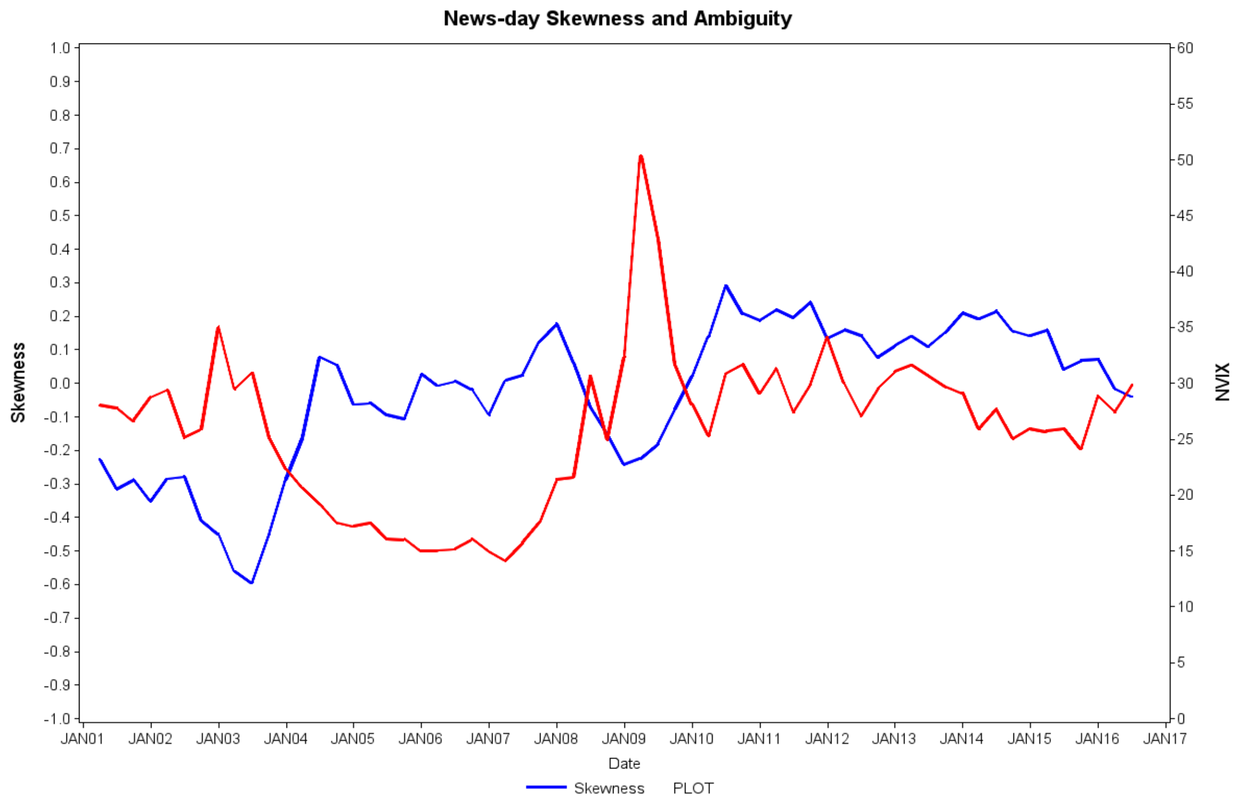

Fig.1. $Skew^{news}$ and NVIX

I plot the quarterly *NVIX* (red line) and aggregate $Skew^{news}$ (construed by averaging of $Skew^{news}$ across all stocks in each quarter) (blue line). The months are on the x-axis. This figure shows that *NVIX* is negatively correlated with aggregate $Skew^{news}$. The sample period is from January 2001 to March 2016.

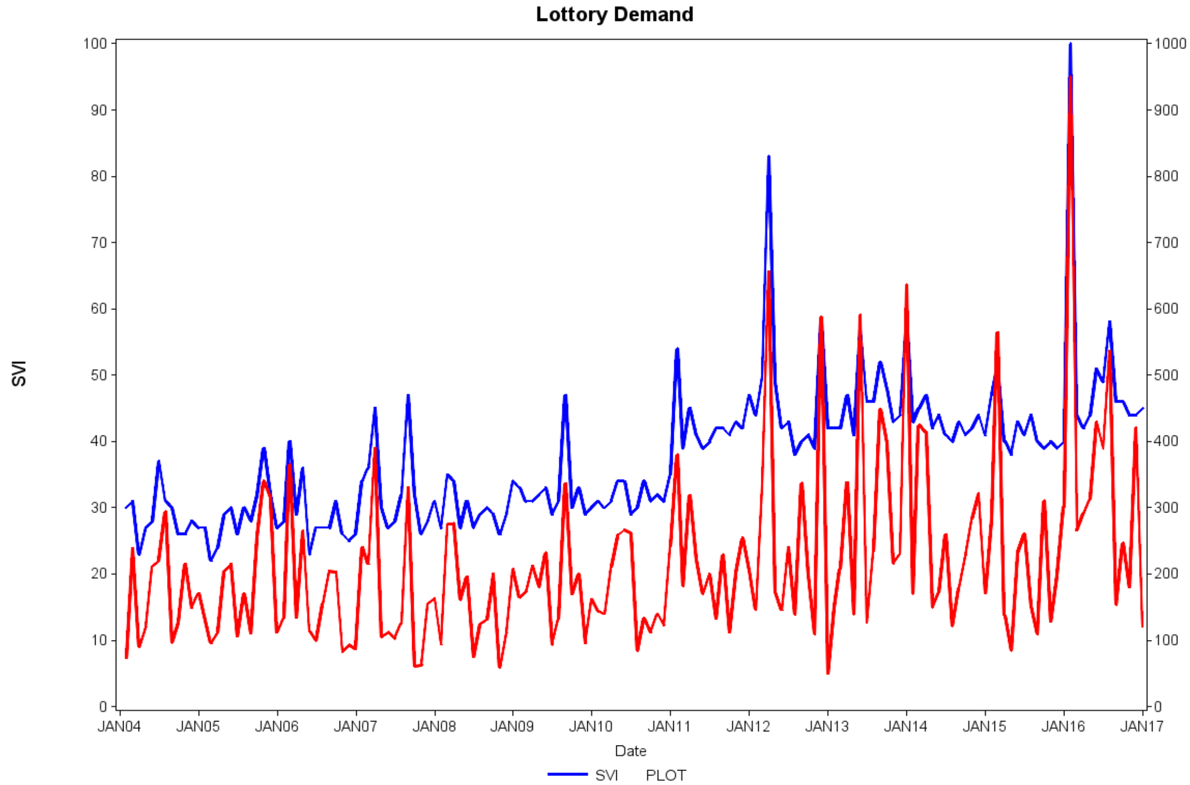

Fig.2. Search volume index and jackpots
I plot the monthly search volume index (blue line) and the maximum value of jackpots (in million U.S. dollars) each month (red line). The months are on the x-axis. This figure shows that the Google monthly search volume index (*SVI*) is highly correlated with large jackpots (above $210 million). The sample period is from January 2004 to December 2016. I manually collect Google monthly search index over the sample period by searching the word "lottery".