Nominal Price Illusion

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December2012

Abstract

Recent work finds that nominal prices influence investor behavior. Why prices matter to investors, however, is a question that is as of yet unanswered. We provide evidence that investors suffer from a nominal price illusion in which they overestimate the "room to grow" for low-priced stocks relative to high-priced stocks. Investor expectations of future skewness increase drastically on days that a stock undergoes a split to a lower nominal price. However, in practice future physical skewness decreases. In the cross-section of stocks, we find that investors overweight the importance of price in their skewness expectations. Asset pricing implications of our findings are borne out in the options market. A zero-cost option portfolio strategy that exploits skewness overestimation for low-priced stocks relative to high-priced stocks earns economically and statistically significant returns.

The authors are grateful for valuable comments received from Yakov Amihud, Kalok Chan, Zhi Da, Laura Liu, Xuewen Liu, Abhiroop Mukherjee, Kasper Nielsen, Mark Seasholes, Rik Sen, Bruno Solnik, John Wei, Chu Zhang and seminar participants at HKUST. We also thank Patrick Dennis for providing the computational code. All errors are the responsibility of the authors.

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1. Introduction

The level of a firm's stock price is arbitrary in that it can be manipulated by the firm via altering the number of shares outstanding. Nevertheless, it has become clear that nominal prices influence investor behavior. For example, Gompers and Metrick (2001), Dyl and Elliot (2006), Kumar and Lee (2006), and Kumar (2009) provide evidence suggesting that individuals hold lower-priced stocks than institutions. Schultz (2000) documents an increase in the number of small shareholders following a split, while Fernando, Krishnamurthy and Spindt (2004) find that IPO offer price plays a strong role in determining investor composition. Green and Hwang (2009) find particularly strong evidence that investors categorize stocks based on price. They show that similarly priced stocks move together; after a stock split, splitting stocks experience increased comovement with low-priced stocks, and decreased comovement with high-priced stocks.

Recent work finds evidence that firms are well aware of the importance of nominal prices to investor perceptions, and frequently engage in active management of share price levels in an effort to cater to investor demand. Despite the lack of a rational explanation, Weld, Michaely, Thaler, and Benartzi (2009) find that firms have proactively managed share prices to stay in a relatively constant nominal range since the Great Depression. Baker, Greenwood, and Wurgler (2009) find that investors have time-varying preferences for stocks of different nominal price levels, and that firms actively manage their share price levels to maximize firm value by catering to these time-varying investor preferences. Dyl and Elliot (2006) also find evidence that firms manage share prices to appeal to the firm's investor base in an effort to increase the value of the firm. The rationale for investor focus on nominal prices is not well understood, as past work has focused on the implications of these preferences while only hypothesizing about the potential underlying drivers. In short, while the past research has shown that nominal prices clearly influence the behavior of investors, *why* prices matter to investors is an as of yet unanswered question.

The lack of empirical evidence has not dissuaded speculation regarding why investors are influenced by nominal prices. For example, Kumar (2009) states that "as with lotteries, if investors are searching for 'cheap bets', they are likely to find low-priced stocks attractive." Green and Hwang (2009) hypothesize that "investors may perceive low-priced stocks as being closer to zero and farther from infinity, thus having more upside potential." While Baker, Greenwood, and Wurgler (2009) state that "One question that the results raise, and that we leave to future work, is why nominal share prices matter to investors...Perhaps some investors suffer from a nominal illusion in which they perceive that a stock is cheaper after a split, has more 'room to grow', or has 'less to lose'."

In this paper, we provide evidence that investors exhibit psychological biases in the manner in which they relate nominal prices to expectations of future return patterns. Specifically, we find evidence that investors suffer from the illusion that low price stocks "have more upside potential." In doing so, we identify one potential driver of investor demand shifts that have been shown to lead to supply responses from corporations.

Our results suggest that investors view low-priced stocks as being "cheap". Following a split to a lower price, investor expectations of skewness drastically increase. In practice, however, future physical skewness decreases following splits. We find similar evidence of investor expectational errors following reverse splits. On the day of a stock price increase due to a reverse split taking effect, expectations of future skewness drastically decrease. In contrast to investor expectations, future physical skewness actually increases. Evidence from the cross-section of stocks further supports the view that investors suffer from a nominal price illusion. We find that in forming expectations of future skewness, investors overweight the importance of price relative to its observed relationship with physical skewness or model-predicted expected skewness. Evidence from options trading also suggests that investors exhibit increased optimism toward low-priced stocks relative to high-priced stocks, and take lottery-like bets in low-priced stocks to a greater extent than high-priced stocks. Finally, we find that investor nominal price biases have asset pricing implications. We document that, consistent with investors overestimating the upside potential for low relative to high-priced stocks, abnormal returns accrue to a zero-cost strategy that exploits investor overestimation of upside potential for low-priced relative to high-priced stocks.

Empirically, we rely on the options market to extract investor beliefs regarding nominal prices. A key insight of our analysis is the use of option-implied risk-neutral skewness (RNSkew), which is a market-based ex-ante measure of investors' expectations. By utilizing risk-neutral skewness extracted from option prices, we are able to circumvent the need for a long time series of returns to estimate skewness; instead we can assess how market expectations of an asset's future skewness change on a daily basis.

We first examine how investor beliefs regarding future skewness change on the day that a stock splits to a lower price level. Multiple potential motivations for stock splits have been suggested, including signaling (Brennan and Copeland (1988), McNichols and Dravid (1990), and Ikenberry, Rankine, and Stice (1996)), and liquidity arguments (Muscarella and Vetsuypens (1996), and Angel (1997)). However, splits do not seem to be correlated with future corporate profitability (Lakonishok and Lev (1987), and Asquith, Healy, and Palepu (1989)), nor is it clear that they increase liquidity (Conroy, Harris and Benet (1990), Schultz (2000), and Easley, O'Hara and Saar (2001)). Instead, the prevailing view is that firms split their shares to return prices to a normal trading range (Baker and Gallagher (1980), Lakonishok and Lev (1987), Conroy and Harris (1999), Dyl and Elliot (2006), and Weld, Michaely, Thaler, and Benartzi (2009)). Thus, stock splits provide a clean laboratory to examine the effect of nominal prices on investor expectations.

On the day of a split to a lower price we find a greater than 40% increase in skewness expectations. In sharp contrast to increases in expected skewness, we find a substantial physical skewness *decrease* following stock splits. This is not surprising given that splits occur after a long run-up in price, and therefore periods of high past skewness, which makes the observed expected skewness increase all the more surprising. Importantly, we find no such increase in RNSkew on the day of the stock split announcement. The increase of RNSkew around the ex-date rather than the announcement date is consistent with investors reacting to the change in stock price, and inconsistent with an informational signaling story. We also examine reverse splits and find supportive evidence among this smaller sample; on the date of a reverse split RNSkew decreases drastically, but this decrease is not accompanied by a decrease in physical skew. The evidence is consistent with investors assigning greater upside potential (and/or lower downside potential) to stocks trading at lower prices.

We complement the split results by undertaking a second, separate, test of the hypothesis that investors suffer from nominal price biases. To do so, we examine the cross-section of all stocks. We find that while there is a strong cross-sectional inverse relationship between price and physical skewness, there is a much stronger inverse relationship between price and RNSkew. That is, investors overweight the importance of price as a factor in determining expectations of skewness. Taken together, the evidence supports the idea that investors overestimate the lottery-like properties of low-priced stocks.

Utilizing option open interest and volume data, we also find evidence that investors display increased optimism toward low-priced stocks. Specifically, the ratio of call to put open interest and volume is substantially higher for low-priced stocks than it is for high-priced stocks. While past work has shown investor preferences for lottery-like assets (Barberis and Huang (2008), Kumar (2009), Boyer, Mitton and Vorkink (2010), Boyer and Vorkink (2011), and Bali and Murray (2012)), we build upon this evidence by showing that investors also have a preference for utilizing the leverage benefits options provide to take lottery-like bets on these lottery-like stocks.

We next explore the asset-pricing implications of investor biased perceptions regarding nominal prices. We have already found that investor errors in assessing expected future skewness are manifested in option prices. The overestimation of expected skewness for low-priced stocks relative to high-priced stocks that we observed in option prices suggests the potential overpricing of a portfolio of OTM calls relative to OTM puts on low-priced stocks relative to similar portfolios of options for high-priced stocks. Following Bollen and Whaley (2004) and Goyal and Sarreto (2009) we estimate the returns to delta-hedged portfolios, and find that the relative performance between call options and put options decreases when the underlying stock price decreases. The results are consistent with relative investor overestimation of skewness for low-priced stocks leading to relatively larger overpricing of call options relative to puts on low-priced stocks as compared to high-priced stocks. Overall, the evidence is consistent with investors suffering from a nominal price illusion in which they overestimate the "cheapness" or "room to grow" of low-priced stocks relative to high-priced stocks. Our evidence also suggests that this nominal price bias has asset-pricing implications.

The paper proceeds as follows. Section 2 discusses methodology, and introduces the data. Section 3 presents the stock split analysis. Section 4 finds evidence of investor nominal price biases in the cross-section of stocks. Section 5 examines option trading. Section 6 assesses asset-pricing implications of investor nominal price bias, and Section 7 concludes.

2. Risk-neutral Skewness and Data

2.1 Risk-neutral skewness

In order to examine whether nominal share price is systematically related to investors' misperception of skewness, we need measures of both investor expected skewness as well as an unbiased measure of skewness. We use risk-neutral skewness implied from option prices to capture investor expectations of skewness and use realized skewness as a measure of unbiased expected skewness.[1] Realized skewness (*Skew*) is calculated using daily return data over a one year period. We use the

[1] We also adopt two other methods to calculate unbiased measures of expected skewness. We discuss these measures in section 4.

model-free methodology of Bakshi, Kapadia, and Madan (2003)[2] to measure risk-neutral skewness (*RNSkew*).

Risk-neutral skewness is a prominent variable in our analysis, utilized to capture changing investor expectations of asymmetry in return distributions. Because the option prices from which risk-neutral moments are extracted are updated daily, they reflect an up-to-date measure of investor ex-ante expectations.

Bakshi, Kapadia, and Madan (2003) show that the risk neutral skewness is

$$\begin{aligned} RNSkew_{i,t}(\tau) &= \frac{E_t^Q\left\{(R(t,\tau)-E_t^Q[R(t,\tau)])^3\right\}}{\left\{E_t^Q(R(t,\tau)-E_t^Q[R(t,\tau)])^2\right\}^{3/2}} \\ &= \frac{e^{r\tau}W_{i,t}(t,\tau)-3\mu_{i,t}(t,\tau)e^{r\tau}V_{i,t}(t,\tau)+2\mu_{i,t}(t,\tau)^3}{[e^{r\tau}V_{i,t}(t,\tau)-\mu_{i,t}(t,\tau)^2]^{3/2}} \end{aligned}, \tag{1}$$

where i, t, and τ represent stock, current time, and time to maturity, respectively. r is the risk free rate, $E_t^Q(.)$ is the expectation under the risk-neutral measure, $R(t,\tau)$ is the return from time t to $t+\tau$, and $\mu_{i,t}(t,\tau)=e^{r\tau}-1-\frac{e^{r\tau}}{2}V_{i,t}(t,\tau)-\frac{e^{r\tau}}{6}W_{i,t}(t,\tau)-\frac{e^{r\tau}}{24}X_{i,t}(t,\tau)$. Bakshi, Kapadia and Madan (2003) further show that, $V_{i,t}(t,\tau)$, $W_{i,t}(t,\tau)$ and $X_{i,t}(t,\tau)$ can be extracted from OTM options, and are defined as

$$\begin{aligned} V_{i,t}(t,\tau) = E_t^Q\left\{e^{-r\tau}R(t,\tau)^2\right\} &= \int_{S(t)}^{\infty}\frac{2(1-\ln[K/S(t)]}{K^2}C(t,\tau;K)dK \\ &+\int_0^{S(t)}\frac{2(1+\ln[K/S(t)]}{K^2}P(t,\tau;K)dK, \end{aligned} \tag{2}$$

$$W_{i,t}(t,\tau) = E_t^Q\left\{e^{-r\tau}R(t,\tau)^3\right\} = \int_{S(t)}^{\infty}\frac{6\ln[K/S(t)]-3(\ln[K/S(t)])^2}{K^2}C(t,\tau;K)dK$$

[2] The model-free risk neutral measure of Bakshi, Kapadia and Madan (2003) has been widely used in the literature (Dennis and Mayhew (2002), Han (2008), Bali and Murray (2012), Chang, Christoffersen, and Jacobs (2012), Conrad, Dittmar and Ghysels (2012), Friesen, Zhang and Zorn (2012), and Rehman and Vilkov (2012)).

$$-\int_0^{S(t)} \frac{6\ln[K/S(t)] + 3(\ln[K/S(t)])^2}{K^2} P(t,\tau;K)dK\,, \tag{3}$$

$$X_{i,t}(t,\tau) = E_t^Q\left\{e^{-r\tau}R(t,\tau)^4\right\} = \int_{S(t)}^{\infty} \frac{12\ln[K/S(t)]^2 - 4(\ln[K/S(t)])^3}{K^2} C(t,\tau;K)dK$$

$$+\int_0^{S(t)} \frac{12\ln[K/S(t)]^2 + 4(\ln[K/S(t)])^3}{K^2} P(t,\tau;K)dK\,. \tag{4}$$

Ideally, $V_{i,t}(t,\tau)$, $W_{i,t}(t,\tau)$ and $X_{i,t}(t,\tau)$ should be calculated based on a continuum of European options with different strikes. However, in reality, only a limited number of options are available for each stock/expiration combination and individual equity options are not European. To accommodate the discreteness of options strikes, we follow Dennis and Mayhew (2002) to estimate the integrals in expressions (2) to (4) using discrete data[3].

Price per se should not be mechanically related to RNSkew, since RNSkew is homogeneous of degree zero with respect to the underlying price, that is, altering the underlying price will increase or decrease the numerator and denominator of equation (1) by the same proportion. However, options for stocks with different price may have different strike structures, potentially imposing a systematic bias to the calculation of RNSkew.

Dennis and Mayhew (2002) examine two potential sources of bias in RNSkew estimation. The first arises due to the use of discrete strike prices, and the second arises from the potential asymmetricy in the domain of integration.Dennis and Mayhew (2002) show that the bias in RNSkew is negative and increasing in absolute magnitude when the relative option strike interval (option strike increment/underlying

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[3] We thank Patrick Dennis for providing us the code.

stock price) increases.[4] In practice, standard stock option strike prices are in increments of \$2.50 for strikes at or below \$25, \$5.00 for strikes above \$25 but below \$200, and \$10 for strikes above \$200. However, Dennis and Mayhew (2002) show that the bias in RNSkew induced by option strike interval is quite small. The bias is approximately -0.01, -0.05 and -0.07 when the relative option strike intervals (option strike incremental/underlying stock price) are 2%, 5% and 10%, respectively.

Dennis and Mayhew (2002) also investigate the potential bias arising due to an asymmetric domain of integration. They show that RNSkew will be biased downward when there is a lesser number of OTM puts relative to OTM calls and will be biased upward when there is a greater number of OTM puts relative to OTM calls. However, Dennis and Mayhew (2002) show that the bias is essentially zero if there are at least two OTM puts and two OTM calls. As a result, we require at least two OTM put options and at least two OTM call options. Finally, we standardize *RNSkew* to 30 days by linearly interpolating the skewness of the option with expiration closest to, but less than 30 days, and the option with expiration closest to, but greater than 30 days. If there is no option with maturity longer than 30 days (shorter than 30 days), we choose the longest (shortest) available maturity.[5]

2.2 Data

IvyDB's OptionMetrics database provides data on option prices, volume, open interest, and Greeks for the period from January 1996 to December 2011. IVs and Greeks are calculated using the binomial tree model by Cox, Ross and Rubinstein

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[4] Dennis and Mayhew (2002) use simulations to evaluate the bias of option discreetness. Specifically, they choose the underlying stock price to be \$50 and evaluate the magnitude of bias induced by option strike increments from \$1 to \$5.

[5] All results are robust to the use of 60 day or 100 day skewness.

(1979). We include options on all securities classified as common stock. To minimize the impact of data errors, we remove options missing best bid or offer prices, as well as those with bid prices less than or equal to $0.05. We also remove options that violate arbitrage bounds, options with special settlement arrangement, and options for which we can't calculate *RNSkew* or *Skew*.[6] The mid-quote of the best bid and best offer is taken as the option price. Data on stocks is from Center for Research in Security Prices (CRSP). We obtain data on stock splits from the CRSP distribution file. We define stock splits as events with a CRSP distribution code of 5523. Regular splits are splits with a split ratio of at least 1.25 to 1, and reverse splits are those with a ratio below 1. Finally, we obtain company accounting information from Compustat.

For both the large cross-sectional sample (all optionable stocks) and the stock split sample, we only include observations for which we are able to calculate *RNSkew*. The full stock sample includes 263,571 firm-month observations.[7] The regular split sample has 2,094 observations, and the reverse split sample has 158 observations. To mitigate the effect of outliers, we winsorize all continuous variables at the 1% level.

Table 1 shows the summary statistics for the three different samples.[8] The average pre-split price of the regular splits is 76.006 which is more than double the price of an average optionable stock. The average split ratio is 1.975. The average post-split stock price is 38.5204. The average pre-split price of a stock undergoing a reverse split is

[6] OptionMetrics defines an option as having a standard settlement if 100 shares of the underlying security are to be delivered at exercise and the strike price and premium multipliers are $100 per tick. For options with a non-standard settlement, the number of shares to be delivered may be different from 100, and additional securities and/or cash may be required.

[7] Among the 263,571 observations, only 2,027 observations have stock prices less than $5. The results are robust to the exclusion of these observations.

[8] Please refer to Table A1 in the Appendix for detailed definitions of all variables.

6.868, which is much lower than the average stock price. The average split ratio is 0.240, resulting in an average post-split price of 24.307.

Not surprisingly, relative to the large sample, regular splits are larger, have higher valuation ratios (lower B/M), and higher past performance (momentum), while reverse splits are smaller, have lower valuation ratios, and lower past performance. Furthermore, regular splits have slightly lower past volatility than the larger sample, while the past volatility of reverse splits is much higher than the average optionable stock.

The average *RNSkew* for the full sample, regular splits and reverse splits are-0.528, -0.687 and 0.431, respectively. Future physical skewness (Skew) of these three groups of stocks is 0.277, 0.172 and 1.106, respectively. The pattern of *RNSkew* across the three groups is generally consistent with the view that price is negatively related to the expected skewness, however, Skew exhibits no clear pattern. We begin our analysis by focusing on stock splits, in order to examine the effects of large, exogenous price changes in a relatively clean setting.

[Insert Table 1 here]

3. Nominal price and skewness: sample of split stocks

In this section we examine investor nominal-price driven biases by utilizing a setting where nominal prices changes are seemingly exogenous to changes in expectations of future return distributions. To do so, we examine the effect of stock splits on investor skew expectations.

The prevailing view in the literature is that stock splits are motivated by an effort to return prices to a normal trading range (Baker and Gallagher (1980), Lakonishok and Lev (1987), Conroy and Harris, (1999), Dyl and Elliot (2006), and Weld, Michaely, Thaler, and Benartzi (2009)).[9] Because stock splits do not change firm fundamentals, they provide a clean environment to examine the effect of nominal changes in price on investor expectations.

[Insert Figure 1 here]

Figure 1 provides a preview of the main split results. RNSkew is plotted against days relative to ex-date. Figure 1 shows the behavior of RNSkew in the period around the ex-date. It is clear that RNSkew increases at the date when price is adjusted downward (regular splits), and it decreases when price is adjusted upward (reverse splits). It is interesting to note that as price declines in the months leading up to a reverse split, RNSKew also exhibits an increasing pattern. From Figure 1, it is evident that stocks undergoing splits see large jumps in RNSkew on the ex-date, while those undergoing reverse splits see large decreases in RNSkew that occur precisely on the ex-date.

3.1 Skewness around regular splits

Panel A of Table 2 examines whether risk neutral skew expectations are affected by split-induced changes in nominal price. Panel A1 explores changes in risk neutral skew around the ex-date. The results indicate that investor expectations are greatly affected by the nominal change in price. *RNSkew* increases by 0.31 on the day of the stock split. The effect is statistically significant, and persists in the weeks and months after the split. That investors respond so immediately to a split-induced change in

[9] Past work does not find evidence that splits are motivated by factors correlated with firm fundamentals. For example, signalling and liquidity motives do not seem to be correlated with the decision to split (see Lakonishok and Lev(1987), and Asquith, Healy, and Palepu (1989) for evidence against splits as a signalling mechanism, and Conroy, Harris and Benet (1990), Schultz (2000), and Easley, O'Hara and Saar (2001) for evidence disputing liquidity arguments as driving split decisions).

price is not unexpected. Schultz (2000) finds a large and immediate increase in small shareholders at the ex-date, as he documents an increase in net small trade buy volume from slightly above zero in the day prior to the split to about two million shares on the ex-date.

[Insert Table 2 here]

As previously mentioned, past work has found that splits do not seem to be motivated by factors correlated with firm fundamentals. To further verify that our results reflect a response to the change in price, rather than a change in fundamentals, we examine whether there is also a skewness change at the announcement date. If splits signal changes in fundamentals and the change in RNSkew is driven by this change in investors' information set, then we should expect to see an effect at the announcement date rather than the ex-date. Panel A2 shows that this is not the case. Indeed, we see no effect on the date of the announcement. There is some increase in RNSkew beginning on the day after announcement, but the magnitude is much smaller than the change at the actual date of the split. Rather, RNSkew reaches its max on the day of the ex-date.[10] The evidence suggests that nominal changes in price levels around stock splits affects investor expectations regarding future return distribution.

The lack of change in perception on the announcement day suggests that changes in investor expectations are not driven by expectations of changes in fundamentals. We nevertheless, assess whether physical skew does change in the period following

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[10] In unreported results, we examine the change of RNSkew around the announcement date separately for options with maturity before the ex-date and options with maturity after the ex-date. We find that RNSkew does not change around the announcement date if the options used to calculate RNSkew will expire before the ex-date. This finding also suggests that the RNSkew change around stock splits is not driven by release of new information.

splits. A priori, expectations of post-split increases in skew seem especially hard to rationalize given that splits occur after a run-up in stock price, and therefore a period of above-average skewness.

To further ensure that the change in physical skewness that we observe post-split does not reflect a change in fundamentals, we compare splitting firms to a matched sample of non-splitting firms. The matching firms are similar in that they've experienced a similar price run-up, and are of similar size, book-to-market, and similar past skewness. A detailed discussion of the matching procedure is documented in the table description.[11] These are firms that can reasonably be expected to have equal expectations ex-ante of undergoing a split. After matching, our sample firms reduce to 1,528. This is mainly driven by missing Compustat or CRSP data.

The last row of Panel B in Table 2 displays the change in physical skew. In contrast to the expected increase in skewness, physical skewness actually *decreases* in the period after the split. The decrease is substantial, with daily skewness in the year following a split decreasing by over 50% (from 0.378 to 0.151) relative to the year leading up to the split. That physical skewness actually decreases following splits, makes the evidence of investor biased expectations of increased upside potential for recently split stocks all the more compelling.

Alleviating the concern that split stocks undergo a change in fundamentals, we find no difference in future skewness between the split and the matched sample. The lack of a difference in skewness provides evidence that the post-split decrease in skewness is not an unpredictable artifact of the split. The findings strengthen our

[11] The results are similar if we vary the matching method.

argument that investor nominal price biases lead them to attribute irrationally high skewness to low-priced stocks relative to high-priced stocks.

3.2 Skewness around reverse splits

[Insert Table 3 here]

As an additional test of our hypothesis we examine what happens when firms undergo reverse splits. The results are reported in Table 3. Despite a much smaller sample size, the results are quite clear. Consistent with nominal prices affecting investor expectations, we find that RNSkew drastically decreases on the day that prices increases due to a reverse split taking effect (Panel A of Table 3).[12] Panel B of Table 3 confirms that the physical skewness changes do not reflect the risk neutral changes in expectations. In fact, we find that in contrast to the observed decrease in risk-neutral skewness, physical skewness increases substantially in the year following a reverse split.

3.3 Robustness

Importantly, stock splits are handled in such a way that they do not have microstructure implications for the options market. Historically, when splitting stock split occurs, the option contracts were adjusted accordingly by the split factor. Effective September 4, 2007, The Options Clearing Corporation (OCC) adopted a new rule to govern the post-split administration of options contracts. Rather than decreasing the option strikes by the split factor, the new rule leaves the option contracts untouched, and instead recalculates the stock price to the hypothetical price it would trade had the split not occurred (for details of the rule, please refer to the

[12] We are not able to compare the RNSkew change around the announcement date, as the announcement dates in CRSP are missing for most reverse splits.

information Memos 22687, 22232, 23211, 23348 and 23484 of OCC). The empirical findings we document are robust in both the pre and post-rule-change periods. Figure 2 shows the effect of splits on RNSkew on the subsample of splits occurring after September 4, 2007. The results for both regular and reverse splits are consistent with the results over the entire sample period, suggesting that the relationship between RNSkew and price is not driven by options market microstructure concerns.

In summary, we find sharp changes of RNSkew precisely at the date that a stock splits to a lower price. In stark contrast to investor expectations of post-split skewness increases, we find a drastic decrease in physical skewness following a split. The evidence is further strengthened by consistent results among the smaller sample of stocks undergoing reverse splits. The evidence is consistent with nominal prices biasing investor expectations of future return distributions.

4. Nominal price and skewness: all optionable stocks

4.1 Characteristics of stocks with different nominal prices

In this section we undertake a second test of the hypothesis that investors suffer from nominal price illusions. We do so by examining the entire cross-section of stocks. We first explore the relationship between nominal price and skewness in the cross-section of stocks, and then examine whether this is consistent with the relationship between price and RNSkew that investors price into options. As we are interested in isolating only the effect of nominal price on investor behavior, we first examine how price is correlated with firm characteristics. Table 4 reports the summary statistics of stocks that are sorted into price quintiles based on end-of-month prices.

On average, our sample stocks have a large dispersion in stock prices. The average stock price for the lowest quintile is 10.632 while the average price of the highest quintile is 68.359. We examine how a number of variables differ for stocks of different price levels. Relative to high priced stocks, low priced stocks are smaller, have higher betas, lower book-to-market ratios, worse past performance and are more likely to list on NASDAQ. Table 4 also shows that low priced stocks have higher past volatility, lower past skewness, and slightly higher turnover.

[Insert Table 4 here]

Our first measure of unbiased skewness is physical skewness. We also utilize a measure of expected skewness (E(Skew)) first introduced by Boyer, Mitton, and Vorkink (2010) that incorporates all relevant past information to best form a future prediction of skewness. E(Skew) is a forward looking measure of skewness constructed following the methodology of Boyer, Mitton, and Vorkink (2010). This methodology utilizes the parameters from a cross-sectional regression of skewness on lagged skewness, volatility, momentum, turnover, size, industry, and NASDAQ affiliation in order to estimate expected skewness.[13]

The last rows of Table 4 examine the relationship between price and our main measures of skewness. Both future realized skewness and expected skewness from the model of Boyer, Mitton, and Vorkink (2010) are decreasing in nominal stock price. However, the magnitude of the cross-sectional relationship between each of these measures and price is much smaller than that between price and investor expectations reflected in *RNSkew*. Unconditionally, the variance of realized skew is actually larger than that of the *RNSkew* measure (Table 1), however, conditional on price, the

[13] The details of the methodology will be discussed in the empirical sections.

difference in *RNSkew* between the top and bottom price quintiles is more than twice that of the difference for future realized skew and E(Skew). The strength of the univariate relationship between price and *RNSkew* provides preliminary evidence that investors perceive the relationship between price and future skewness to be much stronger than the true ex-post relationship realized in the data, as well as much stronger than is predicted by a rational model of expected skewness that incorporates all relevant current and past information available. While the univariate evidence is consistent with the notion that investors overweight the informativeness of price when predicting future skewness, we next employ a multivariate analysis to control for other factors and firm characteristics potentially correlated with both skewness and price.

4.2 Nominal price and skewness: Fama-MacBeth regression

We use Fama-MacBeth regressions to analyze the cross-sectional relationship between our various skewness measures and price, while controlling for variables that the past literature has found to be important in explaining skewness. As in Dennis and Mayhew (2002), we use stock Beta to control for systematic risk. Beta is calculated following Fama and French (1992). For each month, we use the past 60 months' excess return data and CRSP value-weighted monthly excess market return to calculate beta. Implied volatility (*IV*) contains additional information beyond past volatility in forecasting future return distribution (Goyal and Sarreto, 2009) and has been shown to be positively correlated with *RNSkew* (Dennis and Mayhew, 2002). We thus also include IV in our model. We follow the past literature and use IV calculated from at the money options (ATM). Following Bollen and Whaley (2004), ATM options are defined as call options with delta higher than 0.375 and not higher than 0.625 and put options with delta higher than -0.625 and not higher than -0.375.[14]

The leverage effect predicts that after a decrease in equity value, a levered firm's leverage will increase, resulting in increased volatility after decreases in equity value that are larger than the decreases in volatility that occur after increases in equity value. This asymmetry implies that the implied volatility of out-of-money put is higher than the implied volatility of out-of-money calls. While existing empirical findings do not support the leverage effect (Dennis and Mayhew, 2002; Bakshi, Kapadia and Madan, 2003), we nevertheless include leverage in the model.

We also control for firm size, book-to-market, past volatility, past skewness, turnover, momentum, and a dummy variable indicating whether a firm is listed on NASDAQ. The inclusion of firm size, book-to-market, momentum and turnover is motivated by Chen, Hong and Stein (2001) who find that each of these variables is negatively correlated with future skewness.[15] We also include past skewness and past volatility in the model, as Boyer, Mitton, and Vorkink (2010) show that skewness is persistent and highly positively correlated with return volatility. Finally, following Boyer, Mitton, and Vorkink (2010) we include a dummy variable for NASDAQ firms. We also include industry fixed effects to control industry heterogeneity. Industry definitions are based on Fama-French 48 industry classification scheme.

[Insert Table 5 here]

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[14] Our results are robust to defining ATM as options with a ratio of strike to stock price between 0.975 and 1.025 (as in Goyal and Sarreto, 2009).

[15] Boyer, Mitton and Vorkink (2010) find that allowing for a nonlinear relationship between firm size and skewness can fit the data better. They do so by using two dummy variables indicating small firms and medium-sized firms based on the NYSE breakpoints. Our results are similar if we adopt their non-linear methodology.

Table 5 reports the results of monthly Fama-MacBeth regressions of our different measures of skewness regressed on the beginning of period independent variables.[16] Standard errors are corrected for heteroskedasticity and autocorrelation up to 12 lags. We examine *RNSkew*, *Skew*, *RN skew gap* (*RNSkew-Skew*), and the *RN expected skew gap* (*RNSkew-E*(*Skew*)) separately. For each dependent variable, we analyze three different models: a univariate specification that includes only log nominal price, a multivariate specification including all control variables, and finally a multivariate specification that includes industry fixed effects.

As expected, the first six columns of the table show that there is a strong inverse relationship between price and both *RNSkew* and *Skew*. However, regardless of specification, the relationship is more than twice as strong for *RNSkew* as it is for *Skew*. The remaining columns show that the difference in this relationship is statistically and economically significant for *RNSkew* relative to *Skew* and the *E*(*Skew*) measure of Boyer, Mitton, and Vorkink (2010). The multivariate results confirm the earlier univariate results. In short, investor expectations of future return distribution asymmetry are biased, as they allow price to play an irrationally large role in the shaping of their perceptions.

Consistent with the finding of Dennis and Mayhew (2002) *RNSkew* is negatively related to beta. Beta is also negatively related to *Skew*. The difference in the effect of beta is not statistically significant. Most of the control variables enter the *RNSkew* and *Skew* specifications with the same signs. This is true for beta, size, IV, momentum, ILLIQ, and the NASDAQ dummy. A couple of the variables enter significantly and in a consistent direction in explaining both the *RN skew gap* and the *RN expected skew*

[16] All the results hold if we lag the independent variables by one month.

gap. Specifically, low book-to-market, low leverage, low past skew, high IV stocks have higher *RNSkew* than can be justified based on expected skew or future realized skew.

Finally, we compare RNSkew to a hypothetical measure of RN Skew constructed from index options. Bakshi, Kapadia and Madan (2003) show that risk neutral skewness can also be derived without the use of options traded on the firm, but instead from a combination of market risk neutral skewness and physical distribution attributes of the stock. Bakshi, Kapadia, and Madan (2003)[17] show that when the stock return follows a single-factor model of the form $r_i = \alpha_i + \beta_i r_m + \varepsilon_i$,

$$RNSkew_i = (1 + \frac{V_\varepsilon}{\beta_i^2 IV_m})^{-3/2} RNSkew_m + (1 + \frac{\beta_i^2 IV_m}{V_\varepsilon})^{-3/2} RNSkew_\varepsilon , \qquad (5)$$

where $RNSkew_i$, $RNSkew_m$, and $RNSkew_\varepsilon$ are the risk-neutral skewness of stock *i*, risk-neutral skewness of the market, and the risk-neutral skewness of idiosyncratic return of stock *i* (i.e. ε). IV_m and V_ε are the risk-neutral variance of the market, and the risk-neutral variance of stock *i*.

From Equation (5), we can construct a hypothetical RNSkew measure ($RNSkew_{hypothetical}$) that does not use information contained in a firm's own options, but instead is derived from the market risk-neutral skewness, and the firm's implied volatility, beta, and idiosyncratic volatility. If investor expectations are not affected by nominal price, we should expect that the difference between the real RNSkew and the hypothetical RNSkew will not be systematically related to nominal price.

[17] For details, please refer to Theorem 3 in Bakshi, Kapadia, and Madan (2003).

In order to calculate $\text{RNSkew}_{\text{hypothetical}}$, we need proxies for $RNSkew_m$, IV_m, beta, risk-neutral idiosyncratic skewness and risk-neutral idiosyncratic variance. $RNSkew_m$ and IV_m are calculated based on the S&P 500 index options. Since the idiosyncratic return component requires no measure-change conversions, $RNSkew_\varepsilon$ and V_ε are the same under both the physical measure and the risk neutral measure. Beta is estimated following Fama and French (1992). In the empirical analysis, we use two different methods to estimate idiosyncratic skewness and idiosyncratic variance. First, we predict idiosyncratic skewness and idiosyncratic variance following the method from Boyer, Mitton, and Vorkink (2012). Second, we use past realized idiosyncratic skewness and idiosyncratic variance to proxy for expected idiosyncratic skewness and idiosyncratic variance. Realized idiosyncratic skewness and idiosyncratic variance are calculated using daily return from the past one year.

In Table 6 we examine the relationship between our current measure of risk neutral skewness extracted from options in the actual underlying stock, and the hypothetical risk neutral skew measure. Comparing our risk neutral skew measure to another risk neutral skew measure, rather than the physical skewness or expected skew measures used before does not change the results. Consistent with the results in Table 5, the results in Table 6 show that investors overweight price in their assessment of skewness expectations. The economically and statistically significant negative coefficients on the price variable in the RNSkew-Skew, RNSkew-E(Skew) regressions in Table 5, as well as the negative coefficients on the price variable in Table 6 confirm our main hypothesis; investors perceive the relationship between price and future skewness to be much stronger than the relationship documented between price and realized skewness, or E(Skew), or $\text{RNSkew}_{\text{hypothetical}}$. The results are consistent with investors suffering from nominal-price driven biases in which they overestimate the extent to which low-priced stocks have more room to grow relative to high-priced stocks, leading to investors overweighting the importance of price when forming expectations of future skewness.

[Insert Table 6 here]

5. Nominal price and option trading

Mitton and Vorkink (2007), and Barberis and Huang (2008) incorporate investor preferences for skewness into models explaining stock returns, while Kumar (2009) finds empirical evidence that retail investors prefer stocks with lottery features. The evidence presented thus far is consistent with low-priced stocks possessing attributes of lottery-like goods, and with investors perceiving them as such, and indeed, of overestimating these lottery-like qualities. We next provide evidence that investors exhibit increased optimism, as well as gambling-like behavior toward these lottery-like assets. We do so by examining the ratio of call to put volume and open interest. The ratio of call to put option trading volume is commonly believed to be a sentiment measure, with more call option trading volume indicating optimism (for example, Lemmon and Ni (2010)). If price does affect investor perceptions of upside potential, we should expect to see a negative correlation between stock price and the call-put volume ratio. Option volume reflects both option writing and position closing. Open interest measures the total existing position, and thus can potentially better measure the view of the investors. Thus, we also examine the relationship between nominal price and the call to put open interest ratio.

We define our volume ratio (VolRatio) and open interest ratio (OIRatio) as VolRatio=log (1+ volume of call options)-log (1+ volume of put options), and OIRatio=log (1+ options interests of call options)-log (1+ options interests of put options). We add one to deal with the cases of zero trading volume or open interest.

[Insert Table 7 here]

The results in Table 7 show that price is strongly negatively related to the call-to-put volume ratio and open interest ratio. The evidence is consistent with investors perceiving low-priced stocks to be more lottery-like and with investors possessing more optimistic perceptions of the upside potential of low-priced stocks relative to high-priced stocks. We next examine the asset-pricing implications of investor biases regarding nominal prices.

6. Asset Pricing Implications

Biased beliefs regarding the upside potential of low relative to high-priced stocks will also have asset pricing implications. If investors overestimate the skewness of low-priced relative to high-priced stocks, a potential implication is that relative to put options, call options will be more overvalued for low-priced stocks than for high-priced stocks. This will particularly be the case for OTM options. To test this hypothesis we construct delta-hedged put and call portfolios and examine whether differences in call and put portfolio returns are systematically related to underlying stock price. Our methodology and analysis largely follows that of Goyal and Sarreto (2009).

Portfolios are formed on the expiration Friday (or Thursday if Friday is a public holiday) of the month, and the option portfolio strategies are initiated on the first trading day (typically a Monday) after the expiration Friday of the month. On each portfolio formation day, we choose only the put and call options expiring within one month, and all stocks with available options are sorted into quintiles based on the stock price on the portfolio formation day. For each option series, we construct delta-hedged portfolios and hold them until option expiration. All the portfolios are equal weighted. As in Goyal and Saretto (2009), we use the absolute position value as the reference beginning price to calculate delta-hedged portfolio return. Specifically, the formula we use to calculate the delta-hedged call return and the delta-hedged put return are.[18]

$$R_{call} = \frac{(c_T - c_0) - \Delta_0 (S_T + \sum_{t=1}^{T} D_t e^{r(T-t)} - S_0)}{|\Delta_0 S_0 - c_0|}, \tag{6}$$

$$R_{put} = \frac{(p_T - p_0) - \Delta_0 (S_T + \sum_{t=1}^{T} D_t e^{r(T-t)} - S_0)}{|\Delta_0 S_0 - p_0|}, \tag{7}$$

The results are reported in Table 8. We report the returns for the delta-hedged call and delta-hedged put portfolios by price quintile. Relative to ATM and ITM options, OTM options better reflect investors' view on skewness. Thus, we focus on the OTM options. As a comparison, we also report the results for ATM options.

We define option moneyness following Bollen and Whaley (2004). ATM options are defined as call options with delta higher than 0.375 and not higher than 0.625 and put options with delta greater than -0.625 and not greater than -0.375. OTM options are call options with delta above 0.02 and not greater than 0.375 and put options with delta greater than -0.375 and not greater than -0.02. Options with absolute delta below 0.02 are excluded due to the distortions caused by price discreteness.

[Insert Table 8 here]

Table 8 reports the results of delta-hedged portfolio return analysis. We report the average returns for call portfolios, put portfolios and the difference between put and

[18] We consider stock splits and use the adjustment factor given by OptionMetrics to do the adjustment.

call portfolios (Put-Call). Besides reporting the raw return of the delta-hedged option portfolios, similar to Goyal and Sarreto (2009), we also report the risk-adjusted returns using model (8).

$$R_{put,t} - R_{call} = \alpha + \beta' F_t + \varepsilon_t \tag{8}$$

To obtain risk-adjusted returns, we regress the Put-Call returns on a linear pricing model consisting of the three Fama-French factors and the momentum factor,[19] and an aggregate factor reflecting the average Put-Call return of S&P 500 index options. The average Put-Call return of S&P 500 index options may capture the compensation to jump risk (Pan, 2002). We use the same method (Equation (6) and (7)) to calculate the average Put-Call return of S&P 500 index options by moneyness. The Put-Call index option returns will be matched to the Put-Call individual stock option returns with the same moneyness. The intercept from the regression can be interpreted as mispricing relative to the factor model. We will refer to the adjusted return as the five-factor adjusted return.

Panel A of Table 8 reports the results on OTM options. Both delta-hedged call option return and delta-hedged put option return increases when the underlying stock price increases. From the lowest price quintile to the highest price quintile, the average return of the call portfolio increases by 2.856% from -3.844% to -0.988%, and the average return of the put portfolio increases by 1.506% from -2.915% to -1.409%. The increase in return of both put and call option portfolio suggests that investors may overestimate both the upside and also the downside of the low-priced

[19] We compound the daily factor return to get monthly factor returns to match the timing of the option strategy.

stocks relative to the high-priced stocks, though the upside substantially more than the downside.

More importantly, put-call return difference decreases from 0.929% in the lowest price quintile to -0.421% in the highest price quintile. The five-factor adjusted Put-Call return decreases from 1.142% in the lowest price quintile to 0.117% in the highest price quintile. The Put-Call high minus low portfolio raw return and the five-factor adjusted return is 1.350% and 1.025%, respectively. Both are statistically significant at 1% level. We also find supportive evidence from the ATM options. For ATM options, the raw and five-factor adjusted return of the Put-Call portfolio decreases as a function of the underlying stock price. The magnitude of the change of OTM Put-Call portfolio return is larger than that of the ATM options, consistent with the view that skewness misperception most greatly affects the price of the OTM options.[20]

7. Conclusions

The findings provide the first evidence that investors link nominal share price to return skewness and systematically overestimate the skewness of low-priced stocks relative to high-priced stocks. The evidence presented is consistent with investors suffering from the illusion that low-priced stocks "have more upside potential."

We also find that investors take lottery-like bets on low-priced stocks. Investor overweighting of nominal prices in assessing return distribution expectations also has

[20] Note that our results are not driven by directional exposure to the underlying stocks. Within a given moneyness category and option type (call vs. put), delta-hedged option strategies across different price groups have similar level of exposure to the underlying stocks. Furthermore, when the underlying stocks are sorted into the same price groups, their performance exhibits no patter across quintiles. Specifically, the average return of stocks sorted by nominal price is 0.909%, 1.036%, 0.929%, 0.863% and 0.863% from the lowest price quintile to the highest quintile.

asset-pricing implications. We find that options of low-priced stocks are more overvalued than options of high-priced stocks.

Firms have long engaged in the costly management of share price through stock splits, despite nominal prices lacking real economic content. Recent work provides further evidence that investors view stocks of similar price as sharing similar attributes. Green and Hwang (2009) find that investors categorize stocks by nominal price, while Baker, Greenwood, and Wurgler (2009) find that firms exploit the fact that nominal prices matter to investors by increasing the supply of low-priced securities when investors are willing to pay a premium for them. While it is clear that nominal prices matter to investors, it has thus far been less clear why prices matter. We provide the first empirical insight into why prices matter to investors. Specifically, we find evidence that is consistent with the notion that investors view low-priced stocks as “cheap” assets with “more room to grow”.

Appendix

A1. Definitions of variables

Variable name	Descriptions
Price	Stock price at the end of month t
Log (Price)	Natural log of stock price at the end of month t
Beta	Calculated using monthly return data over the past 5 years, following Fama and French (1992)
Log (Size)	Size is the product of stock price and the number of shares outstanding, calculated at the end of month t
Log (BM)	Book-to-Market is the ratio between book value of common equity and market value of common equity, and is matched to the CRSP data following Fama and French (1992)
Leverage	Leverage is the ratio of total liability divided by total assets, and is matched to the CRSP data following Fama and French (1992)
Past Volatility	Volatility is calculated using past daily returns over the past year. Daily standard deviation is annualized by multiplying by the square root of 252.
Past Skewness	Skewness is calculated using daily returns over the past year
Volume	Natural log of total number of traded in month t
Momentum	Momentum is the cumulative return from month t-12 to month t-1.
ILIIQ	The illiquidity measure of Amihud (2002)
NASDAQ	A dummy variable equal to 1 if the firm is listed in NASDAQ, and 0 otherwise.
IV	Implied volatility, calculated from ATM options.
RNSkew	Risk-neutral skewness implied from option prices, calculated following Bakshi, Kapadia and Madan (2003).
Skew	Future skewness, calculated using future one year daily returns

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Figure 1. RNSkew around stock splits
This figure shows the RNSkew around the stock splits (the dotted line is for reverse splits and the solid line is for the regular splits). The x-axis is trading days relative to the ex-date, and the y-axis is the average RNSkew. Day 0 is the ex-date. RNSkew is calculated following Bakshi, Kapadia and Madan (2003). The method is detailed in the text. The sample period is from January 1996 to December 2011.

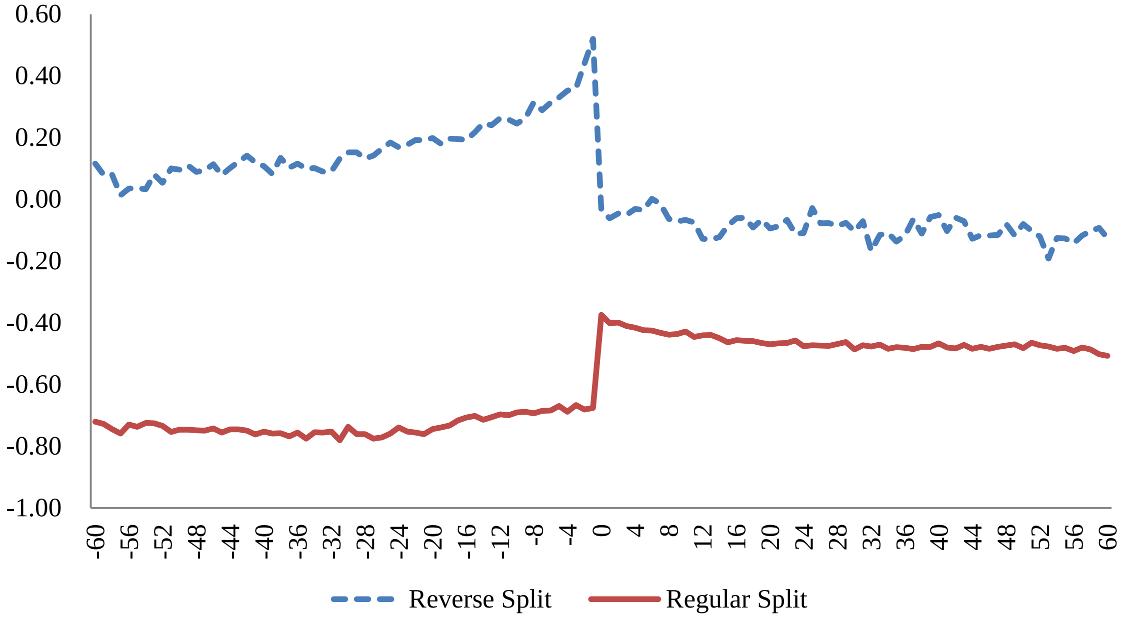

Figure 2. RNSkew around stock splits: new rule period

This figure shows the RNSkew around the stock splits (the dotted line is for reverse splits and the solid line is for the regular splits). The x-axis is trading days relative to the ex-date, and the y-axis is the average RNSkew. Day 0 is the ex-date. RNSkew is calculated following Bakshi, Kapadia and Madan (2003). The method is detailed in the text. The sample period is from September 4, 2007 to December 2011.

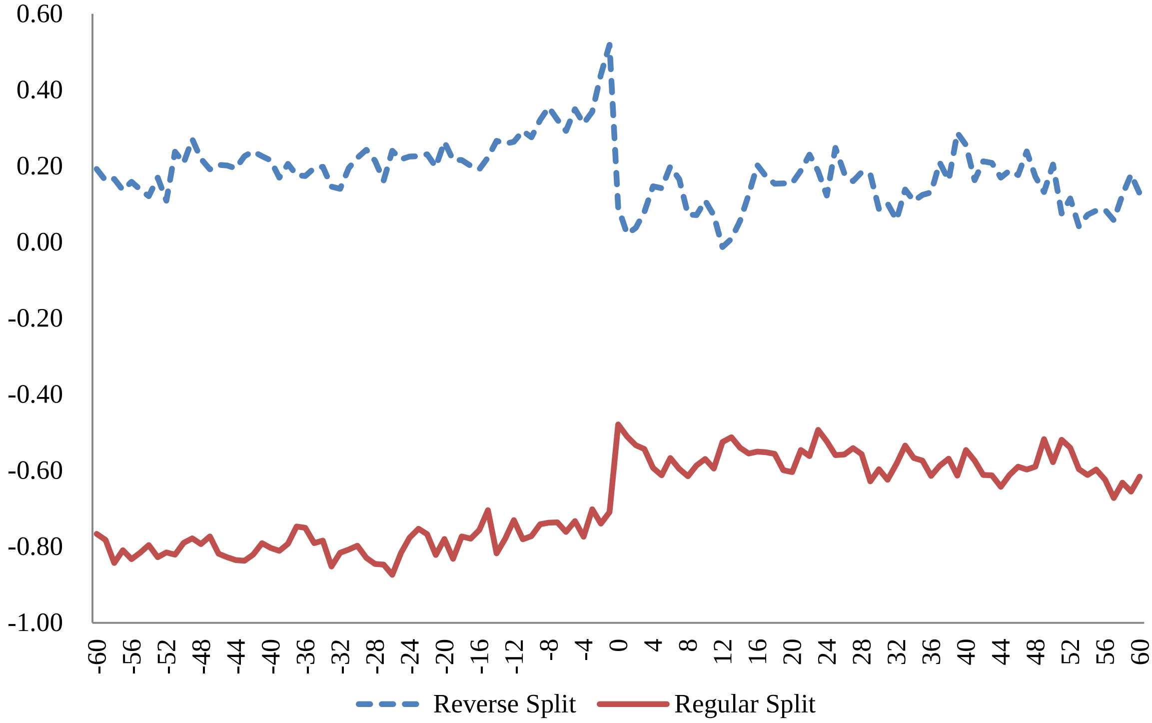

Table 1. Summary statistics

This table reports summary statistics for three different samples. "All optionable stocks" includes all the stocks on which we can calculate RNSkew and Skew. Regular splits and reverse splits are the split stocks that are also covered by OptionMetrics. Regular splits and reverse splits are defined as splits with split ratio greater than 1.25-to-1 and lower than 1-to-1, respectively. Beta is calculated following Fama and French (1992), that is, for each month, we use the past 60 months' monthly excess return data and CRSP value weighted excess market return to calculate Beta. B/M is the ratio between book value of common equity and market price. Leverage is the ratio between total liability and total assets. Volatility and Skewness are calculated using the 1 year's daily returns. We reach annualized volatility by multiplying daily standard deviation by the square root of 252. Volume is the total number of shares traded from the last month. ILLIQ is measured following Amihud (2002). Both Volume and ILLIQ are measured in natural log. Momentum is the cumulative return from month t-12 to month t-1. We also report the implied volatility (IV), RNSkew and future skewness (Skew). IV is directly from OptionMetrics. We calculate IV from the options that are at the money. RNSkew is calculated following Bakshi, Kapadia and Madan (2003) and is detailed in the paper. Skew is calculated using daily data from month t+1 to month t+12. The sample period is from January 1996 to December 2011.

	All optionable stocks (N=263,571)		Regular Splits (N=2,094)		Reverse Splits (N=158)	
Variables	Mean	STDEV	Mean	STDEV	Mean	STDEV
Price	32.629	29.992	76.006	84.985	6.868	13.257
Log (Price)	3.256	0.665	4.188	0.491	0.493	1.723
Beta	1.344	0.895	1.299	1.099	2.109	1.565
Log (Size)	14.435	1.515	15.045	1.337	12.043	2.458
Log (BM)	-1.179	0.866	-1.725	0.931	-0.079	1.331
Leverage	0.210	0.199	0.185	0.191	0.237	0.227
Past Volatility	0.518	0.257	0.486	0.270	1.064	0.594
Past Skewness	0.233	1.032	0.425	0.856	0.693	1.584
Volume	11.845	1.382	12.224	1.313	10.447	1.918
Momentum	0.222	0.694	1.266	2.239	-0.422	0.777
ILLIQ	-18.512	2.015	-19.062	1.780	-15.867	2.684
NASDAQ	0.616	0.486	0.691	0.462	0.813	0.392
IV	0.499	0.235	0.504	0.260	0.850	0.425
RNSkew	-0.528	0.844	-0.687	0.925	0.431	0.922
Skew	0.277	1.271	0.172	1.114	1.106	1.570
Price after split	NA	NA	38.504	18.645	24.307	36.647
Split ratio	NA	NA	1.975	1.161	0.240	0.193

Table 2. RNSkew around regular stock splits

Regular stock splits are events with a CRSP distribution code of 5523 and the split ratio greater than 1.25-for-1. RNSkew is calculated following Bakshi, Kapadia and Madan (2003) and is detailed in the paper. Panel A and Panel B report the change of RNSkew and physical skewness around splits (comparing to matched sample), respectively. For RNSkew, we report the change of RNSkew around the ex-date and around the announcement date. We report the average RNSkew before and after the event, and also the difference between them. We use the paired t-test to gauge the statistical significance. Different windows are chosen. For example, for (-3, 0) the Before column displays RNSkew day -3 relative to the event date, and the after column displays RNSkew on day 0 relative to the event date (ie the date of the event). For each given window, we require RNSkew of a given stock can be measured both before and after the event. For each split stock, we require the matched stock and the split stock to be in the same size quintile, BM quintile, momentum quintile and skewness quintile. We also require that the skewness difference between the matched stock and the split stock is lower than 0.25. If more than one stock satisfies the above criteria, we choose the one with the smallest price difference with the split stock. All the information used for matching is available at the time of split. B/M is the ratio between book value of common equity and market price. Momentum is the cumulative return from month t-12 to month t-1. Size is equal to the log market capitalization at the end of month t. Pre-matching skewness is calculated using daily return from month t-11 to month t, and post-matching skewness is calculated using daily return from month t+1 to month t+12. The sample period is January 1996 to December 2011.

Panel A. RNSkew change

Window	N	Before	After	Change	t
Panel A1. Ex-date					
(-10, 0)	2042	-0.694	-0.382	0.312***	5.09
(-5, 0)	2054	-0.667	-0.381	0.286***	4.76
(-3, 0)	2066	-0.668	-0.38	0.288***	4.84
(-1, 0)	2082	-0.684	-0.381	0.303***	5.08
(-1, 1)	2081	-0.684	-0.452	0.232***	9.06
(-1, 3)	2079	-0.684	-0.455	0.228***	8.87
(-1, 5)	2078	-0.683	-0.499	0.184***	8.02
(-1, 10)	2069	-0.683	-0.487	0.197***	8.22
Panel A2. Announcement					
(-10, 0)	1775	-0.828	-0.828	0.000	0.00
(-5, 0)	1827	-0.821	-0.819	0.002	0.10
(-3, 0)	1846	-0.84	-0.819	0.021	1.00
(-1, 0)	1869	-0.834	-0.815	0.018	1.06
(-1, 1)	1841	-0.83	-0.791	0.039*	1.95
(-1, 3)	1772	-0.834	-0.764	0.070***	3.40
(-1, 5)	1717	-0.837	-0.716	0.121***	5.41
(-1, 10)	1490	-0.843	-0.692	0.151***	5.76

Panel B. Physical skewness change: Matched sample analysis (N=1,528)

	Before				After			
	Treated	Matched	Dif.	t	Treated	Matched	Dif.	t
Log (BM)	-1.759	-1.75	-0.010	-0.53				
Log (Price)	4.101	3.95	0.151***	18.79				
Momentum	1.271	1.128	0.143**	2.36				
Size	14.946	14.963	-0.017	-0.93				
Skew	0.378	0.382	-0.004	-1.12	0.151	0.208	-0.058	-1.27

Table 3. RNSkew around reverse stock splits

Reverse stock splits are events with a CRSP distribution code of 5523 and the split ratio lower than 1-for-1. RNSkew is calculated following Bakshi, Kapadia and Madan (2003) and is detailed in the paper. Panel A and Panel B report the change of RNSkew and physical skewness around splits (comparing to matched sample), respectively. For RNSkew, we report the change of RNSkew around the ex-date and around the announcement date. We report the average RNSkew before and after the event, and also the difference between them. We use the paired t-test to gauge the statistical significance. Different windows are chosen. For example, for (-3, 0) the Before column displays RNSkew day -3 relative to the event date, and the after column displays RNSkew on day 0 relative to the event date (ie the date of the event). For each given window, we require RNSkew of a given stock can be measured both before and after the event. For each split stock, we require the matched stock and the split stock to be in the same size quintile, BM quintile, momentum quintile and skewness quintile. We also require that the skewness difference between the matched stock and the split stock is lower than 0.25. If more than one stock satisfies the above criteria, we choose the one with the smallest price difference with the split stock. All the information used for matching is available at the time of split. B/M is the ratio between book value of common equity and market price. Momentum is the cumulative return from month t-12 to month t-1. Size is equal to the log market capitalization at the end of month t. Pre-matching skewness is calculated using daily return from month t-11 to month t, and post-matching skewness is calculated using daily return from month t+1 to month t+12. The sample period is January 1996 to December 2011.

Panel A. Change of RNSkew

Window	N	Before	After	Change	t
(-10, 0)	155	0.214	-0.068	-0.283***	-3.61
(-5, 0)	157	0.317	-0.073	-0.391***	-5.30
(-3, 0)	157	0.28	-0.073	-0.354***	-4.87
(-1, 0)	158	0.438	-0.076	-0.514***	-7.60
(-1, 1)	154	0.447	-0.063	-0.509***	-7.40
(-1, 3)	154	0.447	-0.073	-0.520***	-7.40
(-1, 5)	152	0.435	-0.027	-0.462***	-6.11
(-1, 10)	147	0.449	-0.035	-0.484***	-6.72

Panel B. Change of physical skewness (N=69)

	Before				After			
	Treated	Matched	Dif	t	Treated	Matched	Dif	t
Log (BM)	-0.492	-0.501	0.009	0.05				
Log (Price)	0.863	1.167	-0.304***	-4.01				
Momentum	0.013	-0.114	0.127	1.28				
Size	13.013	12.181	0.832***	4.93				
Skew	0.57	0.556	0.014	0.79	1.013	0.749	0.265	0.92

Table 4. Summary statistics: by price quintiles

This table reports summary statistics for the main variables of interest, sorted based on price at month t-1. Beta is calculated following Fama and French (1992), that is, for each month, we use the past 60 months' monthly excess return data and CRSP value weighted excess market return to calculate Beta. B/M is the ratio between book value of common equity and market price. Leverage is the ratio between total liability and total assets. Volatility and Skewness are calculated using the 1 year's daily returns. We reach annualized volatility by multiplying daily standard deviation by the square root of 252. Volume is the total number of shares traded from the last month. ILLIQ is measured following Amihud (2002). Both Volume and ILLIQ are measured in natural log. Momentum is the cumulative return from month t-12 to month t-1. We also report the implied volatility (IV), RNSkew and future skewness (Skew). IV is directly from OptionMetrics. We calculate IV from the options that are at the money. RNSkew is calculated following Bakshi, Kapadia and Madan (2003) and is detailed in the paper. Skew is calculated using daily data from month t+1 to month t+12. E(Skew) is the expected future physical skewness, calculated following Boyer, Mitton and Vorkink (2010). The sample period is from January 1996 to December 2011.

Price Portfolio	Lowest	2	3	4	Highest
Price	10.632	18.486	26.864	38.812	68.359
Log (Price)	2.321	2.900	3.275	3.643	4.142
Beta	1.821	1.446	1.290	1.136	1.025
Log (Size)	13.154	13.849	14.394	14.985	15.793
Log (BM)	-0.985	-1.039	-1.177	-1.278	-1.402
Leverage	0.200	0.209	0.206	0.214	0.221
Past Volatility	0.694	0.552	0.498	0.445	0.401
Past Skewness	0.215	0.179	0.231	0.243	0.294
Volume	11.475	11.557	11.778	12.017	12.386
Momentum	-0.007	0.138	0.227	0.306	0.440
ILLIQ	-16.871	-17.844	-18.501	-19.210	-20.095
NASDAQ	0.785	0.693	0.634	0.544	0.425
IV	0.681	0.530	0.476	0.426	0.383
RNSkew	0.026	-0.342	-0.645	-0.768	-0.909
Skew	0.492	0.341	0.233	0.193	0.126
E(Skew)	0.474	0.329	0.251	0.184	0.103

Table 5. The relationship between nominal price and skewness: Fama-MacBeth regressions

For each month, the following cross-sectional regression is run.

$$DV_{i,t} = \alpha_t + \beta_1 Log(Price_{i,t}) + X_{i,t} + \varepsilon_{i,t},$$

where DV is one of the followings: RNSkew, Skew, RNSkew-Skew and RNSkew-E(Skew). RNSkew is calculated following Bakshi, Kapadia and Madan (2003) and is detailed in the paper. Skew is calculated using daily data from month t+1 to month t+12. E(Skew) is a forward looking skewness measure constructed following the method of Boyer, Mitton, and Vorkink (2010).

The independent variables include price, log price, beta, log of firm market capitalization, log of B/M, Leverage, past volatility, past skewness, implied volatility, volume, ILLIQ, momentum and a NASDAQ dummy indicating listing exchange. Beta is calculated following Fama and French (1992), that is, for each month, we use the past 60 months' monthly excess return data and CRSP value weighted excess market return to calculate Beta. B/M is the ratio between book value of common equity and market equity. Leverage is the ratio of total liabilities to total assets. Volatility and Skewness are calculated using the past one year daily returns. Annualized volatility is calculated by multiplying daily standard deviation by the square root of 252. Volume is the total number of shares traded from the last month. ILLIQ is measured following Amihud (2002). Both Volume and ILLIQ are measured in natural log. Momentum is the cumulative return from month t-12 to month t-1). IV is directly from OptionMetrics. We calculate IV from options that are at the money. ATM options are defined as call options with delta higher than 0.375 and not higher than 0.625 and put options with delta higher than -0.625 and not higher than -0.375. The sample period is from January 1996 to December 2010. Reported t-statistics are Newey-West adjusted with 12 lags.

	RNSkew			Skew			RNSkew-Skew			RNSkew-E(Skew)		
Log (Price)	-0.529***	-0.309***	-0.309***	-0.203***	-0.080***	-0.086***	-0.326***	-0.229***	-0.222***	-0.327***	-0.205***	-0.196***
	(-19.29)	(-9.38)	(-9.80)	(-8.26)	(-2.58)	(-2.81)	(-9.35)	(-5.49)	(-5.20)	(-8.96)	(-6.66)	(-6.03)
Beta		-0.001	-0.012**		-0.004	-0.017		0.002	0.004		0.012	0.012
		(-0.19)	(-2.13)		(-0.19)	(-0.97)		(0.12)	(0.28)		(0.55)	(0.71)
Size		-0.056***	-0.061***		-0.542***	-0.570***		0.486***	0.509***		-0.047***	-0.040***
		(-5.83)	(-6.83)		(-6.23)	(-6.60)		(5.74)	(5.93)		(-2.67)	(-2.77)
BM		-0.030***	-0.032***		0.016	0.006		-0.046***	-0.038***		-0.065***	-0.069***
		(-7.26)	(-6.94)		(1.09)	(0.45)		(-3.04)	(-2.64)		(-3.97)	(-4.62)
Leverage		-0.142***	-0.163***		0.101*	0.045		-0.243***	-0.208***		-0.350***	-0.328***
		(-5.57)	(-7.96)		(1.74)	(0.94)		(-5.18)	(-4.87)		(-9.02)	(-7.98)
Past Volatility		-0.139	-0.129		0.263**	0.305**		-0.402**	-0.434**		-0.201	-0.225
		(-1.38)	(-1.48)		(1.99)	(2.47)		(-1.97)	(-2.45)		(-1.34)	(-1.65)
Past Skew		-0.007	-0.006		0.036***	0.032***		-0.043***	-0.038***		-0.067***	-0.031***
		(-1.35)	(-1.33)		(6.33)	(5.17)		(-5.81)	(-5.11)		(-7.49)	(-3.26)
IV		0.955***	0.928***		0.657***	0.650***		0.298***	0.278***		0.702***	0.699***
		(22.95)	(27.36)		(7.25)	(7.51)		(3.55)	(3.23)		(7.79)	(8.03)
Volume		-0.019***	-0.017***		0.086***	0.098***		-0.106***	-0.115***		-0.002	-0.008
		(-2.55)	(-2.50)		(3.99)	(4.96)		(-5.12)	(-5.87)		(-0.25)	(-0.95)
Momentum		-0.127***	-0.133***		-0.103***	-0.092***		-0.025	-0.041*		-0.021	-0.038*
		(-8.32)	(-10.45)		(-6.25)	(-6.27)		(-0.95)	(-1.93)		(-0.92)	(-1.84)
ILLQ		-0.01*	-0.01*		-0.44***	-0.45***		0.43***	0.44***		-0.01*	-0.01**
		(-1.72)	(-1.88)		(-7.22)	(-7.21)		(6.91)	(6.90)		(-1.91)	(-1.99)
NASDAQ		-0.046***	-0.040***		-0.040**	-0.051**		-0.006	0.012		-0.012	0.022
		(-5.77)	(-5.19)		(-2.08)	(-2.48)		(-0.30)	(0.52)		(-0.52)	(0.84)
Constant	1.178***	1.043***	1.103***	0.930***	-1.377***	-1.265***	0.248**	2.420***	2.368***	0.246**	0.248	0.098
	(15.37)	(4.97)	(5.73)	(10.36)	(-6.16)	(-5.26)	(2.49)	(7.47)	(7.62)	(2.17)	(0.75)	(0.33)
Industry FE	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Adj-R^2	0.197	0.292	0.333	0.017	0.115	0.157	0.026	0.127	0.169	0.08	0.184	0.312
Obs.	180	180	180	180	180	180	180	180	180	167	167	167

Table 6. The relationship between nominal price and Adjusted skewness gap: Adjusted based on BKM (2003)
For each month, the following cross-sectional regression is run.

$$DV_{i,t} = \alpha_t + \beta_1 Log(\Pr ice_{i,t}) + X_{i,t} + \varepsilon_{i,t},$$

where DV is: (RNSkew-RNSkew$_{hypothetical}$)

RNSkew is calculated following Bakshi, Kapadia and Madan (2003) and is detailed in the paper. The methodology to calculate RNSkew$_{hypothetical}$ is detailed in the appendix. The independent variables include price, log price, beta, log of firm market capitalization, log of B/M, Leverage, past volatility, past skewness, implied volatility, volume, momentum, ILLIQ and a NASDAQ dummy indicating listing exchange. Beta is calculated following Fama and French (1992), that is, for each month, we use the past 60 months' monthly excess return data and CRSP value weighted excess market return to calculate Beta. B/M is the ratio between book value of common equity and market equity. Leverage is the ratio of total liabilities to total assets. Volatility and Skewness are calculated using the past one year daily returns. Annualized volatility is calculated by multiplying daily standard deviation by the square root of 252. Volume is the total number of shares traded from the last month. ILLIQ is measured following Amihud (2002). Both Volume and ILLIQ are measured in natural log. Momentum is the cumulative return from month t-12 to month t-1). IV is directly from OptionMetrics. We calculate IV from options that are at the money. ATM options are defined as call options with delta higher than 0.375 and not higher than 0.625 and put options with delta higher than -0.625 and not higher than -0.375. The sample period is from January 1996 to December 2010. Reported t-statistics are Newey-West adjusted with 12 lags.

	(RNSkew-RNSkew$_{hypothetical}$) method 1			(RNSkew-RNSkew$_{hypothetical}$) method 2		
Log (Price)	-0.606***	-0.412***	-0.412***	-0.548***	-0.301***	-0.303***
	(-16.04)	(-13.20)	(-13.52)	(-14.23)	(-9.33)	(-9.96)
Beta		0.232***	0.221***		0.364***	0.349***
		(6.00)	(5.69)		(12.55)	(12.12)
Size		-0.030**	-0.024*		-0.021	-0.027**
		(-2.12)	(-1.88)		(-1.61)	(-2.11)
BM		0.103***	0.116***		0.001	-0.001
		(6.89)	(8.30)		(0.10)	(-0.21)
Leverage		-0.215***	-0.162***		-0.145***	-0.142***
		(-8.07)	(-5.93)		(-4.15)	(-4.81)
Past Volatility		-0.555***	-0.561***		-0.908***	-0.904***
		(-3.81)	(-4.23)		(-9.00)	(-9.81)
Past Skew		-0.027**	-0.026**		-0.757***	-0.757***
		(-2.51)	(-2.50)		(-35.84)	(-35.53)
IV		0.806***	0.796***		0.771***	0.753***
		(8.82)	(8.30)		(19.69)	(21.18)
Volume		-0.004	-0.009		-0.026***	-0.023***
		(-0.36)	(-0.98)		(-3.10)	(-2.72)
Momentum		-0.039	-0.044		-0.189***	-0.193***
		(-0.82)	(-1.08)		(-12.28)	(-13.85)
ILLIQ		-0.01	-0.01		0.00	0.00
		(-1.02)	(-1.64)		(-0.85)	(-0.85)
NASDAQ		-0.032*	-0.016		-0.041***	-0.038***
		(-1.71)	(-0.85)		(-3.71)	(-3.52)
Constant	1.558***	1.159***	1.032***	1.381***	0.973***	1.033***
	(10.78)	(5.90)	(5.62)	(13.12)	(5.22)	(5.99)
Industry FE	No	No	Yes	No	No	Yes
Adj-R^2	0.182	0.322	0.406	0.085	0.54	0.562
Obs.	168	168	168	180	180	180

Table 7. Nominal Price and Option Trading

For each month, we run the cross-sectional regression

$$DV_{i,t} = \alpha_t + \beta_1 Log(\Pr ice_{i,t}) + X_{i,t} + \varepsilon_{i,t},$$

where DV is one of the followings: put and call option trading volume ratio (VolRatio), or the put and call option open interest ratio (OIRatio). VolRatio=log (1+ volume of call options)-log (1+ volume of put options). OIRatio=log (1+ options interests of call options)-log (1+ options interests of put options). The independent variables include price, log price, beta, log of firm market capitalization, log of B/M, Leverage, past volatility, past skewness, implied volatility, volume, momentum, ILLIQ and a NASDAQ dummy indicating listing exchange. Beta is calculated following Fama and French (1992), that is, for each month, we use the past 60 months' monthly excess return data and CRSP value weighted excess market return to calculate Beta. B/M is the ratio between book value of common equity and market equity. Leverage is the ratio of total liabilities to total assets. Volatility and Skewness are calculated using the past one year daily returns. Annualized volatility is calculated by multiplying daily standard deviation by the square root of 252. Volume is the total number of shares traded from the last month. ILLIQ is measured following Amihud (2002). Both Volume and ILLIQ are measured in natural log. Momentum is the cumulative return from month t-12 to month t-1). IV is directly from OptionMetrics. We calculate IV from options that are at the money. ATM options are defined as call options with delta higher than 0.375 and not higher than 0.625 and put options with delta higher than -0.625 and not higher than -0.375. The sample period is from January 1996 to December 2011. Reported t-statistics are Newey-West adjusted with 12 lags.

	VolRatio			OIRatio		
Log (Price)	-0.396***	-0.481***	-0.486***	-0.107***	-0.251***	-0.260***
	(-18.87)	(-26.11)	(-24.26)	(-6.82)	(-14.64)	(-15.81)
Beta		0.008	-0.003		0.007	0.001
		(1.24)	(-0.55)		(0.58)	(0.13)
Size		0.121	0.120***		-0.019	-0.028**
		(5.80)	(6.37)		(-1.43)	(-2.36)
BM		-0.014*	-0.024***		0.001	-0.003
		(-1.93)	(-3.16)		(0.11)	(-0.45)
Leverage		-0.042**	-0.069***		-0.154***	-0.158***
		(-2.15)	(-3.22)		(-4.51)	(-4.40)
Past Volatility		0.002	-0.008		0.020	0.009
		(0.04)	(-0.13)		(0.18)	(0.07)
Past Skew		0.013**	0.013***		0.015	0.018**
		(2.42)	(3.10)		(1.64)	(2.01)
IV		-0.001	-0.049		-0.757***	-0.801***
		(-0.02)	(-0.86)		(-8.21)	(-8.23)
Volume		-0.129***	-0.121***		-0.068***	-0.066***
		(-7.38)	(-7.31)		(-9.14)	(-8.77)
Momentum		0.113***	0.111***		0.337***	0.331***
		(7.10)	(9.07)		(11.40)	(12.25)
ILLQ		0.030**	0.040***		-0.020**	-0.020**
		(2.36)	(3.27)		(-2.25)	(-2.63)
NASDAQ		0.007	0.005		0.038***	0.022***
		(0.63)	(0.45)		(4.27)	(2.67)
Constant	2.069***	2.660***	2.847***	0.994***	2.459***	2.642***
	(15.45)	(12.86)	(13.30)	(10.64)	(9.81)	(9.91)
Industry FE	No	No	Yes	No	No	Yes
Adj-R^2	0.051	0.081	0.127	0.008	0.071	0.117
Obs.	179	179	179	180	180	180

Table 8. Option Trading Strategy

Portfolios are formed on the expiration Friday (or Thursday if Friday is a public holiday) of the month and the option portfolio strategies are initiated on the first trading day (typically a Monday) after the expiration Friday of the month. We do the analysis for OTM. OTM options are call options with delta higher 0.02 and not higher than 0.375 and put options with delta higher than -0.375 and not higher than -0.02. As in Bollen and Whaley (2004), we exclude options with absolute delta below 0.02 due to the distortions caused by price discreteness. On each portfolio formation day, we choose the put and call options for any given moneyness that will expire within one month. On each portfolio formation day, all stocks with available options are sorted into quintiles based on the stock price on the portfolio formation day. For each option series, we construct delta-hedged portfolios and hold them until option expiration. As in Goyal and Sarreto (2009), we use the absolute value of the position as the reference price to calculate the delta-hedged return. Specifically, the formulae are

$$R_{call} = \frac{(c_T - c_0 e^{rT}) - \Delta_0 (S_T + \sum_{t=1}^{T} D_t e^{r(T-t)} - S_0 e^{rT})}{|\Delta_0 S_0 - c_0|}, \quad R_{put} = \frac{(p_T - p_0 e^{rT}) - \Delta_0 (S_T + \sum_{t=1}^{T} D_t e^{r(T-t)} - S_0 e^{rT})}{|\Delta_0 S_0 - p_0|}.$$

Besides reporting the raw return of each option portfolio, we also report the average abnormal return adjusting Fama and French three factors, Carhart (1997) momentum factor and a factor reflecting the market level put-call return differences. The last row of each panel reports the results. The portfolio returns are equal-weighted. The sample extends from January 22, 1996 to December 16, 2011.

Price	Lowest	2	3	4	Highest	Lowest-Highest
Panel A. OTM						
Call	-3.844	-3.337	-2.790	-1.649	-0.988	-2.856
	(-8.55)	(-7.79)	(-6.15)	(-3.83)	(-2.08)	(-8.07)
Put	-2.915	-2.332	-2.319	-1.732	-1.409	-1.506
	(-7.48)	(-5.89)	(-5.42)	(-3.75)	(-2.97)	(-5.72)
Put-Call	0.929	1.005	0.471	-0.083	-0.421	1.350
	(2.50)	(2.61)	(1.15)	(-0.21)	(-0.96)	(4.04)
Put-Call adjusted	1.142	1.269	0.708	0.233	0.117	1.025
	(4.12)	(4.73)	(2.40)	(0.86)	(0.42)	(3.75)
Panel B. ATM						
Call	-0.744	-0.048	-0.054	0.087	0.004	-0.748
	(-2.43)	(-0.18)	(-0.20)	(0.32)	(0.01)	(-3.74)
Put	-1.347	-0.920	-0.901	-0.806	-0.857	-0.489
	(-6.52)	(-4.84)	(-4.53)	(-3.91)	(-4.06)	(-3.52)
Put-Call	-0.602	-0.871	-0.847	-0.893	-0.861	0.259
	(-4.93)	(-8.65)	(-8.66)	(-9.53)	(-8.82)	(3.05)
Put-Call adjusted	-0.552	-0.807	-0.781	-0.854	-0.786	0.233
	(-4.90)	(-8.58)	(-8.61)	(-9.55)	(-8.29)	(2.80)