JOURNAL OF FINANCIAL AND QUANTITATIVE ANALYSIS Vol. 51, No. 2, Apr. 2016, pp. 515–540
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doi:10.1017/S002210901600020X

https://doi.org/10.1017/S002210901600020X Published online by Cambridge University Press

Gambling Preferences, Options Markets, and Volatility

Benjamin M. Blau, T. Boone Bowles, and Ryan J. Whitby*

Abstract

This study examines whether the gambling behavior of investors affects volume and volatility in financial markets. Focusing on the options market, we find that the ratio of call option volume relative to total option volume is greatest for stocks with return distributions that resemble lotteries. Consistent with the theoretical predictions of Stein (1987), we demonstrate that gambling-motivated trading in the options market influences future spot price volatility. These results not only identify a link between lottery preferences in the stock market and the options market, but they also suggest that lottery preferences can lead to destabilized stock prices.

I. Introduction

Theoretical research has long studied the potential role of speculative trading and gambling preferences by investors.[1] Markowitz (1952), for instance, suggests that some investors might prefer to purchase stocks that have a small probability of obtaining a large payoff. Barberis and Huang (2008) build on work by Kahneman and Tversky (1979) and Benartzi and Thaler (1995) that examines the effect of prospect theory on asset prices. Barberis and Huang (2008) posit that some investors will overweight the tails in the return distribution and show preferences for positive skewness. They also demonstrate that skewness preferences can affect asset prices. Empirical research tends to support the argument that i) some investors prefer positive skewness (see Mitton and Vorkink (2007), Kumar (2009), and Kumar, Page, and Spalt (2011)) and ii) investors' preferences for positive skewness lead to price premiums and subsequent underperformance (Zhang (2005),

*Blau (corresponding author), ben.blau@usu.edu, Whitby, ryan.whitby@usu.edu, Utah State University, Huntsman School of Business, Logan, UT 84322; and Bowles, boone.bowles@gmail.com, University of North Carolina at Chapel Hill, Kenan-Flagler Business School, Chapel Hill, NC 27599.
We gratefully acknowledge helpful and constructive comments by an anonymous referee and Stephen Brown (the editor). The study has also benefited from suggestions by seminar participants at the University of Mississippi and Utah State University. All errors are the responsibility of the authors.

[1]Examples include Markowitz (1952), Arditti (1967), Simkowitz and Beedles (1978), Scott and Horvath (1980), Conine and Tamarkin (1981), Stein (1987), Shefrin and Statman (2000), Statman (2002), Brunnermeier and Parker (2005), Brunnermeier, Gollier, and Parker (2007), and Barberis and Huang (2008).

Mitton and Vorkink (2007), Boyer, Mitton, and Vorkink (2010), and Bali, Cakici, and Whitelaw (2011)).

Both theoretical and empirical research support the idea that some investors prefer skewness or lottery-type stock characteristics. In this study, we extend this literature in two ways. First, we examine whether stocks with characteristics that resemble lotteries have higher levels of call option volume. Second, and perhaps more importantly, we examine whether preferences for lotteries that are exhibited in higher call option volume influence future spot price volatility. Although prior research indicates that informed trading might explain the motive to trade in the options market (Black (1975), Easley, O'Hara, and Srinivas (1998), and Pan and Poteshman (2006)), others have suggested that speculative trading might also motivate investors to trade options (Stein (1987)). In this paper, we attempt to measure speculative trading in a variety of ways while focusing primarily on investors' preferences for lottery-like returns (Golec and Tamarkin (1998) and Garrett and Sobel (1999)). Furthermore, the unique payoff structure of call options, such as limited downside risk and unlimited upside potential, might make options attractive for those investors with preferences for lotteries. Understanding the relation between preferences for lotteries and option markets is important given the findings of Pan and Poteshman (2006) and Johnson and So (2012), who show that option trading volume contains information about future returns in underlying stocks.

We follow prior research and approximate lottery stocks in several ways. First, we proxy for lottery stocks by examining both positive *total* and positive *idiosyncratic* skewness in returns during the prior quarter (see Barberis and Huang (2008), Mitton and Vorkink (2007), Kumar et al. (2011), and Kumar and Page (2014)).[2] Second, we follow Bali et al. (2011) and approximate lottery stocks as those with the largest maximum daily return. Third, following Kumar (2009) and Kumar and Page (2014), we approximate lottery stocks by calculating indicator variables that capture low-priced stocks that have the highest idiosyncratic volatility and the highest idiosyncratic skewness during the previous quarter. Using these approximations for lottery stocks, we then examine the fraction of total option volume that is made up from call options, which we denote as the call ratio for brevity. Observing a direct relation between call ratios and these approximations of lottery stocks can provide an important contribution to the literature suggesting that some investors have strong preferences for assets with lottery-like returns.

Our univariate results show a monotonically positive relation between call ratios and last quarter's total skewness. Similar results are found when examining the relation between call ratios and both last quarter's idiosyncratic skewness and last quarter's maximum daily return. When we approximate stock lotteries using low-priced stocks with the highest idiosyncratic volatility and the highest idiosyncratic skewness, we again show that call ratios are highest for these stocks. These results indicate that preferences for lottery-type stocks are

[2]Following Kumar (2009), we also calculate systematic (or co-) skewness. However, because Kumar (2009) and others generally use total and idiosyncratic skewness to measure lottery preferences, we focus most of our tests on these two measures of skewness instead of systematic skewness.

https://doi.org/10.1017/S002210901600020X Published online by Cambridge University Press

reflected in a higher proportion of total option volume that is made up from call options.

We use a variety of multivariate tests to determine whether call ratios are higher for lottery stocks. After controlling for a variety of factors that influence the call ratio, we show a robust positive relation between call ratios and our approximations for lottery stocks. These results support our univariate tests and indicate that investors' penchant for lottery stocks, which has been identified in previous research (Zhang (2005), Mitton and Vorkink (2007), Kumar (2009), Boyer et al. (2010), and Bali et al. (2011)), is also reflected in higher call ratios.

Our second set of tests might have more important implications as we seek to explain whether call option investors with gambling preferences generate greater levels of volatility in underlying stock prices. In particular, we determine whether the relation between call ratios and lottery-like characteristics, as well as other speculative trading measures, affects the stability of underlying spot prices. These tests are motivated by Stein's (1987) theory, which shows that speculative trading in derivatives markets can lead to more volatility in the spot market. Stein's (1987) idea is that speculation can increase the level of noise trading, which adversely affects informed investors' ability to stabilize prices. Our objective is to determine whether gambling and speculation in the options market lead to greater volatility in spot prices.

We first show that next-quarter volatility in spot prices is monotonically increasing across call ratios. We then decompose the call ratio into a speculative and a nonspeculative component. The speculative component of the call ratio contains the portion of the call ratio that is related to lottery-like characteristics and other speculative trading measures. The nonspeculative component of the call ratio is the portion of the call ratio that is orthogonal to these characteristics. For brevity, we refer to the portions of the decomposed call ratio as the speculative call ratio and the nonspeculative call ratio, respectively. We show that next-quarter idiosyncratic volatility is directly related to the speculative call ratio. However, next-quarter idiosyncratic volatility is unrelated to the nonspeculative call ratio.

Our multivariate tests show that, after controlling for other factors that influence next-quarter volatility, the relation between the total call ratio and future volatility is only marginally significant. However, the speculative call ratio is directly related to next-quarter idiosyncratic volatility, and the relation is both statistically significant and economically meaningful. When including the same controls, we do not find a significant relation between next-quarter idiosyncratic volatility and the nonspeculative portion of the call ratio. These results indicate that speculative call option activity adversely affects the stability of underlying stock prices, whereas nonspeculative call option activity does not.

Our study contributes to the literature in two important ways. First, our finding that call ratios are directly related to stock characteristics that resemble lottery-like features supports the growing line of research suggesting that some investors have strong preferences for lottery stocks (Zhang (2005), Mitton and Vorkink (2007), Barberis and Huang (2008), Kumar (2009), Boyer et al. (2010), Bali et al. (2011), Kumar et al. (2011), and Kumar and Page (2014)). Second, our results that identify a link between future spot price volatility and speculative call ratios

https://doi.org/10.1017/S002210901600020X Published online by Cambridge University Press

https://doi.org/10.1017/S002210901600020X Published online by Cambridge University Press

are consistent with Stein's (1987) theory, which posits that speculative trading activity in the derivatives market can lead to increased volatility in the spot market.

II. Related Literature and Hypothesis Development

Barberis and Huang (2008) show that investors tend to overweight the tails of return distributions, which leads to observed preferences for positive skewness. Skewness preferences can result in an equilibrium that leads to overpriced, positively skewed stocks. Price premiums that are caused by skewness preferences will underperform stocks that are not positively skewed. Empirical research tends to support the predictions of Barberis and Huang (2008). For instance, Mitton and Vorkink (2007) find that some investors sacrifice mean-variance efficiency in their portfolios by underdiversifying. Furthermore, portfolios that are underdiversified exhibit more positive skewness than portfolios that are well diversified. Both Zhang (2005) and Boyer et al. (2010) show that stocks with positive skewness underperform stocks with negative skewness, which is consistent with the idea that skewness preferences lead to price premiums and subsequent underperformance.

In a related study, Kumar (2009) approximates lottery-type stocks as those stocks with the lowest prices, the highest idiosyncratic volatility, and the highest idiosyncratic skewness. Kumar (2009) finds that individual investors have greater preferences for lottery-type stock characteristics than do institutional investors. Furthermore, Kumar (2009) shows that investors with preferences for lottery stocks have socioeconomic characteristics similar to those of individuals who participate in state lotteries. These results support the idea that some investors have preferences for stocks with lottery-like payoffs. Using a variety of different empirical tests, Kumar (2009) shows that lottery stocks significantly underperform nonlottery stocks, thus supporting the predictions of Barberis and Huang (2008). Similar conclusions are drawn by Bali et al. (2011), who show that stocks with the largest maximum daily return underperform other stocks. Again, these results support the idea that stocks with a low probability of an extreme payoff exhibit price premiums and subsequent underperformance.

Stein (1987) posits that the availability of financial derivatives, such as options and futures, provides investors with a natural way to speculate about spot price movements. For instance, a call option allows the buyer the opportunity to limit the downside risk while having unlimited upside potential. It is natural, therefore, to suggest that call options provide investors the opportunity to trade on their preferences for positive skewness or other lottery-like features. Our first hypothesis indirectly examines the conjecture made by Stein (1987) that derivative markets augment speculative trading in the spot market. The first null hypothesis is as follows:

Hypothesis 1. Call ratios are unrelated to features that resemble lottery-type stock characteristics.

Null Hypothesis 1 suggests that the call ratio is unrelated to past total skewness, past idiosyncratic skewness, stocks with the largest maximum daily return, or stocks that have the lowest prices, the highest idiosyncratic volatility, and

the highest idiosyncratic skewness. If call options are an important avenue for speculative gambling based on characteristics of the return distributions of the underlying asset, then we will reject the null Hypothesis 1 if call ratios are directly related to lottery-like features.[3]

In a recent study that is related to our first hypothesis, Boyer and Vorkink (2014) investigate the relation between total skewness and returns on equity options. They find that total skewness is negatively related to average option returns. Given the inherent speculative properties in options, they conclude that investor demand for lottery-like options results in larger option premiums that could be compensation for nonhedgeable risk encountered by intermediaries that make markets in options. Whereas they focus entirely on the distribution of option returns, our tests are different because we focus on option trading activity and the distribution of underlying stock returns. Our tests, however, are complementary in that both studies examine the impact that preferences for lottery-like securities can have on the intertemporal dynamics of traded assets.

Gambling in the options market may or may not have an effect on the stability of prices in the spot market. A theoretical debate about whether speculation stabilizes or destabilizes asset prices has been contested in the literature. Ross (1976) uses Arrow's (1964) state space approach and argues that the availability of options can improve the efficiency of markets by opening new spanning opportunities. Although there may be a finite number of stocks an investor can buy, there is a virtually infinite number of combinations of options an investor can buy. Ross (1976) therefore argues that increasing the number of opportunities to trade can lead to greater market efficiency. Friedman (1953), Danthine (1978), and Turnovsky (1983) also argue that speculative behavior can provide a stabilizing influence to prices.

On the other hand, Salant (1984) and Hart and Kreps (1986) show that in general equilibrium, speculation can lead to price destabilization. Stein (1987) presents a model that allows for speculation in derivatives markets and partitions the effect of speculation into two categories. Stein's (1987) 2-period model allows for both spot market traders and secondary (i.e., derivatives) market traders. Under various scenarios, the increase of speculators in the derivatives market actually stabilizes prices. When derivative traders are perfectly or completely uninformed, speculation results in more stable prices because there are no informational externalities present to offset the risk-sharing benefits associated with increased trading in the derivatives market. However, for cases when derivative traders have less-than-perfect information, an increase in speculation results in more volatile spot prices. Specifically, when derivative traders have intermediate levels of information, their actions are unpredictable, and risk-averse spot traders back away from the market, which leads to destabilized prices. In general, the imperfect information environment can create uncertainty that can result in greater

[3]We recognize an important limitation in our study. We are unable to determine the initiators of the call volume used in this study. Whereas prior research has obtained signed option volume from proprietary sources, we do not have access to this type of data. However, other studies have used total call volume ratios instead of signed call option volume to determine the effect of call volume on asset prices. For instance, Johnson and So (2012) examine the relation between call-to-put ratios and future skewness.

https://doi.org/10.1017/S002210901600020X Published online by Cambridge University Press

spot price volatility. The Stein's (1987) model does not rely on any irrationality or behavioral assumption, but rather on imperfect information held by speculators. This assumption does not seem overly restrictive, given our setting in the stock and options markets. In fact, assuming that options traders have perfect or zero information seems much less likely.

Stein (1987) therefore contends that the availability of options provides a greater level of risk sharing among investors, which can improve social welfare by stabilizing spot prices. However, in an imperfect information environment, greater levels of speculation in derivatives markets can produce noisy prices that adversely affect the ability of informed investors to transmit information into prices, thus leading to more volatility. Speculation in the options market can become destabilizing when the effect of less information transmission due to noisy prices outweighs the effect of greater risk sharing. If this condition holds, then our second null hypothesis is as follows:

Hypothesis 2. Speculative call ratios will have an effect on future spot price volatility that is similar to that of nonspeculative call ratios.

Null Hypothesis 2 suggests that the speculative portion of the call ratio will have the same effect on future spot price volatility as the nonspeculative portion of the call ratio. If speculative option trading destabilizes spot prices, then we can reject Hypothesis 2 by showing that speculative call option activity directly affects future spot price volatility more than does nonspeculative call option activity. We test these two hypotheses later in the paper.

III. Data Description

The data used in this study are obtained from several different sources. From the Center for Research in Security Prices (CRSP), we gather daily and monthly stock prices, volume, returns, and market capitalization. From Bloomberg, we gather daily call option volume and put option volume.[4] From Compustat, we obtain quarterly financial statement information such as total assets and total liabilities. We also obtain institutional holdings from 13F filings. After merging the Compustat data with the available stocks from our other data sources, we are left with 3,112 stocks and 61,689 stock-quarter observations. Our sample time period is 1997–2007.

We aggregate stock trading volume and option volume to the quarterly level for each stock. We also obtain the closing price and the market capitalization on the last day of each quarter. Table 1 reports statistics that summarize the data. The table shows that the average stock has a quarterly market capitalization (SIZE) of nearly \$6.8 billion and a price (PRICE) of \$29.68. Using institutional holdings, we estimate the fraction of shares outstanding that are held by institutions (INST_OWN). The average stock has INST_OWN of 0.6677, a book-to-market ratio (BM) of 0.2029, and a debt-to-assets ratio (DA) of 0.5075. Using quarterly stock trading volume, we calculate the share turnover (TURN), or the portion of

[4]The daily option volume obtained from Bloomberg is the total volume for options at all strike prices for all expirations.

https://doi.org/10.1017/S002210901600020X Published online by Cambridge University Press

TABLE 1

Summary Statistics

Table 1 reports statistics that summarize the data used in the analysis. The table reports distributional statistics for various stock characteristics used throughout the sample. SIZE is the market capitalization obtained from CRSP (in $billions). PRICE is the average monthly closing price. INST_OWN is the fraction of shares outstanding that are held by institutions. BM is the book-to-market ratio, and DA is the debt-to-assets ratio. TURN is the share turnover, or the ratio of quarterly volume scaled by shares outstanding. IDIO_VOLT is the standard deviation of daily residual returns that are obtained from estimating a daily Fama–French (1997) 4-factor model. SPEC is the estimate of speculative trading according to Llorente et al. (2002). TOT_SKEW is total skewness of daily returns, and IDIO_SKEW is the skewness of daily residual returns obtained from fitting a 2-factor (market risk premium and market risk premium squared) model. SYST_SKEW is the coefficient of the squared market risk premium factor in the 2-factor model. MAX_RET is the maximum daily return during a particular quarter following Bali et al. (2011). LOTTERY1 is a dummy variable that equals 1 if a stock has idiosyncratic skewness in the highest 2 quartiles, idiosyncratic volatility in the highest 2 quartiles, and a closing price in the lowest 2 quartiles. LOTTERY2 is the dummy variable that captures whether a stock-quarter observation has idiosyncratic skewness in the highest quartile, idiosyncratic volatility in the highest quartile, and a closing price in the lowest quartile. The table also reports statistics for options data, which are gathered from Bloomberg. CALL_VOL is the average quarterly call option volume, and PUT_VOL is the average quarterly put option volume. CR is the fraction of total option volume that is made up from call options. The total number of stocks in the sample is 3,112, and the total number of stock-quarter observations is 61,689.

	Mean	Std. Dev.	Minimum	P10	P25	Median	P75	P90	Maximum
	1	2	3	4	5	6	7	8	9
SIZE	6.7619	23.8437	0.0567	0.2092	0.4843	1.2978	3.9742	12.6466	111.0887
PRICE	29.68	23.34	2.30	7.01	13.52	24.91	39.87	57.15	104.73
INST_OWN	0.6677	0.2373	0.0814	0.3232	0.5107	0.6995	0.8550	0.9803	0.9976
BM	0.2029	6.3105	−0.0102	0.0115	0.0223	0.0384	0.0613	0.0913	0.2938
DA	0.5075	0.2877	0.0525	0.1587	0.2903	0.5020	0.6854	0.8670	1.1734
TURN	6.3730	6.344	0.6890	1.6891	2.6514	4.5745	7.9064	12.9350	29.7151
IDIO_VOLT	0.0256	0.0166	0.0062	0.0103	0.0145	0.0213	0.0320	0.0462	0.0830
TOT_SKEW	0.2331	1.1774	−3.6975	−0.8527	−0.2027	0.2402	0.7109	1.3648	3.7275
IDIO_SKEW	0.2478	1.2988	−4.0035	−1.0075	−0.2422	0.2540	0.7913	1.5555	4.0834
SYST_SKEW	−0.2062	5.7557	−12.0360	−4.0242	−1.6480	−0.1151	1.3233	3.4360	10.5207
MAX_RET	0.0938	0.0801	0.0189	0.0326	0.0473	0.0727	0.1154	0.1765	0.3751
LOTTERY1	0.1926	0.3944	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	1.0000
LOTTERY2	0.0510	0.2201	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000
CALL_VOL	65,041.18	268,187.25	44	488	1,611	6,301	28,625	123,532	1,093,604
PUT_VOL	39,396.72	167,957.55	4	146	585	2,743	14,994	72,976	694,864
CR	0.6726	0.1726	0.1947	0.4452	0.5662	0.6871	0.7995	0.8844	0.9890

shares outstanding that are traded during a particular quarter. The mean turnover is 6.37. We calculate idiosyncratic volatility (IDIO_VOLT) by taking the standard deviation of residual returns from a daily Fama–French (1997) 4-factor model during each quarter. The average stock has an IDIO_VOLT of 0.0256.

Table 1 also reports stock characteristics that resemble lotteries. To obtain estimates of these characteristics, we use daily returns and estimate total skewness by taking the third moment using the following formula:

$$\text{TOT_SKEW} = \frac{n}{(n-1)(n-2)} \left(\frac{\sum_{t=1}^{n} (r_t - \bar{r})^3}{\hat{\sigma}^3} \right), \tag{1}$$

where r_t is the CRSP raw return for a particular stock on day t, $\bar{r}$ is the mean return for a particular stock during a particular quarter, and $\hat{\sigma}$ is the estimate for the standard deviation of returns for the stock during the quarter. We also calculate idiosyncratic skewness and systematic skewness (or co-skewness) following Kumar (2009). In particular, we estimate idiosyncratic skewness (IDIO_SKEW) by first fitting a daily 2-factor model where the factors are the market risk premium and the market risk premium squared. We then estimate equation (1) using residual returns from this 2-factor model instead of using CRSP raw returns. From

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the 2-factor model, systematic skewness (SYST_SKEW) is the coefficient on the market risk premium squared. We note that the literature that discusses preferences for lottery-type stocks generally uses total skewness or idiosyncratic skewness instead of systematic skewness. However, we include systematic skewness in some of our initial tests, following Kumar (2009). These measures of skewness are estimated in each quarter from 1997 to 2007.[5] The motivation to use skewness to approximate lotteries is based on the theory of Barberis and Huang (2008). Lotteries exhibit positively skewed return distributions, where a large majority of the distribution is at values less than the mean and a small portion of the distribution is in the long tail that is greater than the mean. The average stock has TOT_SKEW of 0.2331, IDIO_SKEW of 0.2478, and SYST_SKEW of −0.2062.

As an additional proxy for lottery-type characteristics, we follow Bali et al. (2011) and estimate the maximum daily return during a particular quarter for each stock in our sample (MAX_RET). Table 1 reports that the mean MAX_RET is 0.0938. In addition to examining these low-probability and high-payoff events, we also follow Kumar (2009) and construct two indicator variables: LOTTERY1 and LOTTERY2. We sort stock-quarter observations into quartiles based on last quarter's stock price, last quarter's idiosyncratic volatility, and last quarter's idiosyncratic skewness. If a particular stock has i) a price that is less than the median, ii) idiosyncratic volatility greater than the median, and iii) idiosyncratic skewness that is also greater than the median, then LOTTERY1 is equal to 1, and 0 otherwise. Additionally, LOTTERY2 is equal to 1 if a particular stock has i) a price that in the lowest price quartile, ii) idiosyncratic volatility in the highest idiosyncratic volatility quartile, and iii) idiosyncratic skewness in the highest idiosyncratic skewness quartile.[6] The average stock has a LOTTERY1 value of 0.1926 and a LOTTERY2 value of 0.0510. We note that when we calculate these indicator variables, we re-sort stock-quarter observations into quartiles during each quarter.

Table 1 also reports summary statistics for option activity. CALL_VOL is the number of call option contracts traded during a particular quarter, and PUT_VOL is the number of put option contracts traded during the same quarter. The average stock has a CALL_VOL value of 65,041 and a PUT_VOL value of 39,397 during a particular quarter. The main variable of interest in this study is the call ratio. We calculate the call ratio (CR) as the fraction of total option volume that is made up from call options. The average stock has a CR of 0.6726.

Figure 1 provides an important description of the data used throughout the analysis. The figure reports the time-series percentages of i) the universe of stocks that are considered lottery-type stocks according to Kumar (2009), ii) stocks that have tradable options, and iii) lottery-type stocks that have tradable options. The percentage of the universe of stocks available on CRSP that are considered lottery stocks (LOTTERY1 = 1) remains relatively close to 20% during our sample

[5]We use the quarterly frequency based on Xu's (2007) arguments suggesting that when estimating higher moments, such as return skewness, more observations are required. Xu (2007) requires 40 days of returns to estimate return skewness. We therefore estimate skewness at the quarterly level, thus allowing for a greater number of observations when calculating higher moments.

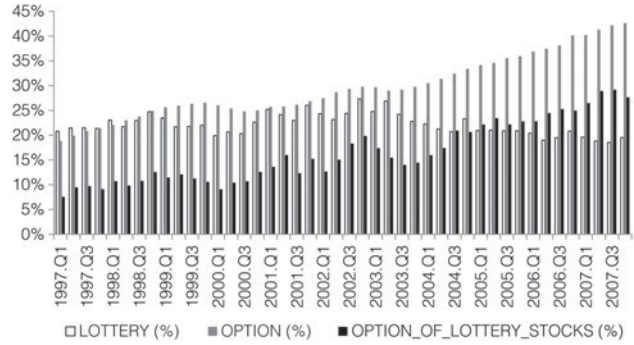
[6]For a more extensive discussion on these last two approximations of lotteries, see Kumar ((2009), p. 1896).

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FIGURE 1

Lottery Stocks and Optionability

Figure 1 shows the time series of i) the percentage of the universe of stocks on CRSP that are considered lottery stocks according to Kumar's (2009) definition (LOTTERY (%)), ii) the percentage of the universe of stocks on CRSP that have tradable options (OPTION (%)), and iii) the percentage of lottery stocks that also have tradable options (OPTION_OF_LOTTERY_STOCKS (%)).



time period.[7] On the other hand, the percentage of stocks that have tradable options increases from less than 20% to nearly 43% during our sample. Similarly, the percentage of lottery-type stocks that have tradable options begins at approximately 7% and increases to more than 27%.

IV. Empirical Results

In this section, we first test Hypothesis 1 by examining the relationship between option trading activity and our approximations for stock lotteries. Second, we test Hypothesis 2 by determining whether the speculative and nonspeculative portion of call option trading activity affects next-quarter spot price volatility.

A. The Relation between Call Ratios and Stock Lotteries: Univariate Tests

We begin our tests of Hypothesis 1 by sorting stock-quarter observations into quartiles based on the lottery-type stock characteristics discussed in the previous section. We then report call ratios across quartiles. Table 2 reports the results of the analysis. Panel A shows the results when we sort by the continuous proxies for lottery stocks, and Panel B presents the findings when we sort based on the indicator variables LOTTERY1 and LOTTERY2. We re-sort stock-quarter observations at the beginning of each quarter. In column 1 of Panel A, we see that call ratios increase monotonically across increasing $\text{TOT_SKEW}_{i,t-1}$ quartiles.

[7]It might also be noteworthy to discuss some of the stock characteristics that are related to the variable LOTTERY1. In unreported tests, we estimate the correlation between LOTTERY1 and some of the other variables discussed in Table 1. We find that LOTTERY1 is inversely related to market cap, share price, institutional ownership, and debt-to-asset ratio. We also find that LOTTERY1 is directly related to book-to-market ratio, share turnover, and (by construction) idiosyncratic volatility and idiosyncratic skewness.

https://doi.org/10.1017/S002210901600020X Published online by Cambridge University Press

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TABLE 2

Call Ratios and Lottery-Type Characteristics

Table 2 reports the call ratio (CR) across continuous lottery-type characteristics (Panel A) and discrete, or indicator, variable lottery-type characteristics (Panel B). TOT_SKEW is total skewness of daily returns, and IDIO_SKEW is the skewness of daily residual returns obtained from fitting a 2-factor (market risk premium and market risk premium squared) model. SYST_SKEW is the coefficient of the squared market risk premium factor in the 2-factor model. MAX_RET is the maximum daily return during a particular quarter, following Bali et al. (2011). LOTTERY1 is a dummy variable that equals 1 if a stock has idiosyncratic skewness in the highest 2 quartiles, idiosyncratic volatility in the highest 2 quartiles, and a closing price in the lowest 2 quartiles. LOTTERY2 is the dummy variable that capturers whether a stock-quarter observation has idiosyncratic skewness in the highest quartile, idiosyncratic volatility in the highest quartile, and a closing price in the lowest quartile. In Panel A, we sort by each of these lottery-type characteristics during the prior month and then report call ratios across quartiles. We then estimate the difference between extreme quartiles and report *p*-values obtained from *t*-statistics testing whether differences are different from 0. We also report the correlation coefficient with the corresponding *p*-value. In Panel B, we estimate the mean call ratio for both lottery classifications and then report the difference with the corresponding *p*-value. As in Panel A, we also report the correlation coefficient with the corresponding *p*-value. All *p*-values are in parentheses. * and ** indicate significance at the 5% and 1% levels, respectively.

Panel A. Call Ratios across Continuous Lottery-Type Characteristics

	Call Ratios across Lottery Characteristics			
	Sort by TOT_SKEW_{t-1}	Sort by $IDIO_SKEW_{t-1}$	Sort by $SYST_SKEW_{t-1}$	Sort by MAX_RET_{t-1}
	1	2	3	4
Q I (low)	0.6566	0.6496	0.6841	0.6432
Q II	0.6701	0.6719	0.6731	0.6558
Q III	0.6775	0.6840	0.6665	0.6806
Q IV (high)	0.6863	0.6850	0.6668	0.7083
Q IV – Q I	0.0297** (<0.0001)	0.0354** (<0.0001)	−0.0173** (<0.0001)	0.0651** (<0.0001)
Correlation	0.0557** (<0.0001)	0.0624** (<0.0001)	−0.0164** (<0.0001)	0.1235** (<0.0001)

Panel B. Call Ratios across Indicator Variables Representing Lottery-Type Characteristics

	Sort by LOTTERY1	Sort by LOTTERY2
	1	2
LOTTERY = 0	0.6595	0.6680
LOTTERY = 1	0.7275	0.7589
Difference	−0.0680** (<0.0001)	−0.0909** (<0.0001)
Correlation	0.1552** (<0.0001)	0.1159** (<0.0001)

Column 1 reports that the difference between extreme quartiles (Q IV − Q I) is 0.0297 (p-value ≤ 0.0001). We also estimate correlation coefficients between CR and TOT_SKEW_{t-1} and find that call ratios are directly related to $TOT_SKEW_{i,t-1}$ (correlation = 0.0557, p-values ≤ 0.0001). These results indicate that the fraction of total option volume that is made up of call options depends on the level of total skewness of the spot asset during the previous quarter.

Column 2 of Table 2 reports the results when sorting by last-quarter idiosyncratic skewness. Similar to our findings in Panel A, we find that call ratios increase monotonically across last-quarter idiosyncratic skewness. Furthermore, we show that call ratios are highest in stocks with the highest idiosyncratic skewness. In column 3, we do not find that call ratios increase monotonically across quartiles sorted by systematic skewness. In fact, we find that call ratios are generally decreasing. These results are somewhat expected given the findings of Kumar (2009) showing that investors (and in particular, individual investors) have lower preferences for stocks with systematic skewness. Furthermore, other studies (Mitton and Vorkink (2007), Kumar (2009), Boyer et al. (2010), Kumar et al. (2011), and

https://doi.org/10.1017/S002210901600020X Published online by Cambridge University Press

Kumar and Page (2014)) focus on idiosyncratic skewness when identifying preferences for lottery-type stocks. Therefore, systematic skewness might not be the best proxy for gambling preferences and tests of Hypothesis 1. Column 4 shows the results when we sort stocks into quartiles based on the prior-quarter maximum daily stock return. Consistent with our findings in columns 1 and 2, we show that call ratios increase monotonically across increasing quartiles. Furthermore, the difference between extreme quartiles is positive and significant, and the correlation is also economically meaningful. Results in columns 1, 2, and 4 seem to reject Hypothesis 1 and suggest that call ratios are directly related to past skewness and indicate that preferences for skewness are reflected in higher call ratios.

Next, we test Hypothesis 1 by examining the relation between call ratios and the two indicator variables that are used to approximate stock lotteries. We partition our sample of stock-quarter observations into two subsamples based on the indicator variables. Focusing first on column 1, we find that the mean call ratio for stock-quarter observations when LOTTERY1 $= 1$ is 0.7275. The mean call ratio in the subsample LOTTERY1 $= 0$ is 0.6595. The difference in means is -0.0680 and is statistically significant (p-value ≤ 0.0001). In economic terms, this difference is more than 10% of the call ratio in stocks where LOTTERY1 $= 0$. We also find that the correlation is 0.1552 (p-value ≤ 0.0001), suggesting that the call ratios are markedly higher in stocks that resemble lotteries. In column 2, the mean call ratio is also statistically and economically larger in the subsample of stocks where LOTTERY2 $= 1$. The difference between classifications is -0.0909 (p-value ≤ 0.0001). This difference is nearly 14% of the call ratio for stocks where LOTTERY2 $= 0$. Results in Panel B further support our findings in Panel A and reject Hypothesis 1. These univariate tests seem to suggest that call ratios are directly related to spot asset characteristics that approximate lotteries. Furthermore, our findings are stronger in economic magnitude when we identify stock lotteries using the definition in Kumar (2009), Kumar et al. (2011), and Kumar and Page (2014).

B. The Relation between Call Ratios and Stock Lotteries: Multivariate Tests

In the previous section, our univariate tests reject Hypothesis 1 and show a positive relation between call ratios and stock lotteries. We recognize the need to control for other factors that might influence the level of call ratios. Therefore, we estimate the following equation using pooled data:

$$\begin{aligned}(2)\quad \text{CALL_RATIO}_{i,t} \;=\; & \alpha + \beta_1 \ln(\text{SIZE}_{i,t}) + \beta_2 \ln(\text{PRICE}_{i,t}) \\ & + \beta_3 \text{INST_OWN}_{i,t} + \beta_4 \text{BM}_{i,t} + \beta_5 \text{DA}_{i,t} \\ & + \beta_6 \text{TURN}_{i,t} + \beta_7 \text{IDIO_VOLT}_{i,t} + \beta_8 \text{RETURN}_{i,t} \\ & + \beta_9 \text{LOTTERY_CHARACTERISTICS}_{i,t-1} + \varepsilon_{i,t}\,.\end{aligned}$$

The dependent variable is the call ratio for stock i in quarter t ($\text{CALL_RATIO}_{i,t}$). The independent variables include the natural log of market capitalization ($\ln(\text{SIZE}_{i,t})$), the natural log of the stock price ($\ln(\text{PRICE}_{i,t})$), institutional ownership ($\text{INST_OWN}_{i,t}$), the book-to-market ratio ($\text{BM}_{i,t}$), the debt-to-assets ratio ($\text{DA}_{i,t}$), the quarterly share turnover ($\text{TURN}_{i,t}$), idiosyncratic volatility

https://doi.org/10.1017/S002210901600020X Published online by Cambridge University Press

(IDIO_VOLT$_{i,t}$), and the quarterly return (RETURN$_{i,t}$). The independent variables of interest are the six LOTTERY_CHARACTERISTICS described earlier. We note that a Hausman test rejects the presence of random effects, whereas an F-test finds observed differences across both stocks and days. Therefore, we estimate equation (2) while controlling for both stock and quarter fixed effects.[8] The estimate for β_9 determines whether we reject or fail to reject the null hypothesis.

Table 3 reports the 2-way fixed effects estimates. It is possible that our results might be biased due to multicollinearity. We handle this possibility in two ways. First, we estimate variance inflation factors and find that these factors that estimate the magnitude of inflation in standard errors caused by multicollinearity are all below 3. These unreported tests indicate that our results are not subject to an abnormal amount of multicollinearity bias. Second, we estimate variants of equation (2) by including different combinations of control variables. Although the results from these tests are not reported, our findings are qualitatively similar to those reported in Table 3.

Column 1 of Table 3 reports the results when TOT_SKEW$_{i,t-1}$is the variable of interest. We find that market capitalization and quarterly returns are directly related to call ratios, whereas share prices, institutional ownership, share turnover, and idiosyncratic volatility are inversely related to call ratios. Consistent with our univariate tests in the previous table, we find that the estimate for TOT_SKEW$_{i,t-1}$ is positive and significant (estimate $= 0.0062$, p-value ≤ 0.0001). In economic terms, for every 1-standard-deviation increase in total skewness, call ratios increase approximately 75 basis points (bps). Column 2 shows that when including IDIO_SKEW$_{i,t-1}$ as the variable of interest, the coefficient is similar in sign and magnitude. In column 3, we do not find that SYST_SKEW$_{i,t-1}$ produces a coefficient that is reliably different from 0. This result is interesting in light of our findings in Table 2, which show a negative relation between call ratios and systematic skewness. Column 3 suggests that after controlling for other factors that might influence the call ratio, the systematic skewness of returns in the previous quarter is unrelated to call ratios. Again, this result is not surprising because the literature discussing preferences for lottery-type stocks uses total skewness or idiosyncratic skewness to proxy for lottery characteristics.

Column 4 of Table 3 reports the results when including MAX_RET$_{i,t-1}$ as the variable of interest. Consistent with our findings in Table 2, MAX_RET$_{i,t-1}$ produces a positive and significant estimate (estimate $= 0.0457$, p-value ≤ 0.0001). In economic terms, a 1-standard-deviation increase in the prior quarter's maximum daily return increases call ratios by nearly 40 bps.

Columns 5 and 6 of Table 3 present the results when including LOTTERY1 and LOTTERY2 as the independent variables of interest. Consistent with our univariate tests in Table 2, we find that both LOTTERY1 and LOTTERY2 produce coefficients that are reliably different from 0 (estimates $= 0.0149$, 0.0118; p-values ≤ 0.0001, ≤ 0.0001; respectively). Combined with our tests in the previous table, these results again suggest that call ratios are higher for stocks that represent lotteries and reject the null hypothesis (Hypothesis 1).

[8]We note that qualitatively similar results are found when we use pooled ordinary least squares (OLS) regressions and control for conditional heteroskedasticity using White (1980) robust standard errors.

TABLE 3

Panel Regression Analysis

Table 3 reports the results from estimating the following equation using pooled data:

$$\text{CALL_RATIO}_{i,t} = \alpha + \beta_1 \ln(\text{SIZE}_{i,t}) + \beta_2 \ln(\text{PRICE}_{i,t}) + \beta_3 \text{INST_OWN}_{i,t} + \beta_4 \text{BM}_{i,t} + \beta_5 \text{DA}_{i,t} + \beta_6 \text{TURN}_{i,t} + \beta_7 \text{IDIO_VOLT}_{i,t} + \beta_8 \text{RETURN}_{i,t} + \beta_9 \text{LOTTERY_CHARACTERISTICS}_{i,t-1} + \varepsilon_{i,t}.$$

The dependent variable is the CALL_RATIO for stock i in quarter t ($\text{CALL_RATIO}_{i,t}$). The independent variables include the natural log of market capitalization ($\ln(\text{SIZE}_{i,t})$), the natural log of the stock price ($\ln(\text{PRICE}_{i,t})$), institutional ownership ($\text{INST_OWN}_{i,t}$), the book-to-market ratio ($\text{BM}_{i,t}$), the debt-to-assets ratio ($\text{DA}_{i,t}$), the quarterly share turnover ($\text{TURN}_{i,t}$), idiosyncratic volatility ($\text{IDIO_VOLT}_{i,t}$), and the quarterly return ($\text{RETURN}_{i,t}$). The independent variable of interest is LOTTERY_CHARACTERISTICS. We define LOTTERY_CHARACTERISTICS in six separate ways. We include the previous-quarter total skewness of daily returns ($\text{TOT_SKEW}_{i,t-1}$), the previous-quarter systematic skewness ($\text{SYST_SKEW}_{i,t-1}$), and the previous-quarter idiosyncratic skewness ($\text{IDIO_SKEW}_{i,t-1}$). We also include the previous-quarter maximum daily return ($\text{MAX_RET}_{i,t-1}$) and two indicator variables: LOTTERY1 and LOTTERY2. We control for both stock and quarter fixed effects and report corresponding p-values in parentheses. * and ** indicate significance at the 5% and 1% levels, respectively.

	1	2	3	4	5	6
INTERCEPT	0.6136** (<0.0001)	0.6139** (<0.0001)	0.6168** (<0.0001)	0.6056** (<0.0001)	0.6021** (<0.0001)	0.6143** (<0.0001)
$\ln(\text{SIZE}_{i,t})$	0.0076** (<0.0001)	0.0076** (<0.0001)	0.0074** (<0.0001)	0.0070** (<0.0001)	0.0077** (<0.0001)	0.0074** (<0.0001)
$\ln(\text{PRICE}_{i,t})$	−0.0265** (<0.0001)	−0.0267** (<0.0001)	−0.0249** (<0.0001)	−0.0240** (<0.0001)	−0.0233** (<0.0001)	−0.0242** (<.0001)
$\text{INST_OWN}_{i,t}$	−0.0464** (<0.0001)	−0.0465** (<0.0001)	−0.0486** (<0.0001)	−0.0499** (<0.0001)	−0.0470** (<0.0001)	−0.0475** (<0.0001)
$\text{BM}_{i,t}$	−0.0001 (0.327)	−0.0001 (0.326)	−0.0001 (0.388)	−0.0001 (0.329)	−0.0001 (0.384)	−0.0001 (0.371)
$\text{DA}_{i,t}$	−0.0034 (0.478)	−0.0036 (0.445)	−0.0019 (0.686)	−0.0012 (0.802)	−0.0028 (0.561)	−0.0023 (0.632)
$\text{TURN}_{i,t}$	−0.0151** (<0.0001)	−0.0148** (<0.0001)	−0.0153** (<0.0001)	−0.0164** (<0.0001)	−0.0151** (<0.0001)	−0.0153** (<0.0001)
$\text{IDIO_VOLT}_{i,t}$	−0.2392** (0.001)	−0.2427** (0.001)	−0.2406** (0.001)	−0.2508** (<0.0001)	−0.2426** (0.001)	−0.2455** (0.001)
$\text{RETURN}_{i,t}$	0.0995** (<0.0001)	0.0995** (<0.0001)	0.0985** (<0.0001)	0.0988** (<0.0001)	0.0975** (<0.0001)	0.0980** (<0.0001)
$\text{TOT_SKEW}_{i,t-1}$	0.0062** (<0.0001)					
$\text{IDIO_SKEW}_{i,t-1}$		0.0061** (<0.0001)				
$\text{SYST_SKEW}_{i,t-1}$			−0.0006 (0.549)			
$\text{MAX_RET}_{i,t-1}$				0.0457** (<0.0001)		
LOTTERY1					0.0149** (<0.0001)	
LOTTERY2						0.0118** (<0.0001)
Adj. R^2	0.3032	0.3035	0.3016	0.3029	0.3024	0.3018
Stock fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

C. The Effect of Lottery Preferences on Spot Price Volatility: Univariate Tests

In this subsection we test our second hypothesis, Hypothesis 2, which suggests that the speculative portion of the call ratio will have a similar effect on spot price volatility as the nonspeculative portion of the call ratio. Stein (1987) shows that, under certain conditions, speculation in derivatives markets can destabilize prices. We attempt to empirically test this conjecture by examining the relationship

https://doi.org/10.1017/S002210901600020X Published online by Cambridge University Press

between next-quarter volatility and current-quarter speculative/nonspeculative call ratios. Although we are interested in isolating the effect of gambling preferences in the options market on future spot price volatility as part of our tests of Hypothesis 2, we recognize the need to provide a broader definition of speculative trading. Few studies have tested Stein's theory because of the difficulty in determining which trades are speculative in nature and which trades are not. In this section and those that follow, we attempt to decompose the call ratio into speculative and nonspeculative portions. Before doing so, we note that although the theoretical literature is robust when discussing speculative trading, very few empirical studies have provided estimates for speculative trading activity. In order to obtain the speculative portion of the call ratio, we must first measure the amount of speculative sentiment in a particular stock. We do so in three ways.

The first way we approximate speculative sentiment in a particular stock is by accounting for investors' preferences for lottery stocks that are reflected in higher call ratios. Golec and Tamarkin (1998) and Garrett and Sobel (1999) suggest that preferences for skewness represent gambling or speculative preferences. Given the literature that discusses some investors' preferences for lottery stocks, it is possible that these preferences, which might distort the traditional mean-variance preferences assumed by asset pricing theory, can create noisy prices, thus leading to higher levels of volatility in the spot market (Stein (1987)). Therefore, when decomposing the call ratio into speculative and nonspeculative portions, we first account for the relation between call ratios and lottery-type stock characteristics that have been discussed in the previous section.

As a second measure of speculative sentiment in a particular stock, we follow Llorente, Michaely, Saar, and Wang (2002), who develop a theoretical model that examines the dynamic relation between trading volume and stock returns to approximate speculative trading.[9] Their theory suggests that hedging trade volume will generate negatively autocorrelated returns, whereas speculative trade volume will generate positively autocorrelated returns. Because Lo and Wang (2000) show that the daily time series of stock turnover is nonstationary, Llorente et al. (2002) de-trend the time series of the natural log of daily share turnover. We also follow prior research (Campbell, Grossman, and Wang (1993), Llorente et al. (2002), and Covrig and Ng (2004)) and add a small constant (0.00000255) to turnover to account for days without trading volume. This constant is further shown to normalize the distribution of trading volume by Llorente et al. (2002) and Covrig and Ng (2004). Daily turnover is estimated in the following way for stock i on day t:

$$\ln(\text{TURN}_{i,t}) = \ln(\text{TURN}_{i,t} + 0.00000255), \tag{3}$$

[9] In a recent study by Han and Kumar (2013), they find that stocks with a high proportion of retail trading exhibit lottery-like features and suggests that "retail trading proportion" (RTP) can proxy for speculative trading. RTP is obtained by calculating the ratio of dollar volume from small trades (less than $5,000 in dollar volume) to total stock trading dollar volume during a particular time period. Because of order splitting by institutional traders after the decimalization period in 2001, Han and Kumar (2013) suggest that RTP might not capture retail trading, and therefore they truncate their sample at the year 2000. In unreported tests that use proxies for speculative trading, we calculate RTP for the first part of our sample time period (1997–2000) and conduct some robustness tests. In general, we are able to draw similar conclusions whether we use Llorente et al.'s (2002) measure of speculative trading or RTP as in Han and Kumar (2013).

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$$v_{i,t} = \ln(\text{TURN}_{i,t}) - \frac{1}{200}\sum_{s=200}^{-1}\ln(\text{TURN}_{i,t}), \quad (4)$$

where $v_{i,t}$ is the de-trended measure of trading activity and is obtained by taking the difference between the natural log of turnover and the mean of the natural log of turnover from day $t-1$ through $t-200$, where day t is the current trading day. We follow the empirical methods of Llorente et al. (2002) and approximate speculative trading by estimating the following time-series equation for each stock in our sample:

$$\text{RET}_{i,t+1} = \beta_0 + \beta_1\text{RET}_{i,t} + \beta_2\text{RET}_{i,t} \times v_{i,t} + \varepsilon_{i,t+1}. \quad (5)$$

Equation (5) provides a simple autoregressive formula where daily returns for each stock on day $t+1$ are regressed on daily returns for each stock on day t. According to Llorente et al. (2002), the interaction between $\text{RET}_{i,t}$ and $v_{i,t}$ in equation (5) produces the estimate for speculative trading. The idea is that the larger (and more positive) the estimate for β_2, the more likely that trading activity increases the return autocorrelation. To the extent that speculative trades will generate greater return autocorrelation, the estimate for β_2 proxies for speculative trading. Llorente et al. (2002) argue that a positive coefficient for β_2 represents the degree of speculative trading in a particular stock, whereas a negative coefficient for β_2 provides an estimate for hedging activity. We estimate equation (5) and obtain the coefficient β_2, which, for brevity, we denote as SPEC hereafter. The mean for SPEC in our sample is very close to 0 (mean $= -0.0056$) and seems to be normally distributed. Because Llorente et al. (2002) argue that it is positive estimates of β_2 that represent speculative trading in a particular stock, we create an indicator variable SPEC_DUMMY that equals 1 if a stock has an estimate of β_2 in the highest quartile. Stocks with SPEC_DUMMY equal to 1 have the most positive estimates of β_2 and therefore have the most speculative trading according to the arguments in Llorente et al. (2002). Speculative call ratios might lead to higher volatility in underlying security prices for the reasons argued by Stein (1987). When attempting to obtain the speculative portion of the call ratio, we will account for the relation between call ratios and this measure of speculative trading.

The third and final way we measure speculative sentiment is by including a measure of market-wide investor sentiment. Baker and Wurgler (2007) construct an investor sentiment index using principal components analysis on six variables that might influence the sentiment of investors, which we denote as BW_SENTIMENT for brevity.[10] We recognize that investor sentiment does not represent speculative sentiment, per se. However, we argue that the two types of sentiment are related, and when decomposing the call ratio, it will be important to account for the relation between the call ratio and the sentiment index. The correlation coefficient for call ratios and BW_SENTIMENT is 0.0184 (p-value $\leq$ 0.0001). Although investors may use call options for a variety of reasons (information, speculation, hedging, etc.), in our decomposition of the call ratio, we are

[10]The six components are trading volume on the New York Stock Exchange (NYSE), the dividend premium, the closed-end fund discount, the number of initial public offering (IPOs), the first-day returns on IPOs, and the share price of new equity issues.

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interested in capturing the portion of the call ratio that is related to speculative trading and the portion that is unrelated to speculative trading.

With our three measures of speculative sentiment, we decompose the call ratio in the following way. First, we estimate the following four regressions:

$$\text{(6)} \quad \text{CALL_RATIO}_{i,t} = \alpha + \beta_1 \text{LOTTERY1} + \beta_2 \text{SPEC_DUMMY}_{i,t} + \varepsilon_{i,t},$$

$$\text{(7)} \quad \text{CALL_RATIO}_{i,t} = \alpha + \beta_1 \text{LOTTERY1} + \beta_2 \text{MAX_RET}_{i,t-1} + \beta_3 \text{SPEC_DUMMY}_{i,t} + \varepsilon_{i,t},$$

$$\text{(8)} \quad \text{CALL_RATIO}_{i,t} = \alpha + \beta_1 \text{LOTTERY1} + \beta_2 \text{MAX_RET}_{i,t-1} + \beta_3 \text{IDIO_SKEW}_{i,t-1} + \beta_4 \text{SPEC_DUMMY}_{i,t} + \varepsilon_{i,t},$$

$$\text{(9)} \quad \text{CALL_RATIO}_{i,t} = \alpha + \beta_1 \text{LOTTERY1} + \beta_2 \text{MAX_RET}_{i,t-1} + \beta_3 \text{IDIO_SKEW}_{i,t-1} + \beta_4 \text{SPEC_DUMMY}_{i,t} + \beta_5 \text{BW_SENTIMENT}_{i,t} + \varepsilon_{i,t}.$$

We estimate each of these equations for each stock and obtain the predicted values and the residuals. To the extent that the variables included in the specifications properly represent speculative sentiment, the predicted values can be interpreted as the speculative portion of the call ratio. The residuals, on the other hand, contain the portion of the call ratio that is orthogonal to the measures of speculative sentiment and therefore represent the nonspeculative call ratio.[11] We denote $\widehat{\text{CR}}_{(1)i,t}$ and $\varepsilon_{(1)}$ as the speculative call ratio and the nonspeculative call ratio, respectively, for our first specification from equation (6). Likewise, we denote $\widehat{\text{CR}}_{(2)i,t}$ and $\varepsilon_{(2)}$ as the speculative call ratio and the nonspeculative call ratio, respectively, for our second specification from equation (7). Similarly, $\widehat{\text{CR}}_{(3)i,t}$, $\varepsilon_{(3)}$, $\widehat{\text{CR}}_{(4)i,t}$, and $\varepsilon_{(4)}$ are defined using our third and fourth specifications (equations (8) and (9)), respectively.

We recognize the need to highlight the slight differences between equations (6)–(9). Although we include LOTTERY1 and SPEC_DUMMY in each of the regressions, we also add the previous-quarter maximum daily return in equation (7), the idiosyncratic skewness of the previous-quarter returns in equation (8), and the Baker and Wurgler (2007) investor sentiment index in equation (9). Our objective in reporting the results from these four different specifications is to provide some robustness. We further note that in unreported tests, we include LOTTERY2 instead of LOTTERY1 in each specification and find the results to be similar to those reported in this study. Furthermore, we also use total skewness instead of idiosyncratic skewness and find similar results. In addition, we estimate regressions that include various combinations of the measures used in equation (9) and are able to draw similar conclusions.[12]

[11] It is possible to refer to the residuals from the estimated regressions as the hedging portion of the call ratio; however, we are cautious of doing so given the difficultly of identifying speculative sentiment versus hedging sentiment. As discussed earlier, few empirical studies have provided approximations for speculative trading. Even fewer have provided proxies for hedging activity. Therefore, we use the term *nonspeculative call ratios* instead of *hedging call ratios*, recognizing that we do not directly attempt to identify the hedging portion of the call ratio.

[12] In addition to the variety of specifications, we have also estimated simple regressions where the dependent variable is the call ratio and the single independent variable is each of the proxies for lottery

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Table 4 reports summary statistics for the predicted values and residuals obtained from estimating equations (6)–(9). The mean predicted values range from 0.6721 to 0.6726. By construction, the mean of each of the residuals is 0. The table also shows that the medians for both the predicted values and the residuals are close to the means. A closer examination of the table shows that both the predicted values and the residuals are distributed normally.

TABLE 4

Decomposed Call Ratio Summary Statistics

Table 4 reports summary statistics for the predicted values and residuals of the following regressions:

$$(1)\quad \text{CALL_RATIO}_{i,t} = \alpha + \beta_1 \text{LOTTERY1} + \beta_2 \text{SPEC_DUMMY}_{i,t} + \varepsilon_{i,t},$$

$$(2)\quad \text{CALL_RATIO}_{i,t} = \alpha + \beta_1 \text{LOTTERY1} + \beta_2 \text{MAX_RET}_{i,t-1} + \beta_3 \text{SPEC_DUMMY}_{i,t} + \varepsilon_{i,t},$$

$$(3)\quad \text{CALL_RATIO}_{i,t} = \alpha + \beta_1 \text{LOTTERY1} + \beta_2 \text{MAX_RET}_{i,t-1} + \beta_3 \text{IDIO_SKEW}_{i,t-1} + \beta_4 \text{SPEC_DUMMY}_{i,t} + \varepsilon_{i,t},$$

$$(4)\quad \text{CALL_RATIO}_{i,t} = \alpha + \beta_1 \text{LOTTERY1} + \beta_2 \text{MAX_RET}_{i,t-1} + \beta_3 \text{IDIO_SKEW}_{i,t-1} + \beta_4 \text{SPEC_DUMMY}_{i,t} + \beta_5 \text{BW_SENTIMENT}_{i,t} + \varepsilon_{i,t}.$$

The dependent variable is the call ratio ($\text{CALL_RATIO}_{i,t}$), and the independent variables include LOTTERY1, which is equal to 1 if a stock has prior-quarter idiosyncratic skewness in the highest 2 quartiles, prior-quarter idiosyncratic volatility in the highest 2 quartiles, and a closing price during the prior quarter in the lowest 2 quartiles. We also include SPEC_DUMMY, which is an indicator variable equal to 1 if Llorente et al.'s (2002) measure of speculative trading is in the highest contemporaneous quartile, and 0 otherwise. We further include the prior-quarter max daily return ($\text{MAX_RET}_{i,t-1}$) as well as the prior-quarter idiosyncratic skewness ($\text{IDIO_SKEW}_{i,t-1}$). In our fourth specification, we include Baker and Wurgler's (2007) monthly investor sentiment as an additional independent variable. In particular, we average the monthly sentiment to the quarterly level and include the contemporaneous quarterly sentiment as an additional variable capturing the portion of the call ratio that is related to speculation. We report distributional statistics for the predicted values as well as the residuals from estimating each of these equations.

	Mean	Std. Dev.	Minimum	P10	P25	Median	P75	P90	Maximum
	1	2	3	4	5	6	7	8	9
$\widehat{\text{CR}}_{(1)}$	0.6726	0.0948	0.4387	0.5541	0.6144	0.6711	0.7344	0.7927	0.8987
$\widehat{\text{CR}}_{(2)}$	0.6721	0.1029	0.4151	0.5470	0.6076	0.6701	0.7386	0.8014	0.9174
$\widehat{\text{CR}}_{(3)}$	0.6721	0.1084	0.3993	0.5420	0.6055	0.6709	0.7414	0.8066	0.9299
$\widehat{\text{CR}}_{(4)}$	0.6721	0.1156	0.3747	0.5326	0.6008	0.6718	0.7469	0.8151	0.9437
$\varepsilon_{(1)}$	0.0000	0.1442	−0.4119	−0.1808	−0.0785	0.0053	0.0917	0.1731	0.3129
$\varepsilon_{(2)}$	0.0000	0.1388	−0.3992	−0.1724	−0.0740	0.0034	0.0863	0.1664	0.3088
$\varepsilon_{(3)}$	0.0000	0.1353	−0.3992	−0.1666	−0.0715	0.0014	0.0827	0.1625	0.3063
$\varepsilon_{(4)}$	0.0000	0.1393	−0.3728	−0.1574	−0.0672	0.0000	0.0769	0.1541	0.2969

With our approximations for speculative and nonspeculative call ratios, we are ready to provide univariate tests of the null Hypothesis 2, which suggests that the effect of speculative and nonspeculative call ratios on future spot price volatility will be similar. We begin by first sorting the data into quartiles based first on the dependent variable in equations (6)–(9), which we denote for exposition as the total call ratio. This total call ratio contains both the portion of the ratio that is orthogonal to our measures of speculative sentiment (nonspeculative call ratio) and the portion of the ratio that is directly related to our measures of speculative sentiment (speculative call ratio). After sorting the data based on the total call ratio, we then report next-quarter idiosyncratic volatility in the underlying stock across total call ratio quartiles. Column 1 of Table 5 presents these results. In column 1, we find that next-quarter idiosyncratic volatility is increasing monotonically across

stocks. We then take the predicted value of these simple regressions to approximate the speculative call ratio and the residuals to approximate the nonspeculative call ratios. We are able to draw conclusions from these unreported tests that are similar to the conclusions drawn in this study.

https://doi.org/10.1017/S002210901600020X Published online by Cambridge University Press

TABLE 5

The Relation between Speculative and Nonspeculative Call Ratios and Future Spot Price Volatility

Table 5 reports the univariate relation between speculative and nonspeculative call ratios and future idiosyncratic volatility. The decomposition of the call ratios into speculative and nonspeculative portions is obtained using the following regressions:

$$\text{(1)} \quad \text{CALL_RATIO}_{i,t} = \alpha + \beta_1 \text{LOTTERY1} + \beta_2 \text{SPEC_DUMMY}_{i,t} + \varepsilon_{i,t},$$

$$\text{(2)} \quad \text{CALL_RATIO}_{i,t} = \alpha + \beta_1 \text{LOTTERY1} + \beta_2 \text{MAX_RET}_{i,t-1} + \beta_3 \text{SPEC_DUMMY}_{i,t} + \varepsilon_{i,t},$$

$$\text{(3)} \quad \text{CALL_RATIO}_{i,t} = \alpha + \beta_1 \text{LOTTERY1} + \beta_2 \text{MAX_RET}_{i,t-1} + \beta_3 \text{IDIO_SKEW}_{i,t-1} + \beta_4 \text{SPEC_DUMMY}_{i,t} + \varepsilon_{i,t},$$

$$\text{(4)} \quad \text{CALL_RATIO}_{i,t} = \alpha + \beta_1 \text{LOTTERY1} + \beta_2 \text{MAX_RET}_{i,t-1} + \beta_3 \text{IDIO_SKEW}_{i,t-1} + \beta_4 \text{SPEC_DUMMY}_{i,t} + \beta_5 \text{BW_SENTIMENT}_{i,t} + \varepsilon_{i,}.$$

The dependent variable is the call ratio, and independent variables include LOTTERY1, $\text{SPEC_DUMMY}_{i,t}$, $\text{MAX_RET}_{i,t-1}$, $\text{IDIO_SKEW}_{i,t-1}$, and $\text{BW_SENTIMENT}_{i,t}$ (all of which have been defined previously). After obtaining predicted values, which represent the portion of the call ratio related to speculative trading, and residuals, which represent the nonspeculative (or hedging) portion of the call ratio, we sort stocks into quartiles for each quarter by total call ratios, predicted values, and residuals and estimate the mean $\text{IDIO_VOLT}_{i,t+1}$ for each quartile. We also report the mean difference between extreme quartiles along with a corresponding *p*-value. Furthermore, we report the correlation coefficient between speculative and nonspeculative call ratios and future idiosyncratic volatility along with the corresponding *p*-values. All *p*-values are in parentheses. * and ** indicate significance at the 5% and 1% levels, respectively.

	$\text{IDIO_VOLT}_{i,t+1}$								
	Sort by CR	Sort by $\widehat{\text{CR}}_{(1)}$	Sort by $\widehat{\text{CR}}_{(2)}$	Sort by $\widehat{\text{CR}}_{(3)}$	Sort by $\widehat{\text{CR}}_{(4)}$	Sort by $\varepsilon_{(1)}$	Sort by $\varepsilon_{(2)}$	Sort by $\varepsilon_{(3)}$	Sort by $\varepsilon_{(4)}$
	1	2	3	4	5	6	7	8	9
Q I (low)	0.0236	0.0229	0.0229	0.0229	0.0232	0.0251	0.0248	0.0247	0.0244
Q II	0.0246	0.0231	0.0233	0.0235	0.0235	0.0265	0.0266	0.0267	0.0269
Q III	0.0264	0.0249	0.0249	0.0249	0.0251	0.0263	0.0263	0.0264	0.0266
Q IV (high)	0.0277	0.0313	0.0306	0.0304	0.0301	0.0244	0.0242	0.0241	0.0239
Q IV – Q I	0.0041**	0.0084**	0.0077**	0.0075**	0.0069**	−0.0007**	−0.0006**	−0.0006**	−0.0005**
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.001)	(0.001)	(0.002)	(0.004)
Correlation	0.1318**	0.2193**	0.2128**	0.2017**	0.1852**	0.0137**	0.0051	0.0057	0.0095*
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.211)	(0.159)	(0.018)

https://doi.org/10.1017/S002210901600020X Published online by Cambridge University Press

https://doi.org/10.1017/S002210901600020X Published online by Cambridge University Press

total call ratio quartiles. The column also reports the difference between extreme quartiles (difference = 0.0041, p-value $\leq$ 0.0001) as well as the univariate correlation coefficient (correlation = 0.1318, p-value $\leq$ 0.0001). These results suggest that call ratios are directly related to next-quarter idiosyncratic volatility and indicate that higher call ratios destabilize stock prices. Columns 2–5 present the results when sorting stocks into quartiles based on the predicted values from equations (6)–(9). The results in these columns indicate that next-quarter spot price volatility is monotonically increasing across speculative call ratios. We note that this positive relation is robust to each of the predicted values from the four specifications. We further note that the differences between extreme quartiles in columns 2–5 are 68%–105% larger than the difference between extreme quartiles in column 1. Furthermore, the correlation coefficients in columns 2–5 are larger in magnitude than the correlation coefficient in column 1. These results seem to indicate that the direct relation between total call ratios and next-quarter idiosyncratic volatility is driven by the portion of the call ratio that is related to speculative sentiment.

Columns 6–9 of Table 5 present the results when we sort by the estimated residuals from equations (6)–(9). Interestingly, when we sort stocks into quartiles based on our approximations for nonspeculative call ratios, we find that next-quarter volatility is neither increasing nor decreasing. The differences between extreme quartiles are negative instead of positive as in earlier columns. Furthermore, the correlation coefficients are not statistically significant in columns 7 and 8. Combined with our findings in columns 1–5, these results suggest that the portion of the call ratio that is unrelated to our measures of speculative sentiment has little, if any, impact on future idiosyncratic volatility. We are thus able to reject Hypothesis 2 and conclude that whereas nonspeculative call ratios are unrelated to future idiosyncratic volatility, speculative call ratios indeed affect the future idiosyncratic volatility in the spot market.

D. The Effect of Lottery Preferences on Spot Price Volatility: Multivariate Tests

In this section we provide multivariate tests of Hypothesis 2. We begin by estimating the following equation using pooled data:

$$\begin{aligned}(10)\quad \ln(\text{IDIO_VOLT}_{i,t+1}) &= \alpha + \beta_1 \ln(\text{SIZE}_{i,t+1}) + \beta_2 \ln(\text{PRICE}_{i,t+1}) + \beta_3 \ln(\text{IDIO_VOLT}_{i,t}) \\ &\quad + \beta_4 \ln(1 + \text{INST_OWN}_{i,t+1}) + \beta_5 \text{BM}_{i,t+1} + \beta_6 \text{DA}_{i,t+1} \\ &\quad + \beta_7 \text{RETURN}_{i,t} + \beta_8 \text{IDIO_SKEW}_{i,t+1} + \beta_9 \text{FIRM_AGE}_{i,t+1} \\ &\quad + \beta_{10} \text{TURN}_{i,t+1} + \beta_{11} \text{VARIOUS_CALL_RATIOS}_{i,t} + \varepsilon_{i,t+1}.\end{aligned}$$

Equation (10) closely follows the specification of Brandt, Brav, Graham, and Kumar (2010). For example, the dependent variable is the natural log of idiosyncratic volatility for stock i during quarter $t + 1$. The independent variables include the natural log of market capitalization $(\ln(\text{SIZE}_{i,t+1}))$, the natural log of the share price $(\ln(\text{PRICE}_{i,t+1}))$, the natural log of idiosyncratic volatility $(\ln(\text{IDIO_VOLT}_{i,t}))$, the natural log of 1 plus the institutional ownership in quarter

$t + 1$ ($\ln(1+\text{INST_OWN}_{i,t+1})$), the book-to-market ratio ($\text{BM}_{i,t+1}$), the debt-to-assets ratio ($\text{DA}_{i,t+1}$), the return for stock i during quarter t ($\text{RETURN}_{i,t}$), the idiosyncratic skewness during quarter $t+1$ ($\text{IDIO_SKEW}_{i,t+1}$), the age of the firm in years in $t + 1$ ($\text{FIRM_AGE}_{i,t+1}$), and share turnover in $t + 1$ ($\text{TURN}_{i,t+1}$). We note that the market cap, the share price, institutional ownership, the BM ratio, the DA ratio, idiosyncratic skewness, the age of the firm, and share turnover are each measured contemporaneous to the dependent variable, as is done by Brandt et al. (2010). The variables of interest are VARIOUS_CALL_RATIOS. We include in Panel A of Table 6 the total call ratio during quarter t ($\text{CR}_{i,t}$) and each of the previously defined speculative call ratios during quarter t. In Panel B we include as independent variables of interest the nonspeculative call ratios during quarter t. As before, a Hausman test rejects the presence of random effects, and an F-test indicates the presence of fixed effects by both stock and quarter. Therefore, we control for both stock and quarter fixed effects in the estimation of equation (10).

Panel A of Table 6 reports the results from estimating equation (10). In each of the columns, we find that next-quarter idiosyncratic volatility is inversely related to market cap, the share price, and the lagged stock return. Furthermore, next-quarter idiosyncratic volatility is directly related to the current-quarter idiosyncratic volatility, idiosyncratic skewness, and share turnover. These findings are similar to those of Brandt et al. (2010). We do not find reliable estimates for institutional ownership, BM ratios, and DA ratios. One difference between the estimates for the control variables in Table 6 and those reported by Brandt et al. is the sign of the coefficient on the age of the firm. Whereas Brandt et al. report a positive and significant estimate, we consistently find that firm age is negatively related to idiosyncratic volatility. A possible explanation for this difference is the differences in our samples. We require stocks to have tradable options, which limits the number of stocks in our sample relative to the sample used by Brandt et al. (2010). Nevertheless, the many similarities between the coefficients on the control variables in Table 6 and the analysis by Brandt et al. (2010) are important to note.

Focusing now on our tests of Hypothesis 2, column 1 of Table 6 reports an estimate on the total call ratio of 0.0319. However, we note that this coefficient is only marginally significant (p-value $= 0.056$). Relative to our univariate tests, this result suggests that when controlling for other factors that influence next-quarter idiosyncratic volatility, the positive relation between total call ratios and next-quarter idiosyncratic volatility becomes weak, at best. Columns 2–5 of Panel A show that speculative call ratios produce positive and reliably significant coefficients. For instance, in column 2, the coefficient on $\widehat{\text{CR}}_{(1)i,t}$ is 0.1547 (p-value $=$ 0.005). In economic terms, a 1-standard-deviation increase in $\widehat{\text{CR}}_{(1)i,t}$ would represent a nearly 1.5% increase in next-quarter idiosyncratic volatility. Results in columns 3–5 are similar. For instance, a 1-standard-deviation increase in the speculative call ratios in these columns represents an increase in next-quarter idiosyncratic volatility that ranges from 1.3% to 2.2%. In light of the only marginally significant coefficient on the total call ratio in column 1, the highly significant coefficients on the portions of the call ratio that are related to speculative sentiment suggest that speculative call ratios may lead to destabilized stock prices.

Panel B of Table 6 reports the results when the variables of interest are the nonspeculative call ratios or the residuals from the estimation of equations

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(6)–(9). Panel B shows that the coefficients on the control variables are similar in sign and magnitude to those in Panel A. However, the coefficients for the nonspeculative call ratios are consistently close to 0. In fact, in each of the four

TABLE 6

Panel Regression Analysis

Table 6 reports the results from estimating the following equation using pooled data:

$$\ln(\text{IDIO_VOLT}_{i,t+1}) = \alpha + \beta_1 \ln(\text{SIZE}_{i,t+1}) + \beta_2 \ln(\text{PRICE}_{i,t+1}) + \beta_3 \ln(\text{IDIO_VOLT}_{i,t}) + \beta_4 \ln(1 + \text{INST_OWN}_{i,t+1}) + \beta_5 \text{BM}_{i,t+1} + \beta_6 \text{DA}_{i,t+1} + \beta_7 \text{RETURN}_{i,t} + \beta_8 \text{IDIO_SKEW}_{i,t+1} + \beta_9 \text{FIRM_AGE}_{i,t+1} + \beta_{10} \text{TURN}_{i,t+1} + \beta_{11} \text{VARIOUS_CALL_RATIOS}_{i,t} + \varepsilon_{i,t+1}.$$

The dependent variable is the natural log of idiosyncratic volatility for stock i during quarter $t + 1$. Following Brandt et al. (2010), we include the following variables as regressors: the natural log of market capitalization during quarter $t + 1$ ($\ln(\text{SIZE}_{i,t+1})$), the natural log of price during the same quarter ($\ln(\text{PRICE}_{i,t+1})$), the natural log of idiosyncratic volatility during quarter t ($\ln(\text{IDIO_VOLT}_{i,t})$), the natural log of 1 plus the institutional ownership in $t + 1$ ($\ln(1+\text{INST_OWN}_{i,t+1})$), the book-to-market ratio ($\text{BM}_{i,t+1}$), the debt-to-assets ratio ($\text{DA}_{i,t+1}$), the return for stock i during quarter t ($\text{RETURN}_{i,t}$), the idiosyncratic skewness during quarter $t + 1$ ($\text{IDIO_SKEW}_{i,t+1}$), the age of the firm in years in $t + 1$ ($\text{FIRM_AGE}_{i,t+1}$), and share turnover in $t + 1$ ($\text{TURN}_{i,t+1}$). The variables of interest are various call ratios. We include in Panel A the total call ratio during quarter t ($\text{CR}_{i,t}$) and each of the speculative call ratios defined previously during quarter t. Panel B shows the results when we include residual call ratios representing the nonspeculative portion of the call ratio for stock i during quarter t. We control for both stock and quarter fixed effects and report corresponding p-values in parentheses. * and ** indicate significance at the 5% and 1% levels, respectively.

Panel A. Independent Variables of Interest: Total Call Ratios and Speculative Call Ratios

	1	2	3	4	5
INTERCEPT	−2.7385** (<0.0001)	−2.8130** (<0.0001)	−2.8673** (<0.0001)	−2.8400** (<0.0001)	−2.8130** (<0.0001)
$\ln(\text{SIZE}_{i,t+1})$	−0.0246** (0.002)	−0.0245** (0.002)	−0.0243** (0.002)	−0.0242** (0.002)	−0.0241** (0.002)
$\ln(\text{PRICE}_{i,t+1})$	−0.1318** (<0.0001)	−0.1316** (<0.0001)	−0.1307** (<0.0001)	−0.1315** (<0.0001)	−0.1317** (<0.0001)
$\ln(\text{IDIO_VOLT}_{i,t})$	0.2115** (<0.0001)	0.2112** (<0.0001)	0.2112** (<0.0001)	0.2111** (<0.0001)	0.2111** (<0.0001)
$\ln(1+\text{INST_OWN}_{i,t+1})$	−0.0530 (0.172)	−0.0525 (0.175)	−0.0527 (0.173)	−0.0525 (0.175)	−0.0523 (0.177)
$\text{BM}_{i,t+1}$	0.0008 (0.108)	0.0008 (0.106)	0.0009 (0.103)	0.0009 (0.103)	0.0009 (0.103)
$\text{DA}_{i,t+1}$	0.0076 (0.710)	0.0077 (0.704)	0.0077 (0.704)	0.0080 (0.695)	0.0081 (0.691)
$\text{RETURN}_{i,t}$	−0.0610** (<0.0001)	−0.0595** (<0.0001)	−0.0620** (<0.0001)	−0.0613** (<0.0001)	−0.0616** (<0.0001)
$\text{IDIO_SKEW}_{i,t+1}$	0.0067** (0.001)	0.0066** (0.001)	0.0066** (0.001)	0.0066** (0.001)	0.0066** (0.001)
$\text{FIRM_AGE}_{i,t+1}$	−0.0022* (0.020)	−0.0022* (0.019)	−0.0022* (0.020)	−0.0021* (0.022)	−0.0021* (0.022)
$\text{TURN}_{i,t+1}$	0.2463** (<0.0001)	0.2459** (<0.0001)	0.2462** (<0.0001)	0.2462** (<0.0001)	0.2464** (<0.0001)
$\text{CR}_{i,t}$	0.0319 (0.056)				
$\widehat{\text{CR}}_{(1)i,t}$		0.1547** (0.005)			
$\widehat{\text{CR}}_{(2)i,t}$			0.2157** (<0.0001)		
$\widehat{\text{CR}}_{(3)i,t}$				0.1558** (<0.0001)	
$\widehat{\text{CR}}_{(4)i,t}$					0.1192** (<0.0001)
Adj. R^2	0.4741	0.4741	0.4743	0.4743	0.4742
Stock fixed effects	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes

(continued on next page)

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TABLE 6 (continued)
Panel Regression Analysis

Panel B. Independent Variables of Interest: Nonspeculative Call Ratios

	1	2	3	4
INTERCEPT	−2.7171** (<0.0001)	−2.7151** (<0.0001)	−2.7171** (<0.0001)	−2.7173** (<0.0001)
$\ln(SIZE_{i,t})$	−0.0246** (0.002)	−0.0244** (0.002)	−0.0243** (0.002)	−0.0243** (0.002)
$\ln(PRICE_{i,t})$	−0.1321** (<0.0001)	−0.1325** (<0.0001)	−0.1327** (<0.0001)	−0.1327** (<0.0001)
$\ln(IDIO_VOLT_{i,t})$	0.2114** (<0.0001)	0.2113** (<0.0001)	0.2112** (<0.0001)	0.2112** (<0.0001)
$\ln(1+INST_OWN_{i,t})$	−0.0542 (0.162)	−0.0555 (0.152)	−0.0555 (0.152)	−0.0555 (0.152)
$BM_{i,t}$	0.0008 (0.109)	0.0008 (0.109)	0.0008 (0.109)	0.00008 (0.109)
$DA_{i,t}$	0.0075 (0.712)	0.0075 (0.712)	0.0076 (0.710)	0.0076 (0.710)
$RETURN_{i,t}$	−0.0594** (<0.0001)	−0.0574** (<0.0001)	−0.0575** (<0.0001)	−0.0574** (<0.0001)
$IDIO_SKEW_{i,t}$	0.0067** (0.001)	0.0067** (0.001)	0.0067** (0.001)	0.0067** (0.001)
$FIRM_AGE_{i,t}$	−0.0022* (0.020)	−0.0022* (0.020)	−0.0021* (0.023)	−0.0021* (0.022)
$TURN_{i,t}$	0.2460** (<0.0001)	0.2456** (<0.0001)	0.2457** (<0.0001)	0.2456** (<0.0001)
$\varepsilon_{(1)i,t}$	0.0190 (0.274)			
$\varepsilon_{(2)i,t}$		−0.0033 (0.852)		
$\varepsilon_{(3)i,t}$			−0.0008 (0.965)	
$\varepsilon_{(4)i,t}$				−0.0025 (0.897)
Adj. R^2	0.4741	0.4740	0.4741	0.4741
Stock fixed effects	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes

specifications, the nonspeculative call ratios are not reliably different from 0. Compared to our findings in Panel A, the results here suggest that, after controlling for other factors that influence next-quarter idiosyncratic volatility, nonspeculative call ratios are unrelated to future idiosyncratic volatility. These results, combined with those in Panel A, reject Hypothesis 2 and suggest that speculative call option activity increases future spot price volatility, whereas nonspeculative call option activity does not. To the extent that our decomposition of call ratios accurately identifies speculative and nonspeculative intentions by investors, our findings support Stein's (1987) theory suggesting that speculation in the options market can adversely affect the stability of prices in the underlying spot market.

E. Robustness Tests

In this subsection, we discuss various robustness tests that have been carried out. For brevity, we do not tabulate the results from these tests but provide a

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brief description here. First, when we attempt to identify the relation between call ratios and lottery-type stock characteristics, we use an indicator variable approach instead of using continuous variables such as idiosyncratic skewness or the maximum daily return. We create indicator variables by sorting stock-quarter observations into quartiles based on these continuous measures of stock lotteries. Stocks in the highest quartiles are given the value of 1, and 0 otherwise. We then report call ratios based on this classification. Again, we find that call ratios are markedly higher for stocks that are in the highest quartiles, suggesting that call ratios exhibit investors' preferences for lottery-like characteristics. We also find that when including these indicator variables in our specifications that decompose the call ratio, we still find that speculative call ratios increase future idiosyncratic volatility, whereas nonspeculative call ratios do not.

Next, we use alternative measures of both idiosyncratic skewness and idiosyncratic volatility. Instead of obtaining idiosyncratic skewness using a 2-factor model, as Kumar (2009) does, we use the residuals from estimating a daily capital asset pricing model (CAPM) regression to obtain idiosyncratic skewness. The results are qualitatively similar to those discussed throughout the study.[13] We also use two alternative measures of idiosyncratic volatility. The first, which is similar to our alternative measure of idiosyncratic skewness, is the standard deviation of residual returns from a daily CAPM regression. The second measure of idiosyncratic volatility is calculated following Campbell, Lettau, Malkiel, and Xu (2001) and Brandt et al. (2010). Here, we estimate the standard deviation of market-adjusted returns, where the market return is value weighted by industry (using the 48 Fama–French (1997) industry codes). Results using either of these two alternative measures of idiosyncratic volatility are similar to those reported in this paper.[14]

When testing Hypothesis 2, we include as an additional measure of speculative sentiment Han and Kumar's (2013) measure of retail trading proportion (RTP), which is the ratio of dollar volume of small trades (less than $5,000) to total dollar volume during a particular quarter. The idea is that RTP represents the amount of individual or retail trading activity that is likely to be motivated by speculation. One issue with the measure of RTP is that because of order splitting since 2001's decimalization, small trades do not correctly distinguish retail traders from institutional traders. Therefore, Han and Kumar (2013) use only data before decimalization. Using data from 1997–2000, we use RTP as an additional measure of speculative sentiment. We first note that RTP is directly related to the call ratio (correlation $= 0.0779$, p-value ≤ 0.0001) suggesting that at least some of the call ratio is related to speculative trading activity. Second, when we use RTP to decompose the call ratio, we still find a direct relation between speculative call ratios (using RTP) and future idiosyncratic volatility. Similar to the results reported by Han and Kumar (2013), we do not find a direct relation between nonspeculative call ratios and future idiosyncratic volatility when using RTP.

[13]By way of information, the correlation between the measure of idiosyncratic skewness in this study and the measure using a daily CAPM regression is 0.9703 (p-value ≤ 0.0001).

[14]For example, the correlations between these two alternative measures of idiosyncratic volatility and the measure used in this study are 0.9850 and 0.9732 (p-values ≤ 0.0001), respectively.

V. Conclusions

Prior research finds that some investors have preferences for stock with lottery-like characteristics (see Barberis and Huang (2008), Mitton and Vorkink (2007), Kumar (2009), Boyer et al. (2010), and Kumar et al. (2011)). Using similar approximations for lottery-type stocks, we test whether there is proportionately more call option volume relative to put option volume in lottery stocks. The motivation behind these tests is based on the idea that the payoff of a call option (i.e., the limited downside risk and unlimited upside potential) is attractive for investors with lottery preferences. Both our univariate and multivariate tests show that call ratios are the greatest in lottery-type stocks, indicating that preferences for lotteries are reflected in greater levels of call option volume.

To the extent that the relation between call ratios and lottery-type stock characteristics represents speculative trading in the options market, we next examine the effect of this speculative trading behavior on the stability of underlying stock prices. Stein's (1987) theory posits that speculative trading in derivatives markets can lead to destabilized prices when the negative externalities of speculation outweigh the positive externalities of speculation. In particular, whereas options allow the possibility of risk sharing by investors, which can improve the efficiency of spot prices, speculative trading can produce noise, which will adversely affect the ability of informed traders to stabilize spot prices. We attempt to provide an empirical test of Stein's theory.

We begin by separating the call ratio into speculative and nonspeculative portions. We then examine the relationship between both the speculative call ratio and nonspeculative call ratio and the future volatility of the underlying stock. First, our univariate and multivariate tests show a direct relation between the call ratio and the future volatility in spot prices. Second, our tests indicate that the relation between future volatility and total call ratios is driven by the speculative portion of the call ratio. Third, we do not find that nonspeculative call ratios are related to future spot price volatility. Combined, the results suggest that the direct relation between call ratios and future volatility is driven by the speculative portion of the call ratio as opposed to the nonspeculative portion of the call ratio. These tests provide empirical support for Stein's (1987) theory that speculative trading in the options market can destabilize spot prices.

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