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Cross-Sectional Analysis of Risk-Neutral Skewness

S.J. Taylor • P.K. Yadav • Y. Zhang

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Stephen J. Taylor[1], Pradeep K. Yadav[2], and Yuanyuan Zhang[3]

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Abstract

We investigate the association of various firm-specific and market-wide factors with the risk-neutral skewness (RNS) implied by the prices of individual stock options. Our analysis covers 149 U.S. firms over a four-year period. Our choice of firms is based on adequate liquidity and trading interest across different strike prices in the options market, ensuring economically meaningful RNS estimates. We also incorporate significant methodological enhancements. Consistent with earlier results, we find that the RNS of individual firms varies significantly and negatively with firm size, firm systematic risk, and market volatility; and significantly and positively with the RNS of the market index; and most of the variation in individual RNS is explained by firm-specific rather than market-wide factors. We also document several interesting new results that are clearly unambiguous and significantly stronger than in earlier work, or opposite to earlier evidence, or for variables that have been examined for the first time. First, we find that market sentiment has a negative and significant effect on RNS. Second, we find that higher a firm's own volatility, the more negative the RNS, a relationship that is in the same direction as for overall market volatility. Third, greater market liquidity is associated with more negative RNS, but the liquidity that is relevant for RNS is that of the options market, rather than that in the underlying stock. Surprisingly, volatility asymmetry is not relevant for RNS. Finally, the leverage ratio is not negatively but positively and strongly related with RNS.

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[1] Stephen Taylor is Professor of Finance at the Department of Accounting and Finance, Lancaster University Management School, Lancaster LA1 4YX, UK. Tel: +44 (0) 1524 593624; E-mail: s.taylor@lancaster.ac.uk.

[2] Pradeep Yadav is W. Ross Johnston Chair in Finance and Professor of Finance, at the Michael F. Price College of Business, Oklahoma University, 307 W. Brooks, Adam Hall 205A, Norman, OK 73019. Tel: 405-325-6640; E-mail: pyadav@ou.edu. He is also (Visiting) Professor of Finance at the Department of Accounting and Finance, Lancaster University, and Research Fellow of the Center for Financial Research at the University of Cologne.

[3] Yuanyuan Zhang is Assistant Professor of Finance at the Department of Finance and Insurance, Lingnan University, Ho Sin Hang Building, 8 Castle Peak Road, Tuen Mum, Hong Kong. Tel: +852 (0) 2616 8158; E-mail: zhangy@ln.edu.hk.

1 Introduction

Fundamentally, the price of a financial asset equals the present value of its expected payoffs discounted at rates that are suitably adjusted for risk. The risk premium is unobservable, but since an option can be priced through a no-arbitrage based relationship with the underlying asset, and risk preferences are impounded in the underlying asset price, the price of an option can be calculated through expected payoffs based on a risk-neutral probability distribution of underlying asset returns discounted at the risk-free rate. The option-implied risk-neutral probability distribution can accordingly be extracted from market option prices following the methods described, for example, in Jackwerth (1999), Bliss and Panigirtzoglou (2002) and Figlewski (2009). This paper focuses on the third moment of the risk-neutral distribution, i.e. the risk-neutral skewness, for which we will hereafter use the acronym RNS.

It is important to distinguish RNS from the "implied volatility skew" (IVS) that refers to the slope of the function that defines the dependence of the implied volatility IV on the strike price K of an option. The slope of $IV(K)$ is a function of K: it is usually negative for $K<S$ (where S is the underlying asset price), and sometimes positive for $K>>S$. The function $IV(K)$ corresponds to the call option price function $C(K)$ and thence to the risk neutral density (hereafter RND) at that strike, say $f(K)$. The slope and curvature of $IV(K)$ at K will define $f(K)$, but not be informative about $f(x)$ where $x<>K$. RND and IVS are related through a one-to-one mapping. On the other hand, RNS is a single number that depends on and describes an attribute of the RND function. So RNS and IVS are very different concepts. If the implied volatility of out-of-the-money (OTM) puts is higher than that of in-the-money (ITM) puts, the IVS will obviously be negative, and the RNS will be negative as well. A negative RNS also implies that the probability for a sufficiently OTM put to pay off is higher than the probability for a corresponding OTM call. However, overall, the mathematical relationship between IVS and RNS is complicated.

Option implied volatilities provide ex-ante expectations of the volatility of returns up to options maturity, and are understandably subject to intensive tracking and analysis by market participants. However, a significantly more complete picture of expectations can be inferred from knowledge and understanding of the parameters that define the RND, e.g., parameters like the RNS, and hence these parameters are extremely valuable for market participants. Unlike implied volatilities, the extracted second and higher moments of the risk-neutral probability distribution are not dependent on any specific option pricing model[1]. And importantly, they are relevant not just for volatility, but more generally, also for higher moments like RNS and risk-neutral kurtosis, and a spectrum of related attributes like implied risk aversion estimates. Jackwerth and Rubinstein (1996) and Jackwerth (2000) show that the option implied risk-neutral distribution of the S&P500 index, is negatively skewed and more peaked than the lognormal distribution, especially after the 1987 crash. The RND framework enables estimation, knowledge and understanding of “model-free” third and higher moments of the risk-neutral distribution, including RNS, the variable we focus on in this paper. In this context, the risk-neutral distribution specifically impounds information about consensus expectations and marginal value-relevant preferences, information that is very relevant to short-term traders, long-term investors and policy-makers alike. The cross-sectional and time-series variation in these implied parameters potentially indicates how news announcements, economic factors and economic events change market expectations and preferences in an efficient market. An excellent recent example of the valuable insights that can be provided by RND parameters is Birru and Figlewski (2009), who examine the intraday behaviour of the RND for the S&P 500 Index to provide a high-resolution picture of how investors' risk and return expectations changed during the financial crisis in the fall of 2008. Clearly, a richer understanding of the firm-specific factors influencing RNS will enable traders to better infer expectations and preferences, and better manage risks.

This paper follows from earlier pioneering work on RNS by Bakshi, Kapadia and Madan (2003), hereafter BKM, and by Dennis and Mayhew (2002), hereafter DM. BKM provide a framework for extracting RNS from option prices, show that individual risk-neutral distributions are qualitatively distinct from their index counterparts, specifically demonstrating that they are significantly less negatively skewed than the market index, and decompose individual return skewness into a systematic and an idiosyncratic component. DM examine the relationship between RNS and six firm specific factors for 1,421 U.S. firms from 1986 to 1996. DM show that stock trading volume, firm size, firm beta and market volatility are negatively related with the RNS of individual stocks, while firm volatility and market RNS are positively related. DM do not find a consistent relationship between market sentiment and RNS, and their largely positive relation between leverage ratio and RNS is contrary to what Toft and Prucyk (1997) find for 138 U.S. firms from 1993 to 1994[2]. DM also find that individual firm RNS are much less negative than market index RNS, and depend on both market factors and firm specific factors, with the latter much more important than the former[3].

This paper is closely related to DM, but differs in its sample period and firm selection criteria, adds relevant explanatory variables, and also provides methodological enhancements. Our analysis covers 149 U.S. firms over a four-year period 1996-99. Our choice of firms is based on criteria that ensure adequate liquidity and trading interest across different strike prices in the options market, and thereby ensure economically meaningful RNS estimates. We introduce at least two new explanatory variables: the trading volume in the options market (distinct from trading volume in the underlying stock market), and the asymmetric volatility ratio. From a methodological perspective, calculation of risk-neutral moments in BKM requires estimating integrals of function of option prices. DM use the same principle, but use only the discrete market option prices that are available, and there are usually only a few observations available for individual stocks, especially for their earlier sample period. On the other hand, we fit implied volatility curves to better approximate the integral functions involved, and thereby infer a large number of option prices.

Consistent with earlier results, we find that the RNS of individual firms varies significantly and negatively with firm size, firm systematic risk, and market volatility; and significantly and positively with the RNS of the market index; and most of the variation in individual RNS is explained by firm-specific rather than market-wide factors. As in earlier work, we also find that the lagged RNS contains information about the current RNS through potentially omitted variables, but, after controlling for overlapping data, we show that this is much less than what had appeared to exist earlier.

We also document several interesting new results that are clearly unambiguous and significantly stronger than in earlier work, or opposite to earlier evidence, or for variables that have been examined for the first time. First, we find that market sentiment has, consistent with expectation, a negative and significant effect on RNS. Second, unlike DM, we find that higher a firm's own volatility, the more negative the RNS, a relationship that is consistent with that for overall market volatility. Third, greater market liquidity is associated with more negative RNS, but the liquidity that is relevant for RNS is that of the options market, rather than that in the underlying stock, and this options market liquidity has been investigated in this context for the first time. Fourth, another new result, contrary to expectation, is that volatility asymmetry is not relevant for RNS. Finally, consistent with DM, but different from Toft and Prucyk (1997), the leverage ratio is not negatively but positively and strongly related with RNS.

This paper is organized as follows. Section 2 motivates the explanatory variables used. The BKM method used to compute the RNS is introduced in Section 3. Section 4 explains data sources and the construction of variables. Section 5 presents the regression results. Section 6 summarizes the conclusions.

2 Development of hypotheses

In this section, we motivate our choice of the economic variables used for cross-sectional analysis of RNS. Our first explanatory variable for RNS is the *trading volume of the underlying stock*. Hong and Stein (1999) argue that investor heterogeneity is the central force creating return asymmetries. Assuming investors have different opinions about stock values, with short-sale constraints, the Hong-Stein model suggests that negative skewness will be more pronounced in periods when differences in opinions are more pronounced and when trading is more active [Harris and Raviv (1993), Chen, Hong and Stein (2001)]. In empirical tests of Chen, Hong and Stein (2001), differences in opinion, as measured by the detrended level of turnover, has some explanatory power in predicting future conditional skewness in an inverse relationship. We accordingly test the relationship between trading volume and RNS. Given that the above arguments also apply to the option liquidity, we include the *option trading volume* as a new explanatory variable to be examined in this context for the first time.

BKM show that the RNS of stock returns can be decomposed into two components reflecting market skewness and the skewness of idiosyncratic risk component, such that:

$$SKEW_i = \left(1+\frac{VAR_{\varepsilon,i}}{\beta_i^2 VAR_m}\right)^{-2/3} SKEW_m + \left(1+\frac{\beta_i^2 VAR_m}{VAR_{\varepsilon,i}}\right)^{-3/2} SKEW_{\varepsilon,i} \qquad (1),$$

where $SKEW_i$, $SKEW_m$ and $SKEW_{\varepsilon,i}$, respectively, refer to the skewness of firm i's stock returns, market returns skewness and the skewness of idiosyncratic returns; VAR_m and $VAR_{\varepsilon,i}$ are the variance of market returns and the variance of firm i's idiosyncratic returns; beta β_i estimates the co-movement between firm i's stock returns and market returns. As shown in (1), if the RNS of idiosyncratic returns is positive or zero, the RNS of stocks will be less negative than the RNS of market index [BKM]. Combining the relation described by (1) with the empirical findings that RNS of a stock index is always negative, we expect that, firms with higher market risk exposure will tend to exhibit more negative RNS. DM use beta to estimate the market risk exposure of firm's returns, and find a negative correlation between beta and the RNS. Duan and Wei (2006) argue that the systematic risk proportion, i.e., the ratio of the firm's systematic variance over total variance, is a better systematic risk measure than beta, because it measures systematic risk after controlling for total risk, and it ranges just from zero to one. Thus, we estimate the effects of *systematic risk proportion* and of *beta* on RNS and expect both effects to be negative.

According to (1) above, and the findings of DM, the RNS of individual firms tends to move in the same direction as the RNS of market index over time. Hence, we include the *RNS of the S&P100 index* into our analysis, expecting that there is a positive relation between it and the individual RNS.

Both the market volatility and the firm's own volatility are included in (1). DM find that the firm's RNS tends to be more negative when the market volatility is high and when the firm's own volatility is low. We include the *ATM implied volatility of the S&P100 index* and the *ATM implied volatility of the firm's stock* in our tests, and expect the coefficients of both variables to have the same sign.

In addition, we also include *firm size* and *book-to-market ratio* as control variables to ensure that we do not attribute spurious explanatory power to other correlated variables. In Chen, Hong and Stein (2001), *book-to-market ratio* is positively related with the next period's conditional skewness. Their explanation is the stochastic bubble model of Blanchard and Watson (1982).

The leverage effect [Black (1976)] states that a drop in a company's equity value raises the debt-to-equity ratio and, as a result, the equity becomes more risky and its volatility increases. The argument implies that option implied volatilities decline with the option strike prices, as emphasized by Rubinstein (1994), and thus OTM puts are priced more expensively than OTM calls. The leverage effect has been considered as an explanation for volatility smile in equity options. It should arguably also explain the firm's RNS, and hence there should be a negative relationship between RNS and the firm's leverage ratio. However, DM find contradictory results. We include the firm's *leverage ratio* and test its relationship with RNS.

We also examine the relation between RNS and another new variable: the asymmetric volatility phenomenon (hereafter AVP). AVP refers to the fact that negative return shocks tend to imply a higher volatility than do positive return shocks of the same magnitude [Nelson (1991)]. The Heston (1993) option pricing model incorporates AVP by setting a negative correlation between volatility shocks and price shocks. The theoretical work of Harvey and Siddique (1999) notes a link between negative conditional skewness and AVP. Blair, Poon and Taylor (2002) and Dennis, Mayhew and Stivers (2006) document that AVP is stronger for the stock index than for individual firms. Dennis, Mayhew and Stivers (2006) further show that this 'index versus firms' difference in the AVP is consistent with the 'index versus firms' difference in the implied volatility skew (IVS). We would accordingly expect that firms with a stronger AVP would tend to exhibit more negative RNS. Therefore, we include AVP, measured by the *asymmetric volatility ratio* computed from the GJR (1,1) model [Glosten, Jagannathan and Runkle (1993)], as an explanatory variable for the RNS.

The last variable in our study is the proxy for market sentiment or trading pressure. When the market is pessimistic, investors might expect the stock price to decline and thus the future return distribution will appear to be negatively skewed. The ratio of put/call option trading volume is commonly believed to be a sentiment index and Pan and Poteshman (2006) show that the ratio is negatively associated with future stock returns. DM do not find significant evidence that the market sentiment index can explain RNS. We include the ratio of *put-to-all option trading volume* and expect that a higher demand for put options, compared to the demand for calls, indicates pessimism and implies a more negative RNS.

3 Spanning and pricing risk-neutral skewness

The BKM method to find risk-neutral skewness is motivated by a theorem outlined in Bakshi and Madan (2000). Let $S(t)$ refer to the stock price at time t, and $q[S]$ the risk-neutral density for S, with $q[S] \geq 0$ and $\int_0^\infty q[S]dS = 1$. For any claim payoff, $H[S(t+\tau)]$, that is integrable under risk-neutral pricing, the risk-neutral expectation of it at time $t+\tau$ is:

$$E_t^Q\{H[S(t+\tau)]\} = \int_0^\infty H[S(t+\tau)]q[S(t+\tau)]dS \qquad (2),$$

where $E_t^Q\{.\}$ refers to the risk-neutral expectation and $q[S(t+\tau)]$ is the risk-neutral density of S at time $t+\tau$.

Bakshi and Madan (2000) show that any payoff function with bounded expectation can be spanned by a continuum of OTM European call and put option prices. They derive the arbitrage-free price of the claim at time t as:

$$\begin{aligned} E_t^Q\{e^{-r\tau}H[S]\} &= (H[\bar{S}] - \bar{S}H_S[\bar{S}])e^{-r\tau} + H_S[\bar{S}]S(t) \\ &+ \int_{\bar{S}}^\infty H_{SS}[K]C(t,\tau;K)dK + \int_0^{\bar{S}} H_{SS}[K]P(t,\tau;K)dK \end{aligned} \qquad (3),$$

where r refers to the interest rate, $H_S[S]$ and $H_{SS}[S]$ are the first-order and second-order derivatives of the payoff with respective to S evaluated at any selected number $\bar{S}$. The variables $C(t,\tau;K)$ and $P(t,\tau;K)$ are respectively the European call and put option prices at time t with strike price K and expiry date $t+\tau$.

BKM define the volatility contract and cubic contract to have the payoffs respectively equal to $R(t,\tau)^2$ and $R(t,\tau)^3$, where the τ - period stock return is defined as: $R(t,\tau) \equiv \log(S(t+\tau)) - \log(S(t))$. The prices of these two contracts at time t are expressed respectively by $V(t,\tau) \equiv E_t^Q \left\{ e^{-r\tau} R(t,\tau)^2 \right\}$ and $W(t,\tau) \equiv E_t^Q \left\{ e^{-r\tau} R(t,\tau)^3 \right\}$.

BKM derive the value of $V(t,\tau)$ and $W(t,\tau)$ when letting $H[S]$ in (2) and (3) be equal to $R(t,\tau)^2$ and $R(t,\tau)^3$. For the choice $\overline{S} = S(t)$, they are:

$$V(t,\tau) = \int_0^\infty \frac{2(1-\log[\frac{K}{S(t)}])}{K^2} Q(t,\tau;K)dK \qquad (4)$$

and

$$W(t,\tau) = \int_0^\infty \frac{6\log[\frac{K}{S(t)}] - 3(\log[\frac{K}{S(t)}])^2}{K^2} Q(t,\tau;K)dK \qquad (5),$$

where $Q(t,\tau;K)$ is the call option price with strike price K when $K > S(t)$ and otherwise it is the put option price. Hence, the value of each of these two contracts can be expressed by a portfolio of OTM option prices.

By Theorem (1) in BKM, the risk-neutral skewness of logarithm returns at time $t+\tau$, $SKEW(t,\tau)$, can be recovered from (4) and (5), such that:

$$\begin{aligned} SKEW(t,\tau) &\equiv \frac{E_t^Q \left\{ (R(t,\tau) - E_t^Q[R(t,\tau)])^3 \right\}}{\left\{ E_t^Q (R(t,\tau) - E_t^Q[R(t,\tau)])^2 \right\}^{3/2}} \\ &= \frac{e^{r\tau}W(t,\tau) - 3\mu(t,\tau)e^{r\tau}V(t,\tau) + 2\mu(t,\tau)^3}{[e^{r\tau}V(t,\tau) - \mu(t,\tau)^2]^{3/2}} \end{aligned} \qquad (6),$$

with $\mu(t,\tau) \equiv E_t^Q \left\{ \log\left[\frac{S(t+\tau)}{S(t)} \right] \right\} \approx e^{r\tau} - 1 - \frac{e^{r\tau}}{2} V(t,\tau) - \frac{e^{r\tau}}{6} W(t,\tau) - \frac{e^{r\tau}}{24} X(t,\tau)$.

Therefore, the RNS for a future time is derived from a continuum of current OTM option prices with the same maturity. Besides BKM and DM, the method has been adopted by Duan and Wei (2006), and Christoffersen, Jacob and Vainberg (2006).

4 Data

Our options data are from the IvyDB database of OptionMetrics, and includes daily CBOE-based price information for all U.S. listed index and equity options. Our sample period spans 1009 trading days from January 1996 to December 1999. Two criteria are used to select the individual firms analyzed: first, only firms that have options traded throughout the whole sample period are included; and second, a firm must have sufficient option trading activity across different strike prices to allow efficient estimation by enabling fitting of implied volatility curves across different strikes for at least 989 (i.e. 98%) of the 1009 trading days[4]. Hence, our choice of firms is based on liquidity and trading interest across different strike prices in the options market rather than in the underlying stock. We believe this should arguably lead to more reliable option prices and more economically meaningful RNS estimates. This leaves us with a sample of 149 U.S. firms. Options with less than seven days to maturity are excluded. For most trading days, we choose the nearest-to-maturity options[5]. Daily stock data come from CRSP, including trading volume, closing price and shares outstanding. Compustat provides the firm's financial reporting information that is used to estimate leverage and book-to-market ratios.

4.1 Construction of explanatory variables

In order to eliminate the effects of outlying extreme values on regressions, we take the natural log of the stock trading volume in thousands of shares, and the natural log of the firm size in thousands of dollars. Firm size is calculated by multiplying the daily closing stock price by the shares outstanding in the market. Option liquidity is measured as the natural log of option trading volume, which is the number of traded option contracts.

Market sentiment is estimated as the trading volume of put options divided by the trading volume of all options. In robustness tests, the ratio of the daily put open interest to the overall open interest is used. The firm's at-the-money (ATM) implied volatility is the average of the two volatilities implied by the nearest-to-the-money put and call options.

We adopt the volatility index, VOX for the market volatility. This is measured as the weighted average of the eight implied volatilities from the nearest-to-the-money and nearest-to-maturity call and put options; and represents the volatility level of the S&P100 index with 22 trading days (30 calendar days) to expiry. The historical daily levels of VOX index are downloaded from the CBOE website. There is a bias in the calculation of VOX because of a trading time adjustment that typically multiplies the conventional implied volatility by approximate 1.2[6]. With this in mind, our regression models are designed to be robust against the bias[7].

The systematic risk proportion for firm i, defined by Duan and Wei (2006), is the explanatory power, or R^2, of the OLS regression model:

$$R_{it} = \alpha_{it} + \beta_{it} R_{mt} + \varepsilon_{it} \quad (7),$$

where R_{it} and R_{mt} respectively refer to stock i's return and the market return at time t. Following Duan and Wei (2006), we run the regression specified by (7) for day t using daily stock returns from day $t-250$ to day t, with S&P100 index as the proxy for market index. All returns are computed as continuously compounded.

To calculate the asymmetric volatility ratio, we use the GJR(1,1)-GARCH model that incorporates the asymmetric effect of positive and negative returns in the real world. Based on the daily stock returns from Jan 1996 to Dec 1999, we estimate the parameters of the following equations by maximizing the log-likelihood value once for every firm:

$$\begin{aligned} r_t &= \mu_i + \varepsilon_t + \theta\varepsilon_{t-1}, \\ \varepsilon_t &= \sqrt{h_t}\, z_t, \qquad z_t \sim i.i.d.N(0,1), \\ h_t &= \varpi + \alpha\varepsilon_{t-1}^2 + \alpha^- s_{t-1}\varepsilon_{t-1}^2 + \beta h_{t-1} \end{aligned} \quad (8),$$

where s_{t-1} is 1 if $\varepsilon_{t-1} < 0$, and is 0 otherwise. The model specifies α and $\alpha + \alpha^-$ as the measures of the respective effects of positive and negative shocks on the next-period conditional variance. Following Blair, Poon and Taylor (2002), we define the asymmetric volatility ratio for firm i as:

$$A_i = \frac{\alpha}{\alpha + \alpha^-} \qquad (9).$$

Therefore, a more pronounced AVP is consistent with a lower value of A_i.

All explanatory variables, except for A_i in (9), are estimated daily and then averaged to obtain weekly measures. Exhibit 1 contains the summary statistics of the explanatory variables described above. For our data, on average, there is less trading in puts than in calls, with the mean put-to-all trading volume, 0.320, being less than 0.5. The average daily trading volume of underlying stocks of our sample is about 500,000 ($e^{6.187} \times 1{,}000$) shares and the average firm size is \$5.72 billion ($e^{15.559} \times 1{,}000$). The average of the *systematic risk proportion* variable, 18.1%, shows that most of the risk of our sample firms comes from the firm specific component rather than the market.

<Exhibit 1 is inserted about here. >

4.2 Measuring risk-neutral skewness

To empirically estimate the RNS described in (6), we need to evaluate the integrals that appear in (4) and (5). In order to reduce the errors coming from discrete option prices, for each trading day, we estimate an implied volatility curve from the observed option prices, and then extract more option prices from the curve. We implement a variation of the practical strategy described by Malz (1997a, 1997b), who proposed estimating the implied volatility curve as a quadratic function of the Black-Scholes option's delta as against a quadratic function over strike price suggested earlier by Shimko (1993). As argued by Malz (1997a), extrapolating a function of delta provides sensible limits for the magnitudes of the implied volatilities.

The quadratic specification is preferred because it is the simplest function that captures the basic properties of the volatility smile. Furthermore, there are insufficient stock option prices to estimate higher-order polynomials. Delta is defined as the first order derivative of the Black-Scholes call option price with respect to the underlying forward price, with a constant volatility level that permits a convenient one-to-one mapping between delta and strike price [following Bliss and Panigirtzoglou (2002, 2004)].

We use the implied volatility of the observed options provided by the IvyDB directly. The quadratic function is fitted by minimizing the sum of squared errors between the observed and the fitted implied volatilities. For each trading day, we extract 1000 option prices from the estimated implied volatility curve with equal spacing in delta[8].

Daily RNS for 149 firms and the S&P100 index are estimated according to (6). Each weekly estimate is the average of daily estimates. Exhibit 2 provides the summary statistics of weekly RNS, the autocorrelations in RNS at lag 1 to 5 and the number of firms when the Ljung-Box Q-statistic at that specific lag is significant at the 1% level. We also sort the firms according to different industry sectors[9] and report the summary statistics for the firms belonging to these sectors.

<Exhibit 2 is inserted about here. >

We find that, consistent with DM and BKM, the RNS of individual firms are negative overall, though occasionally positive, with a mean of –0.254. The RNS of firms appears to be much less negative than the RNS of S&P100 index with a mean of -1.292. Secondly, the skewness shows high persistence over time for our data. The average autocorrelation is 0.298 at lag 1 and then decreases monotonically from lag 1 to lag 5. These indicate that the period of a negative skewness tends to be followed by a period that also has a negative skewness.

Finally, the summary statistics of RNS for firms in different industry sectors are relatively close to each other.

For each out of 209 weeks over the four years, we calculate the median value of RNS across 149 firms. Exhibit 3 shows the time-series plots of the median RNS across all firms and the plots of weekly index RNS. The median RNS across firms is always negative during our sample period, ranging from –0.028 to –0.56. The RNS of S&P100 index is almost always below the median values of individual firms.

<Exhibit 3 is inserted about here.>

Exhibit 4 presents the correlation matrix of the explanatory variables and the estimated RNS of firms. It appears that option liquidity, underlying stock liquidity and systematic risk proportion are the variables most correlated with the firms' RNS. The correlation coefficients indicate that firms with higher trading volume of options, higher trading volume of underlying stocks and/or higher systematic risk proportion, compared to other firms, tend to have more negative RNS. The market skewness and market volatility, respectively, are positively and a negatively related with the firm's RNS.

<Exhibit 4 is inserted about here.>

It is not surprising to find that the option trading volume, stock trading volume, firm size and systematic risk proportion have high positive correlations with each other. Larger firms tend to have more liquid option trading and are more correlated with market movements.

5 Regression analysis and the results

5.1 Regression specifications

Our analysis starts with a Fama-MacBeth (1973) type cross-sectional approach. Each week, we run the following multivariate regression across 149 firms:

$$\mathrm{RNS}_i = \beta_0 + \beta_1 \mathrm{PUT/ALL}_i + \beta_2 \mathrm{TV\_OP}_i + \beta_3 \mathrm{TV\_STOCK}_i + \beta_4 \mathrm{SIZE}_i + \beta_5 \mathrm{SRP}_i$$

$$+\beta_6 \mathrm{VOL}_i + \beta_7 \mathrm{D/E}_i + \beta_8 \mathrm{B/M}_i + \beta_9 \mathrm{A}_i + \varepsilon_i \quad (10),$$

where RNS_i is the risk-neutral skewness for firm i; $\mathrm{PUT/ALL}_i$ is the ratio of put/all option trading volume; $\mathrm{TV\_OP}_i$ is the option trading volume; $\mathrm{TV\_STOCK}_i$ is the trading volume of underlying stocks; SIZE_i is the market value of firm i's equity; SRP_i is the systematic risk proportion; VOL_i is the firm's ATM option implied volatility; $\mathrm{D/E}_i$ is the debt-to-equity ratio; $\mathrm{B/M}_i$ is the book-to-market ratio; and A_i is the real-world asymmetric volatility ratio .

These regressions investigate the cross-sectional relations between the RNS and the explanatory variables, and generate time-series coefficients throughout 209 weeks during our sample period. For each weekly regression, the significance of the estimated slope coefficient is tested using the White (1980) t-statistic for taking account of heteroscedasticity. For each variable, the average of the weekly coefficients is presented and the null hypothesis that the mean slope coefficient equals zero is tested by the t-statistic adjusted for the autocorrelations in weekly coefficients up to the 10^{th} lag.

Secondly, we run the pooled regressions, which test cross-sectional and time-varying relations simultaneously between the RNS and various firm specific factors. The multivariate model specification is as follows:

$$\begin{aligned}\mathrm{RNS}_{i,t} = \beta_0 + \beta_1 \mathrm{PUT/ALL}_{i,t} + \beta_2 \mathrm{TV\_OP}_{i,t} + \beta_3 \mathrm{TV\_STOCK}_{i,t} + \beta_4 \mathrm{SIZE}_{i,t} + \\ \beta_5 \mathrm{SRP}_{i,t} + \beta_6 \mathrm{VOL}_{i,t} + \beta_7 \mathrm{D/E}_{i,t} + \beta_8 \mathrm{B/M}_{i,t} + \beta_9 \mathrm{A}_i + \beta_{10} \mathrm{RNS\_M}_t + \\ \beta_{11} \mathrm{VOX\_M}_t + \varepsilon_{i,t} \quad (11)\end{aligned}$$

where i indexes for firm and t indexes for week of the observation. The market-wide variables are added to the pooled regressions, which are the RNS of the S&P100 index, $\mathrm{RNS\_M}_t$, and the VOX index, $\mathrm{VOX\_M}_t$. The hypothesis tests are based on the heteroscedasticity and autocorrelation consistent standard errors [Newey and West (1987)].

5.2 Results of cross-sectional regressions

Exhibit 5 presents the results of multivariate cross-sectional regressions defined in (10). The regression is run once a week and the means of the weekly coefficient estimates are shown. From the regression results, we find that the coefficient for *sentiment,* i.e. put-to-all option trading volume, PUT/ALL, is negative and significant. This is consistent with our hypothesis that, when investors are pessimistic and trade more on put options relative to calls, the probability of a lower price level on the risk-neutral distribution tends to increase. DM do *not* find consistent evidence for this hypothesis for their data. We believe that our results are likely to be less noisy and more reliable in this context than theirs because of two reasons. First, while our cross-section is explicitly selected on the basis of trading interest across different option strikes, in their case, because their sample includes all firms, their results may potentially be driven by illiquid (and hence stale) option prices. Second, any liquidity related errors will get significantly attenuated in our case because of our fitting implied volatility curves rather than directly using discrete option prices as they did.

Importantly, opposite to the results of DM, we also find that higher a firm's own volatility, the more negative RNS is. This relationship is consistent in all regressions, and, as we see later, robust to controls for overall market volatility, exists irrespective of how we slice the data, and, unlike DM, is consistent with the dependence observed for overall market volatility.

<Exhibit 5 is inserted about here. >

Liquidity as proxied by the *underlying stock trading volume* is <u>not</u> at all significant in explaining RNS when we include firm size as an explanatory variable, as in DM. To assess collinearity effects, when we estimate the regression again by omitting firm size, there is almost no change to the coefficients for other variables or to the R^2, except that stock trading volume (t-stat. -2.90) and book-to-market ratio (t-stat. 2.17) become significant. However, there is a negative and strongly significant relationship between the *options trading volume* and the individual RNS. This is a variable that has been examined in this context for the first time, and we find that liquidity is important for RNS, but the liquidity that is important is that of the options market, rather than that in the underlying stock. In fact, given that index options are much more liquid than options on individual firms, if the index is viewed as a firm with the correspondingly highest option liquidity, the variation of RNS with options market liquidity goes a long way in explaining the widely documented empirical finding that the option implied risk-neutral distribution of the stock index is much more negatively skewed than that of individual firms.

The *systematic risk proportion* is, as expected, negatively and significantly related with RNS. Firms that contain a higher proportion of systematic risk within their overall risk tend to exhibit more negative RNS. The results are consistent with Duan and Wei (2006) and DM, while the latter uses beta as the proxy of systematic risk. Our mean coefficient of systematic risk proportion, –0.21, is less negative than the coefficient in Duan and Wei (2006), perhaps because they use just the data of the 30 largest U.S. firms, and as a result, their resultant RNS is overall more negative than ours.

The relationship of the *asymmetric volatility ratio*, *A*, with RNS is not statistically significant at the 5% level, though the coefficient is significant and positive in 6.7% of the weeks[10]. This is a variable being examined for the first time in the literature. A higher value of *A* implies a less pronounced AVP, and a positive and significant *A* is consistent with the hypothesis that, when the AVP is less pronounced, the risk-neutral distribution tends to be more positively skewed, i.e. more symmetric.

5.3 Results of pooled regressions

The first column of Exhibit 6 shows the results of the multivariate pooled regression *I*, defined by (11). The numbers in the parentheses are the Newey-West t-statistics. The F-statistic tests the null hypothesis that the coefficients of the explanatory variables in the regression model are all zero.

<Exhibit 6 is inserted about here. >

Nearly all the coefficient estimates of regression *I* have similar magnitudes to the average coefficients obtained from the cross-sectional approach in Exhibit 5. The adjusted R^2 is 5.51% and the null hypothesis that all coefficient estimates are equal to zero is rejected according to the F-statistic. As with the cross-sectional results, the coefficients of stock trading volume, book-to-market ratio and asymmetric volatility ratio are *not* significant at the 5% level.

In regression *I* in Exhibit 6, the market volatility is negatively significant, indicating that the individual RNS tends to be more negative when the overall market is more volatile. The firm's own ATM implied volatility continues to be also significantly and negatively related with the RNS, a dependence opposite to that in DM. This helps to resolve the apparently puzzling result in DM that individual RNS has conflicting relationships with market volatility and the firm's own volatility. Our results indicate that market volatility and firm volatility impact in the same direction, and when either the market volatility and/or the firm's volatility is high, the individual RNS tends to be more negative.

As expected, the RNS of S&P100 index also positively and significantly explains the firm's skewness over time. It is interesting to isolate the effects coming from market skewness and from the firms themselves, and test which is more important. DM show that the market index explains some time-series variation in individual skewness, but the effect is much less important than that from firm-specific factors. We find a similar result. For regression *II* shown in Exhibit 6, we drop the two market variables, which are index RNS and

VOX. Comparing the results with those in regression *I*, there is not much difference in the sign and significance of all the other explanatory variables. The adjusted R^2 is 5.02%, which is only 0.49% lower than that of regression *I*. Therefore, two market factors capture only a small proportion of the time-series variations in the RNS of individual firms.

According to Exhibit 2, the firm's RNS has high autocorrelations at the first few lags. We add the lagged RNS as an additional explanatory variable and the results are shown in regression *III* of Exhibit 6. The coefficient of the lagged RNS is positive and highly significant. The adjusted R^2 increases to 15.82%, which is almost three times that of regression *I*. DM also find that the inclusion of lagged skewness improves the explanatory power of their regression model greatly.

The DM explanation of the highly significant coefficient on lagged skewness is that the lagged estimates subsume the information contained in the omitted firm specific factors. However, our results indicate another reason that we believe is potentially more credible: the overlapping data problem that exists in their sample, and also in our weekly sample above, albeit to a lesser extent[11]. To minimize the effects of the overlapping data problem, we run the pooled regressions by collecting monthly data on the trading day after each month's option maturity date. The monthly sample eliminates most of the effects from overlapping problem that existed in the weekly sample. With the same specifications as those in Exhibit 6, the regression results are shown in Exhibit 7. Overall, the economic and statistical significance of the results are similar to those in Exhibit 6. However this time, in regression *III* of Exhibit 7, after adding the lagged RNS, the adjusted R^2 is only 1.52% higher than the adjusted R^2 of regression *I*. The coefficient estimate of the lagged RNS, 0.13, is still significant, and indicates that there is still some information contained in the RNS observed in the previous month, but clearly, the effect of ostensibly omitted variables cited in DM, is much smaller than what appeared to be from their results.

<Exhibit 7 is inserted about here. >

In both cross-sectional and pooled regressions, we find that, consistent with DM, the coefficients of the leverage ratio, i.e. the debt-to-equity ratio *D/E*, are always positive and strongly significant. It may appear counterintuitive to find that a higher leverage ratio in the firm's capital structure leads to a more positive RNS, but it is important to note that this is a cross-sectional relationship across firms, and not a time-series relationship for a single firm. If the leverage effect holds, higher leverage ratio should be associated with a higher volatility when we examine time-series variation for a single firm, but, consistent with Exhibit 3, the cross-sectional correlation between leverage and a firm's ATM implied volatility is significantly negative instead of positive. This is consistent with the findings of DM and Figlewski and Wang (2000). Independent of this line of argument, our explanation of our results is that market participants consider the increase of debt relative to equity as a positive signal of the firm's borrowing ability. Thus, the market's short-term expectations about the firm's performance are positive. As a result, the level of option implied volatility is low and the risk-neutral distribution with one month to maturity is closer to symmetric.

In summary, we find that the market sentiment ratio, option trading volume, firm size, systematic risk proportion, the firm's ATM implied volatility and leverage, are all important in explaining the movements in RNS. The coefficient estimates for them are all significantly negative, except for the leverage ratio where it is significantly positive. Second, the coefficients for stock trading volume, book-to-market ratio and asymmetric volatility phenomena are insignificant at the 5% level in multivariate regressions. Third, the market RNS and the market volatility index capture some proportion of the movements of individual skewness over time; however, the proportion is small compared to that explained by firm-specific factors. Finally, the lagged RNS contains information about the current RNS through potentially omitted variables, though, after controlling for overlapping data, this is much less than what had appeared to exist from earlier work.

5.4 Alternative measures of variables

To investigate the robustness of our regression results, we repeat the pooled regressions (defined by (11)), using some alternative measures of different variables.

First, in our main results, the weekly RNS is calculated as the mean of daily observations. As sometimes the weekly mean and median of daily values can deviate from each other because of the existence of extreme values, we also estimate the weekly RNS using the median value of daily observations. The resulting weekly RNS has a mean of –0.255, and its correlation with that measured by the mean is 96%. The coefficient estimates and explanatory power of the pooled regression, with RNS measured as median, continue to be very close to those of regression *I* in Exhibit 6.

Second, as the trading volume of options might not capture the number of open contracts, we estimate the market sentiment index as the ratio between the open interest of put options and the open interest of all options. The average ratio measured by open interest for all firms is 35%. The pooled regression specified by (11) is performed again by substituting the market sentiment index measured by open interest for the variable PUT/ALL. The results show that RNS varies negatively and significantly (with a t-statistic of -2.20) with the new variable. The adjusted explanatory power of the regression is only 0.08% less than that of regression *I* in Exhibit 6.

Third, the pooled regression in (11) is done by substituting beta for systematic risk proportion. Beta at time t is computed as the coefficient estimate of (7). The average beta for our sample firms during our sample period is 1.123, and the correlation between it and the systematic risk proportion is 27.02%. The resulting coefficient estimate of beta is -0.03 with a t-statistic of -2.60, again significantly negative.

Overall, there are no qualitative changes to our headline results as a result of our robustness tests.

6 Conclusions

This paper estimates the RNS of a cross-section of 149 U.S. firms using the methods in Bakshi, Kapadia and Madan (2003), and investigates the relationship between various firm specific factors and the RNS of these individual options. Our choice of firms is based on liquidity and trading interest across different strike prices in the options market rather than in the underlying stock, and we believe this enables the use of more reliable option prices, particularly for options that are away from the money, and hence better quality RNS estimates. We also undertake significant methodological improvements by fitting implied volatility curves to minimize the potential for errors from the use discrete option observations, and also by employing methods that mitigate the effect of overlapping observations. Furthermore, besides the variables examined earlier, we investigate the effect of at least two new variables: the options trading volume and the asymmetric volatility ratio.

Consistent with earlier results, we find that the RNS of individual firms varies significantly and negatively with firm size, firm systematic risk, and market volatility; and varies significantly and positively with the RNS of the market index; and the market RNS and the market volatility index capture only a small proportion of the movements of individual RNS over time, with most of the variation being explained by firm-specific factors. As in earlier work, we also find that the lagged RNS contains information about the current RNS through potentially omitted variables, but, after controlling for overlapping data, we show that this is much less than what had appeared to exist earlier.

We also document several interesting results that are clearly unambiguous and significantly stronger than in earlier work, or opposite to earlier evidence, or for variables that have been examined for the first time. First, we find that market sentiment, as proxied by the proportion of put volume to total option volume, has, consistent with expectation, a negative and significant effect on RNS. Second, opposite to the results of DM, we find that higher a firm's own volatility, the more negative the RNS, a relationship that is consistent in all specifications, and robust to controls for overall market volatility, and, as expected, in the same direction as overall market volatility. Third, greater market liquidity is associated with more negative RNS, but the liquidity that is relevant for RNS is that of the options market, rather than that in the underlying stock, and this options market liquidity has been investigated in this context for the first time. Another new result, contrary to expectation, is the relative irrelevance and lack-of-significance of real-world volatility asymmetry for RNS. Finally, consistent with DM, but different from Toft and Prucyk (1997), we find that the leverage ratio is not negatively but positively and strongly related with RNS.

The RNS, and more generally the risk neutral probability distribution, impounds valuable information about consensus expectations and marginal value-relevant preferences, and this information is very relevant to both short-term traders and long-term investors. Further research can potentially generate relevant insights about these market expectations and preferences by investigating the cross-sectional and time-series variation in RNS around specific news announcements and economic events.

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Exhibit 1 Summary statistics for explanatory variables

	Mean	Lower Quartile	Median	Upper Quartile	Standard Deviation
PUT/ALL	0.320	0.188	0.308	0.432	0.191
TV_OP	5.720	4.423	5.734	6.940	1.796
TV_STOCK	6.817	6.046	6.871	7.658	1.242
SIZE	15.559	14.262	15.435	16.847	1.721
SRP	0.181	0.087	0.150	0.244	0.128
VOL	0.488	0.342	0.478	0.607	0.178
D/E	0.122	0.002	0.038	0.154	0.189
B/M	0.312	0.142	0.246	0.394	0.278
A	0.368	0.045	0.220	0.499	0.533
RNS_M	-1.292	-1.545	-1.322	-1.080	0.391
VOX_M	0.232	0.197	0.224	0.256	0.054

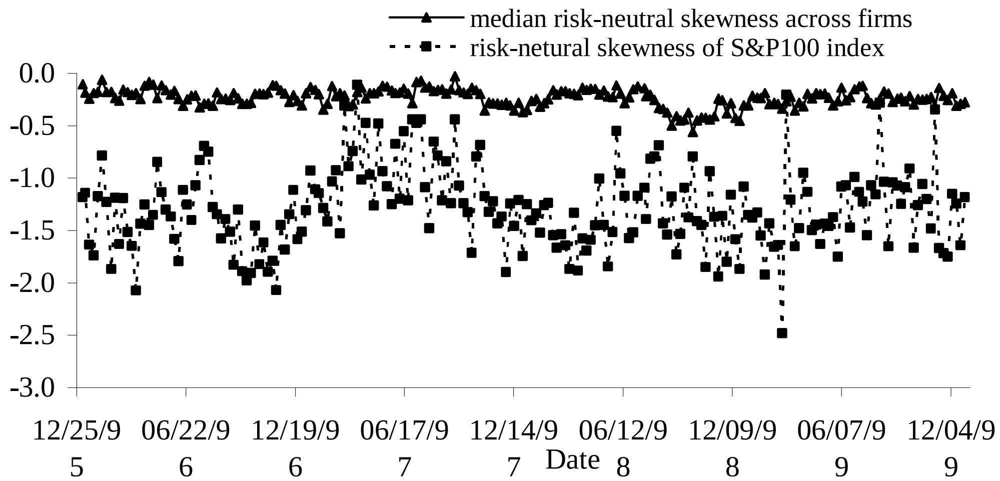
The table contains the summary statistics for explanatory variables used in the paper. The sample consists of 29,729 weekly observations for 149 firms during the period from Jan 1996 to Dec 1999. PUT/ALL is the ratio of put-to-all option trading volume. TV_OP is the natural log of option trading volume in number of contracts. TV_STOCK is the natural log of underlying stock trading volume in thousands of shares. SIZE is the natural log of the firm's market capitalization in thousands of dollars. SRP refers to the systematic risk proportion, which is the explanatory power when regress the firm's daily stock returns onto the S&P100 index returns. VOL is the at-the-money option implied volatility. D/E and B/M respectively refer to the firm's leverage and book-to-market ratio. A is the asymmetric volatility ratio obtained from the GJR (1,1) model estimated using daily stock returns, the statistics of it are across 149 firms. RNS_M is the risk-neutral skewness of the S&P100 index, computed using the method in Bakshi, Kapadia and Madan (2003) and VOX_M is the CBOE's volatility index, VOX, on the S&P100 stock index.

Exhibit 2 Summary statistics of risk-neutral skewness

	Mean	Lower Quartile	Median	Upper Quartile	Standard Deviation	No. of firms with significant Ljung-Box Q-statistic at 1% level
All firms	-0.254	-0.508	-0.228	0.003	0.472	
ρ_1	0.298	0.232	0.292	0.368	0.102	128
ρ_2	0.125	0.046	0.130	0.203	0.108	126
ρ_3	0.082	0.026	0.068	0.129	0.087	120
ρ_4	0.077	0.004	0.074	0.136	0.098	117
ρ_5	0.055	-0.017	0.052	0.108	0.099	117
Sorted by different industry sectors:						
Cnsmr (13)	-0.237	-0.517	-0.203	0.039	0.496	
Manuf (21)	-0.239	-0.515	-0.209	0.036	0.497	
HiTec (69)	-0.267	-0.508	-0.238	-0.019	0.454	
Hlth (23)	-0.262	-0.516	-0.241	0.006	0.485	
Other (23)	-0.235	-0.491	-0.207	0.016	0.475	

The table contains the summary statistics of the risk-neutral skewness, calculated using the Bakshi, Kapadia and Madan (2003) method. The sample consists of 29,729 weekly observations for 149 firms during the period from Jan 1996 to Dec 1999. ρ_τ refers to the autocorrelation of the time-series risk-neutral skewness at lag τ. The last column counts the number of firms when the Ljung-Box Q-statistic at lag τ is significant at the 1% level. In the lower panel, the firms are sorted by five industry sectors, defined by Ken French, with Cnsmr representing Consumer, Manuf referring to manufacturing, HiTech referring to High technology and Hlth referring to Health. The number in parentheses after each sector's name is the number of firms within each industry sector.

Exhibit 3 Time-series plot of risk-neutral skewness



The figure plots the weekly risk-neutral skewness of the S&P100 index and the median values of the weekly risk-neutral skewness across 149 firms, observed from Jan 1996 to Dec 1999.

Exhibit 4 Correlations between explanatory variables

	RNS	PUT/ALL	TV_OP	TV_STOCK	SIZE	SRP	VOL	D/E	B/M	A	RNS_M
PUT/ALL	-6.2										
TV_OP	-17.2	11.7									
TV_STOCK	-17.1	9.9	82.1								
SIZE	-13.2	12.1	63.1	70.4							
SRP	-14.6	12.3	40.4	45.7	67.2						
VOL	-4.2	-4.3	-9.2	-11.6	-61.0	-31.8					
D/E	7.0	3.7	-5.9	-14.8	0.4	7.7	-20.6				
B/M	6.4	1.8	-15.9	-22.0	-25.5	-10.8	-1.2	45.4			
A	3.0	0.9	-6.3	-11.3	-9.0	-16.1	-4.5	-3.7	1.0		
RNS_M	3.0	2.9	-0.3	1.5	0.1	-3.7	-0.8	-0.1	0.2	0.0	
VOX_M	-12.4	9.2	6.3	13.0	7.1	28.8	22.5	0.0	0.5	0.0	8.2

This table contains the correlation matrix of the explanatory variables. The sample consists of weekly observations for 149 firms during the period from Jan 1996 to Dec 1999. RNS refers to the risk-neutral skewness of individual firms. The correlations are stated as percentages. All the variables are defined in the same way as in Exhibit 1.

Exhibit 5 Results of multivariate cross-sectional regressions

	Mean Coef. *(t-stat)*	% t-stat n/p
Intercept	0.48* *(4.8)*	2.4/7.7
PUT/ALL	-0.06* *(-4.2)*	4.8/0
TV_OP	-0.02* *(-6.0)*	9.1/1.0
TV_STOCK	0.00 *(0.1)*	3.8/4.3
Size	-0.03* *(-3.1)*	7.7/2.9
SRP	-0.21* *(-3.1)*	6.7/1.9
VOL	-0.26* *(-8.3)*	7.7/2.4
D/E	0.12* *(3.7)*	0.5/9.6
B/M	0.01 *(0.8)*	3.3/2.9
A	0.01 *(0.8)*	3.3/6.7
Mean R^2	11.34%	
Mean adj.R^2	5.30%	

This table contains the time-series averages of the results from weekly multivariate cross-sectional regressions. The regression model is defined as:

$$\mathrm{RNS}_i = \beta_0 + \beta_1 \mathrm{PUT/ALL}_i + \beta_2 \mathrm{TV\_OP}_i + \beta_3 \mathrm{TV\_STOCK}_i + \beta_4 \mathrm{SIZE}_i + \beta_5 \mathrm{SRP}_i + \beta_6 \mathrm{VOL}_i + \beta_7 \mathrm{D/E}_i + \beta_8 \mathrm{B/M}_i + \beta_9 \mathrm{A}_i + \varepsilon_i .$$

All variables are defined in the same way as in Exhibit 1. The regression is run once a week across 149 firms over 209 weeks. Mean coef. is the mean of weekly coefficient estimates. The t-statistics in the parentheses beside the mean coefficients are computed from weekly coefficients and adjusted for autocorrelations. The column labeled “% t-stat n/p” counts the percentages of weeks when the coefficient is negatively (n)/ positively (p) significant at the 5% level according to the White t-statistics. Mean R^2 and adj. R^2 are the averages of weekly explanatory powers. The asterisk * indicates a significant estimate at the 5% level using a two tailed t-test.

Exhibit 6 Results of multivariate pooled regressions

	I		II		III	
Intercept	0.59*	*(5.5)*	0.53*	*(4.3)*	0.46*	*(6.0)*
PUT/ALL	-0.08*	*(-4.9)*	-0.09*	*(-5.2)*	-0.08*	*(-5.5)*
TV_OP	-0.02*	(-6.0)	-0.02*	*(-5.0)*	-0.02*	*(-5.3)*
TV_STOCK	-0.00	*(-0.1)*	-0.00	*(-0.2)*	0.00	*(0.7)*
Size	-0.02*	*(-2.7)*	-0.03*	*(-3.1)*	-0.02*	*(-3.4)*
SRP	-0.22*	*(-3.9)*	-0.33*	*(-5.7)*	-0.13*	*(-3.3)*
VOL	-0.24*	*(-4.4)*	-0.34*	*(-5.9)*	-0.18*	*(-4.5)*
D/E	0.13*	*(5.0)*	0.13*	*(4.6)*	0.09*	*(4.9)*
B/M	-0.00	*(-0.1)*	-0.01	*(-0.6)*	0.00	*(-0.3)*
A	0.01	*(0.7)*	-0.00	*(-0.2)*	0.00	*(0.9)*
RNS_M	0.04*	*(4.7)*			0.03*	*(4.4)*
VOX_M	-0.65*	*(-7.5)*			-0.47*	*(-7.5)*
Lagged RNS					0.33*	*(42.9)*
Mean R^2	5.55%		5.05%		15.85%	
Mean adj.R^2	5.51%		5.02%		15.82%	
F-statistics	158.62		175.51		464.12	
No. of observations	29,729		29,729		29,580	

The table shows the results of the multivariate pooled regressions defined as:

$$\mathrm{RNS}_{i,t} = \beta_0 + \beta_1 \mathrm{PUT/ALL}_{i,t} + \beta_2 \mathrm{TV\_OP}_{i,t} + \beta_3 \mathrm{TV\_STOCK}_{i,t} + \beta_4 \mathrm{SIZE}_{i,t} + \beta_5 \mathrm{SRP}_{i,t} +$$
$$\beta_6 \mathrm{VOL}_{i,t} + \beta_7 \mathrm{D/E}_{i,t} + \beta_8 \mathrm{B/M}_{i,t} + \beta_9 \mathrm{A}_i + \beta_{10} \mathrm{RNS\_M}_t + \beta_{11} \mathrm{VOX\_M}_t + \beta_{12} \mathrm{RNS}_{i,t-1} + \varepsilon_{i,t},$$

where i and t index the firm and week. All variables are defined in the same way as in Exhibit 1.

The numbers in parentheses besides the coefficient estimates are Newey-West t-statistics computed from the heteroscedasiticity and autocorrelation consistent standard errors. The asterisk * indicates a significant estimate at the 5% level using a two tailed t-test.

Exhibit 7 Results of multivariate pooled regressions with monthly observations

	I		*II*		*III*	
Intercept	0.57*	*(3.5)*	0.49*	*(2.7)*	0.54*	*(3.7)*
PUT/ALL	-0.07	*(-1.9)*	-0.07*	*(-2.1)*	-0.06	*(-1.8)*
TV_OP	-0.02*	*(-2.7)*	-0.01*	*(-2.1)*	-0.02*	*(-2.8)*
TV_STOCK	0.00	*(0.3)*	0.00	*(0.2)*	0.01	*(1.2)*
Size	-0.02*	*(-2.0)*	-0.03*	*(-2.4)*	-0.03*	*(-2.6)*
SRP	-0.28*	*(-3.4)*	-0.41*	*(-4.9)*	-0.20*	*(-2.8)*
VOL	-0.20*	*(-2.5)*	-0.32*	*(-3.7)*	-0.17*	*(-2.3)*
D/E	0.15*	*(3.7)*	0.14*	*(3.5)*	0.14*	*(3.8)*
B/M	-0.01	*(-0.4)*	-0.02	*(-0.7)*	-0.02	*(-0.7)*
A	0.01	*(1.3)*	0.01	*(0.5)*	0.02	*(1.7)*
RNS_M	0.03	*(1.5)*			0.02	*(1.2)*
VOX_M	-0.92*	*(-5.9)*			-0.83*	*(-5.6)*
Lagged RNS					0.13*	*(9.7)*
Mean R^2	5.77%		5.07%		7.30%	
Mean adj.R^2	5.62%		4.95%		7.14%	
F-statistics	39.72		42.39		45.85	
No. of observations	7,152		7,152		7,152	

The table shows the monthly multivariate pooled regressions results, defined as:

$$\mathrm{RNS}_{i,t} = \beta_0 + \beta_1 \mathrm{PUT/ALL}_{i,t} + \beta_2 \mathrm{TV\_OP}_{i,t} + \beta_3 \mathrm{TV\_STOCK}_{i,t} + \beta_4 \mathrm{SIZE}_{i,t} + \beta_5 \mathrm{SRP}_{i,t} + \beta_6 \mathrm{VOL}_{i,t} + \beta_7 \mathrm{D/E}_{i,t} + \beta_8 \mathrm{B/M}_{i,t} + \beta_9 \mathrm{A}_i + \beta_{10} \mathrm{RNS\_M}_t + \beta_{11} \mathrm{VOX\_M}_t + \beta_{12} \mathrm{RNS}_{i,t-1} + \varepsilon_{i,t},$$

where i and t index the firm and week.

All variables are defined in the same way as in Exhibit 1. Monthly observations are collected on the trading day after the option maturity date of each month. The numbers in parentheses besides coefficient estimates are Newey-West t-statistics computed from the heteroscedasiticity and autocorrelation consistent standard errors. The asterisk * indicates a significant estimate at the 5% level using a two tailed t-test.

[1] In view of this, instead of being based on Black-Scholes implied volatilities, the widely used VIX is now based on model-free volatility expectations. See Jiang and Tian (2005) and Taylor, Yadav and Zhang (2008) for an empirical analysis of model-free volatility expectations.

[2] However, as DM argue, Toft and Prucyk (1997)'s measure of volatility smile, which is the slope of implied volatility curve at the at-the-money value, is dubious because it includes effects from both the level and the slope of implied volatility smiles.

[3] There is also other relevant research on and related to RNS. Duan and Wei (2006) find that RNS is negatively and significantly related with the proportion of systematic risk to total risk, using data on the S&P100 index and the 30 U.S. firms with the largest market capitalizations. Christoffersen, Jacobs and Vainberg (2006) show that RNS of individual firms is negatively related with beta and positively related with market skewness, using data on 30 Dow component stocks. Using Spanish index options, Pena, Rubio and Serna (1999) find that option transaction costs, underlying volatility, interest rates and option time to maturity influence the variation of the implied volatility functions over time.

[4] See Taylor, Yadav and Zhang (2008) for details.

[5] We switch to the second-nearest-to-maturity options when there are less than three strike prices available for nearest-to-maturity options.

[6] In the calculation of VOX, the annualized volatility multiplies the implied volatility over 30 calendar days by $\sqrt{365/22}$. Therefore, the resulted VOX is around 20% higher than its conventional level. See Fleming, Ostdiek and Whaley (1995).

[7] We also compute the at-the-money option implied volatility for the S&P100 index in the same way as we calculate the implied volatility for individual firms, but find no significant difference in regression results.

[8] If, following the described procedure, the minimum OTM put (the minimum OTM call) option price is higher than 0.001 cents, we extrapolate option prices by assuming a constant implied volatility level and keep on reducing (increasing) moneyness, defined as the strike price divided by the forward price, by 0.01 each time until the minimum option price reaches 0.001 cents. However, such an extrapolation is not often necessary for our data, because the extreme OTM put (call) option price corresponding to the highest (lowest) level of delta is almost always too small to have any effect on our integral functions.

[9] The definitions of industry sectors are from Professor Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html, with all U.S. firms separated into five main industry sectors.

[10] The percentages of weeks when each coefficient estimate is negatively or positively significant are relatively low in Exhibit 5. This is possibly caused by the relatively small number of observations in every week, compared to the number of explanatory variables in the regression model.

[11] DM estimate RNS with 22 days to maturity and estimate it once a day. In our study, maturity dates are fixed in each month, so that after every four weekly observations the subsequent measure does not overlap with the previous ones.

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centre for financial research
cfr/university of cologne
Albertus-Magnus-Platz
D-50923 cologne
fon +49(0)221-470-6995
fax +49(0)221-470-3992
kempf@cfr-cologne.de
www.cfr-cologne.de