

Real Options, Idiosyncratic Skewness, and Diversification

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Abstract

We show how firm-level real options lead to idiosyncratic skewness in stock returns. We then document empirically that growth option variables are positive and significant determinants of idiosyncratic skewness. The real option impact on skewness is more significant in firms with lottery-type features, small size, high volatility, distressed, low return on assets, and low book-to-market ratio. We also find that expectation on idiosyncratic skewness is associated with lower Sharpe ratios. This suggests investors are willing to sacrifice mean-variance portfolio efficiency for greater skewness deriving from real options. Furthermore, financial flexibility has a positive incremental effect, enhancing the beneficial role of asset flexibility on idiosyncratic skewness.

I. Introduction

Firm-specific skewness has been shown to be priced in the market, commanding a negative return premium (e.g., Barberis and Huang (2008), Mitton and Vorkink (2007), Boyer, Mitton, and Vorkink (2010), Green and Hwang (2012), Chen, Hong, and Stein (2001), and Conrad, Dittmar, and Ghysels (2013)).¹ Given this robust evidence that firm-specific skewness is both statistically significant and economically relevant in asset pricing and portfolio diversification, an understanding of what causes convex value payoffs and skewed equity return distributions is important. In this article, we examine the underlying factors of idiosyncratic skewness and the challenges that skewness poses for the diversification dilemma for firms with different characteristics. Our focus is on examining the role of real

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¹Regressions of firm skewness on firm characteristics are abundant (e.g., Bakshi, Kapadia, and Madan (2003)). Chen et al. (2001) report a link between book-to-market ratio and skewness.

options as key drivers of idiosyncratic skewness. Our main contribution is to introduce real options-generated asset flexibility and the incremental role of financial flexibility as key sources of firm-specific skewness. We also show that real option-based skewness is most prevalent in high-tech industries and firms with lottery-type features, small size, high volatility, low return on assets (ROA), and low book-to-market ratio.

We first show that real options generate skewness in equity returns and confirm our predictions empirically documenting that idiosyncratic skewness is related to real (growth) options. We posit that actively managed firms have real options leading to convex payoffs, which lead to idiosyncratic skewness. Asymmetry in returns is also an important issue for investors in portfolio management. Certain investors are willing to sacrifice mean-variance efficiency (i.e., give up on attaining lowest portfolio variance) in preference for positive idiosyncratic skewness (Kumar (2009), Mitton and Vorkink (2007)). For such investors, portfolio diversification involves a trade-off between enhancing or preserving skewness and lowering portfolio volatility. This trade-off is challenging, as idiosyncratic skewness itself tends to erode as more skewed assets are added to a portfolio.

Enhanced skewness may arise from upside growth options or from investment settings offering a small chance of high returns, what some call lottery-type stocks (e.g., Kumar (2009)), and from various forms of protection against extreme adverse events. On the upside, Trigeorgis and Lambertides (2014) provide empirical support for the hypothesis that investors are willing to accept lower average returns in exchange for growth options. On the downside, Campbell, Hilscher, and Szilagyi (2008) suggest the lower return of distressed stocks may also arise from higher skewness. In the banking context, Gandhi and Lustig (2015) provide evidence that big banks offer lower returns due to the protection offered by government bailout guarantees. These findings suggest that investors may favor idiosyncratic skewness and are willing to sacrifice average return and mean-variance efficiency (see also Mitton and Vorkink (2007)).

For firm-specific skewness to have added value for investors, some fundamental asymmetry is needed, such as subjective beliefs (Brunnermeier, Gollier, and Parker (2007)), heterogeneous preferences (Mitton and Vorkink (2007)), or asymmetric probability weights, as in cumulative prospect theory (Barberis and Huang (2008)). Kumar (2009) and Bali, Cakici, and Whitelaw (2011) provide behavioral and statistical evidence on lottery-type stocks commanding a negative return premium. Kumar defines lottery stocks as those having high volatility and idiosyncratic skewness. Certain types of clienteles are drawn to these stocks as to lotteries. Mitton and Vorkink report an analogous clientele effect with investors. Skewness is related to such features in both financial and real assets.²

Despite the obvious importance of skewness to corporate value creation, asset pricing, and optimal diversification, surprisingly few papers have addressed the issue of its determinants. Conine and Tamarkin (1981) point out that limited

²Numerous studies also document that market coskewness and total skewness command a negative return (e.g., Kraus and Litzenberger (1976), Harvey and Siddique (2000), Chen et al. (2001), Bakshi et al. (2003), Mitton and Vorkink (2007), Bali et al. (2011), Chang, Christoffersen, and Jacobs (2013), and Green and Hwang (2012)).

liability leads to return skewness. Black (1976) and Christie (1982) note that changes in leverage lead to an asymmetric volatility response to stock price changes. Thus, leverage and volatility differences among firms may partly help explain differences in skewness. Leverage has been a key factor in many skewness models. Investor heterogeneity also matters as a source of return skewness differentials. Blanchard and Watson (1983) suggest that bubbles and subsequent crashes may lead to negatively skewed return distributions. Other known drivers of skewness include trading volume (turnover), past average returns, and size.³

Our focus is on real options, representing firm-specific contingent investment opportunities. Growth options are relevant in explaining stock returns (e.g., Anderson and Garcia-Feijóo (2006), Grullon, Lyandres, and Zhdanov (2012), and Trigeorgis and Lambertides (2014)). But the channel through which real options influence stock prices and returns is not as clear. Cao, Simin, and Zhao (2008) view real options as drivers of idiosyncratic volatility.⁴ Yet a defining characteristic of real options (besides deriving more value in more volatile environments) is enhancing asset flexibility, leading to equity value convexity and stock return asymmetry. It is thus equally important to consider real options as drivers of idiosyncratic skewness, besides being drivers of idiosyncratic volatility.⁵ Our results on the determinants of skewness are complementary to Cao et al. on the drivers of idiosyncratic volatility. In both cases real options are viewed as key drivers of idiosyncratic characteristics of the stock return distribution relevant for nonfully diversified investors (Mitton and Vorkink (2007)).

Our work complements Xu (2007), who shows that asymmetric information (related to trading volume and turnover) leads to convexity in payoffs and higher return skewness. From our perspective, the return asymmetry is caused by decision flexibility due to real options. The empirical connection between real options and stock returns is strengthened and justified behaviorally by our findings on the determinants of skewness. Both idiosyncratic skewness and volatility

³Hong and Stein (2003) further argue that high trading volumes lead to more negatively skewed returns when investors are short-sales constrained when previously suppressed market information comes out during market declines. Cao, Coval, and Hirshleifer (2002) present an information blockage theory of sidelined investors causing skewness after price drops and price runs. Chen et al. (2001) provide evidence that trading volume has a negative effect on skewness and that price run-ups (run-downs) are followed by more negative (positive) skewness. They also report that past average returns are negatively associated with skewness. Xu (2007) finds evidence of a positive association of skewness with trading volume (turnover) and a negative association with lagged average returns, size, and institutional ownership. Epstein and Schneider (2008) argue that ambiguity in information leads to more skewness as investors react asymmetrically to good and bad news. As smaller firms are less closely followed by analysts, they may exhibit more positive skewness.

⁴Equityholders' limited liability also implies that greater volatility is associated with greater skewness (see Conine and Tamarkin (1981)), besides idiosyncratic volatility being positively related to corporate growth options (e.g., Kogan and Papanikolaou (2014)).

⁵Amaya, Christoffersen, Jacobs, and Vasquez (2015) show that the impact of volatility on returns is dependent on skewness: For low-skewness firms, volatility is bad (has negative impact on returns), as in standard mean-variance portfolio efficiency; for high-skewness firms, volatility is beneficial, as it implies higher probability of extreme upside returns. In related work on the relation among return asymmetry, volatility, and future returns, Kelly and Jiang (2014) study the relation between tail measures and returns, Patton and Sheppard (2015) show that semivariance improves forecasts of future volatility, and Bollerslev, Osterrieder, Sizova, and Tauchen (2013) use realized volatility to assess the risk–return relation and to forecast future market returns.

are key variables connecting hard-to-observe real options with stock returns. We posit that real options, by providing asset flexibility and a more convex payoff in the value of an actively managed firm, result in more positively skewed equity returns. We therefore consider real options and active firm management as fundamental drivers of firm-specific or idiosyncratic skewness.

An active firm manages an asset portfolio that includes two major categories of real options: i) growth or expansion call options (e.g., sequential investments, excess capacity, early-stage investment) and ii) protective put options (contraction, reorganization, default/exit, and delay). As demand rises beyond an upper threshold, an active firm with asset flexibility can exercise its growth/expansion options to attain a competitive advantage in terms of enhanced market share, lower marginal costs, and higher profits. Conversely, when market demand drops below a critical lower level, an actively managed firm can contract or reorganize operations to reduce fixed costs and achieve downside protection. This dynamic asset adaptation process by an active firm creates a convex value payoff that enhances idiosyncratic skewness. Protective contraction put options reduce downside risk, whereas growth options preserve and enhance upside potential. From a corporate manager's point of view, creation and timely exercise of real options are key value-enhancing managerial activities. From an investor's point of view, investing in (a limited number of) active firms with such growth and contraction real options offers substantial diversification benefits (downside protection) while preserving the upside potential. Investor preferences for enhanced idiosyncratic skewness lead to less than fully diversified investment portfolios with lower average returns. Such investors are willing to trade off mean-variance efficiency to attain positive idiosyncratic skewness. These investments should thus exhibit lower Sharpe ratios at both the individual firm and portfolio levels.

Once the link between real options and firm-specific skewness is clarified, we then examine in which situations and for which type of firm or industry characteristics the impact of real options on idiosyncratic skewness is more significant. We find that lottery-type features and related firm characteristics such as small size, high volatility, high distress, low ROA, and low book-to-market are related to greater significance of real options as a skewness driver, extending related results in Kapadia (2006).⁶ Furthermore, building on Bartram (2017), we find that financial flexibility is an additional determinant of idiosyncratic skewness and has a positive interaction effect. That is, both asset flexibility and financial flexibility are used by active managers to enhance skewness. When management actively pursues growth options and lottery-type projects and values idiosyncratic skewness, it will likely deviate from mean-variance efficiency at the firm level. This will be manifest in i) lower mean-variance efficiency in exchange for an offsetting higher level of idiosyncratic skewness and ii) lower mean (required) returns when investors exhibit a preference for skewness. Underdiversified, skewness-preferring investors will compensate the lower mean-variance efficiency of their

⁶Human capital when managers are compensated through stock option incentives may be another skewed intangible asset leading to convexity that might also influence managerial diversification decisions. We tested this hypothesis but were unable to find empirical support that stock option compensation, measured as the portion of manager's total compensation that is in the form of stock options, has an impact on idiosyncratic skewness.

portfolios of actively managed firms with enhanced skewness. This may result in lower Sharpe ratios for such investors.

Controlling for other standard skewness drivers, we show that real options variables are significant determinants of idiosyncratic skewness. Our findings contribute in several ways: i) We show theoretically and confirm empirically that real options are significant drivers of idiosyncratic skewness, ii) we show that the real option impact on idiosyncratic skewness is more significant in firms with lottery-type and related firm characteristics, iii) we show that expectations on idiosyncratic skewness are associated with lower Sharpe ratios and illuminate how idiosyncratic skewness is related to investment diversification and mean-variance efficiency, and iv) we confirm that idiosyncratic skewness is synergistically driven by active management of both asset flexibility and financial flexibility.

The article is organized as follows: Section II develops the connection between real options, equity value convexity, and stock return skewness. Section III describes our data and addresses methodological issues regarding the measurement of key drivers and the market impact of skewness. Section IV presents our main empirical findings. Section V presents our robustness tests and analysis of firm characteristics. Section VI discusses the relation with diversification discount and the role of financial flexibility. Section VII concludes.

II. Real Options, Value Convexity, Idiosyncratic Skewness, and Diversification

A. Firm Value Perspective

In effect, we argue that firms have real options (both upside calls and downside puts) and these options have convex payoffs leading to equity value convexity and enhanced skewness in returns. To illustrate the connections among real options, equity value convexity, and skewness, let V be the value of an all-equity passive firm with no real options under standard assumptions (e.g., log-normal distribution). Consider an otherwise identical but actively managed firm V' with embedded real protective PUT and expansion (growth) CALL options:

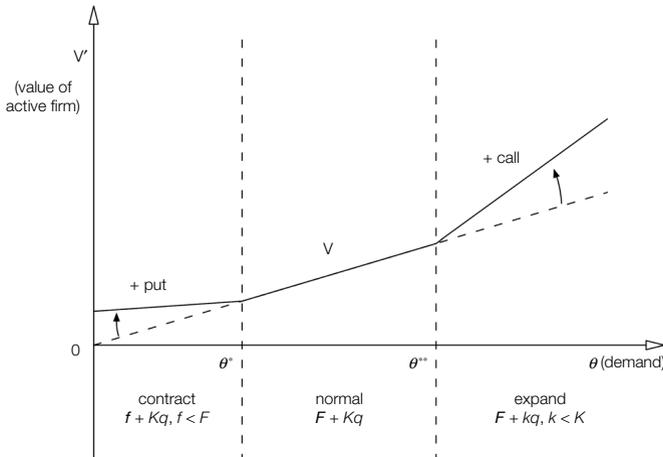
$$(1) \quad V' = V + \text{PUT}(V) + \text{CALL}(V).$$

From basic convexity properties of call and put options (e.g., Black and Scholes (1973)), it can be seen that V' is an increasing convex function of V (since $dV'/dV > 0$ and $d^2V'/dV^2 > 0$; see also Figure 1). According to van Zwet ((1964), thm. 3.1), an increasing and convex transformation of a random variable (V) produces a more skewed random variable (V'). Therefore, the skewness of the value function of an active firm with real options, V' , is higher (more positive) than that of a similar passive firm without real options, V .

Figure 1 illustrates this situation graphically. Active management allows for a more flexible production scale on the downside (via a contraction option) by lowering fixed costs (from F to f). The expansion (growth) and contraction opportunities are a function of future demand realization. If future demand θ increases beyond an upper demand threshold, θ^{**} , the active firm with a strategic growth investment will exercise its expansion option, lowering marginal production costs

FIGURE 1
Value Convexity

Figure 1 provides graphical representation of the adaptive options of an active firm. For a low level of demand ($\theta < \theta^*$) the firm can exercise a contraction option: The scale and fixed costs will be reduced to f ($f < F$). For an intermediate (normal) level of demand ($\theta^* < \theta < \theta^{**}$), neither option is exercised: The firm faces the same production cost function as an identical passive firm without options. For a high level of demand ($\theta > \theta^{**}$) the firm will exercise an expansion option with economies of scale, so the firm is able to produce at a lower marginal cost k ($k < K$). The cost of the passive firm under normal demand is $C = F + Kq$. The expected adaptive cost of an active firm is $(f + Kq)$ and $(F + kq)$.



and increasing profitability. In case of a negative shock in demand, below lower threshold θ^* , exercising the contraction put option enables resizing the firm's scale (lowering fixed costs from F to f) and reducing losses. Thus, the strategic investment effectively enables the active firm to change its operating scale and cost structure depending on demand shock realization, θ , exploiting growth or contraction opportunities accordingly. Under high demand ($\theta > \theta^{**}$), the active firm adopts a larger scale to grow and faces higher fixed costs F ($F > f$) but it achieves lower marginal production costs k ($k < K$). Its total costs are $F + kq$ when $\theta > \theta^{**}$. Conversely, when demand drops below θ^* , the active firm down-scales, facing lower fixed costs f ($f < F$) but higher marginal unit costs K . Its total costs will then be $f + Kq$ for $\theta < \theta^*$. Figure 1 provides a graphical representation of the above reasoning. The value of the active firm (V') is thus the value of a passive firm (V) in a normal demand range ($\theta^* < \theta < \theta^{**}$) plus the contraction (PUT) and expansion (CALL) options, as per equation (1). Without such strategic investment, a passive firm with rigid costs (of value V) faces a total production cost $C = F + Kq$, with $F > f$ and $K > k$.

B. Investor Diversification

Turning now from firm value to investor perspective, we note a common dilemma arising for investors: Efficient diversification of a portfolio lowers idiosyncratic volatility, but it also erodes desirable idiosyncratic skewness. For such investors seeking idiosyncratic skewness, there is a trade-off between preserving desirable idiosyncratic skewness and containing portfolio volatility. Motivated by the observation that most individual investors hold imperfectly diversified

portfolios, Conine and Tamarkin (1981) show that rational investors may hold a limited number of risky assets and address the concern as to whether skewness gets eliminated in a portfolio context. They derive the optimal number of assets and obtain the necessary constraints for optimization and positive asset holdings. The optimal is reached when a marginal increase in expected utility from a reduction in portfolio variance is just offset from the value erosion of skewness. The trade-off depends on the type of utility function (e.g., logarithmic, power, etc.) and whether these constraints hold.⁷ Conine and Tamarkin's analysis assumes a randomly selected portfolio of equally weighted identical assets (a homogeneous asset universe). A careful investor can potentially do better preserving idiosyncratic skewness in a portfolio context than in a random diversification of skewed assets through strategic selection of asset correlations as feasible.

Pursuing strategies that result in higher skewness due to a small chance of a high payoff is common in business settings but is highly risky. Hence, a prudent investor of a portfolio of stocks or a manager of a portfolio of business activities would seek out skewness in a way that allows for partial risk diversification. As noted, full or random diversification as per traditional portfolio theory would tend to erode such idiosyncratic skewness. But partial, select diversification accounting for some strategic correlation among individual lottery-type investments can preserve much of idiosyncratic skewness while containing portfolio volatility. Thus, idiosyncratic skewness is not completely eliminated via portfolio diversification and does matter. We subsequently focus our empirical analysis on the impact of expansion/growth options using the universe of U.S. stocks.

III. Sample and Methodology

A. Data Description

Our sample consists of all active U.S. firms listed on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and National Association of Securities Dealers Automated Quotation (NASDAQ) during 1983–2011. We focus on the period after July 1983, when NASDAQ data are readily available and market volatility and skewness are more prevalent. There are several reasons for this focus. First, many growth stocks are traded on NASDAQ. Second, computerized portfolio management increased after the start of Standard & Poor's (S&P) 500 index futures trading in 1983, enhancing volatility and skewness in the market. Growth options that might lead to more asymmetric returns and a related priced skewness factor are more significant in the presence of increased market volatility, which has become more pronounced since 1983. Xu and Malkiel (2003) argue that idiosyncratic risk has become more important over

⁷Conine and Tamarkin (1981) provide empirical examples with two independent random samples (I and II) of monthly returns of 50 stocks drawn from Compustat from Jan. 1972 to Dec. 1976. They confirm that optimal portfolio size may be limited, for example, with logarithmic utility to 7 random assets (for their sample I). This depends (for their constraint (9) to hold) on the investor trade-off of risk aversion for skewness or the investor speculation preference trading skewness for variance at the margin. In some extreme cases this may reduce to a single asset (see their sample II). Under certain conditions (when their constraint (8) does not hold), the optimal may be full diversification, even when investors have a preference for skewness.

time as stocks listed on NASDAQ increased in number and importance after 1983. Chan and Lakonishok (1993) report that beta was working fine until 1982 but subsequently stopped being significant, in line with a structural break around 1983. Finally, many variables that are used to measure expansion or growth options are only available in Compustat after 1983. For these reasons, we focus our analysis on the post-1983 period.

Our basic analysis uses daily holding-period equity returns from the Center for Research in Security Prices (CRSP). We include ordinary common shares of firms listed on the NYSE/AMEX/NASDAQ from July 1, 1983 to June 30, 2011. Financial firms are excluded. We require each included stock to have at least 100 nonmissing daily observations in a year. Data from CRSP are matched with Compustat using the 8-digit Committee on Uniform Securities Identification Procedures (CUSIP) code and fiscal year. Duplicates of CUSIP–fiscal year are deleted from the sample.

B. Measuring Skewness Determinants

Idiosyncratic skewness is generally estimated from the residuals of time-series regressions. Two approaches are commonly used to estimate the residuals: i) the market model with potential inclusion of a second-order term (Mitton and Vorkink (2007), Bali et al. (2011), and Green and Hwang (2012)) and ii) the Fama and French (1993) 3-factor model (e.g., Boyer et al. (2010), Green and Hwang (2012)). In line with Harvey and Siddique (2000), we use models that rely on market information in determining market-related and firm-specific skewness components. We treat idiosyncratic or firm-specific skewness as that part of total skewness that is not related to market movements, and thus measure idiosyncratic skewness from the residuals of the market model.

As real options represent firm-specific characteristics or contingent idiosyncratic opportunities, we examine their incremental impact on idiosyncratic skewness measured as:

$$(2) \quad \text{IS}_{i,t} = \frac{E[\epsilon_{i,t}^3]}{\sqrt{E[\epsilon_{i,t}^2]^3}},$$

where $\epsilon_{i,t} = r_{i,t} - (\alpha_0 + \beta_i r_{M,t})$ are the residuals from the market model. We estimate idiosyncratic skewness using different horizons from 1 to 5 years, each period starting July 1 and extending to June 30 of the next year. The market model parameters are constant over the chosen horizon, and expectations in equation (2) are on the residuals.⁸ As a robustness test, we also build a skewness measure using monthly holding-period returns over 3 years (36 monthly observations).

We test the impact that real option variables have on idiosyncratic skewness using standard panel regressions with lagged regressors. We test the following

⁸For example, the 2-year horizon skewness is calculated by first fitting the market model on daily returns from July 1 in year $t-2$ to June 30 in year t . We then calculate the skewness as in equation (2) of the obtained daily residuals. The estimation is repeated by moving 1 year ahead and maintaining the fixed 2-year window.

model:

$$(3) \quad \begin{aligned} \text{IS}_{i,t} &= \alpha \text{IS}_{i,t-j} + \mathbf{X}'_{i,t-j} \beta + \epsilon_{i,t}, \\ i &= 1, \dots, N, \\ t &= 1, \dots, T, \\ j &= 1, 3, \end{aligned}$$

where $\text{IS}_{i,t}$ represents the estimated idiosyncratic skewness for asset $i = 1, \dots, N$ in year $t = 1, \dots, T$; $\mathbf{X}_{i,t-j}$ is a $(K \times 1)$ vector of exogenous covariates; and β is a $(K \times 1)$ vector of unknown coefficients. The subscript j denotes the length of the lag (equal to 1 for the 1-year daily data and equal to 3 years for the monthly return case). Model 3 is estimated using standard panel methods. A difficulty arises with use of fixed effects in the context of dynamic panel data, especially when the cross-sectional dimension is large compared to the time-series dimension (see Nickell (1981)). For this reason, we also report the Arellano and Bond (1991) dynamic panel estimators as extended by Arellano and Bover (1995) and Blundell and Bond (1998) to address this problem. All accounting data are lagged 1 year relative to market data if the company fiscal year-end is between July and December, or 2 years if between January and June. This ensures all accounting variables are known at the time considered. The following K exogenous firm-specific variables are used to help explain idiosyncratic skewness and make up the vector $\mathbf{X}_{i,t}$. Variables are described for the base case of skewness calculated on daily returns over 1 year:

- BETA_t . This is estimated as the market loading factor calculated on daily returns from July 1 in year $t - 1$ to June 30 in year t .
- $\text{SIZE}_t = \ln(\text{ME}_t)$, where $\text{ME}_t = \text{PRICE}_t \times \text{SHARE_OUT}_t$. Measured as the natural logarithm of the market value of equity, size is one of the standard Fama and French (1993) factors. Future growth opportunities are more likely to arise in smaller companies. SIZE might thus act as a proxy for future growth options, though this may be challenged because it also captures leverage effects (see Black (1976), Christie (1982)). SIZE is calculated as the natural logarithm of stock price at the end (or last nonmissing available observation) of June in year t (PRICE_t) times the number of shares outstanding at the end of June in year t (SHARE_OUT_t). The main results hold if size is alternatively proxied by the natural logarithm of total assets or sales.
- $\text{BM}_t = \text{CEQ}_{t-fy} / (\text{ME}_t)$. Book-to-market ratio is included as a basic Fama and French (1993) factor, potentially proxying for the existence of future growth options or for distress (see Fama and French (1993)). Book-to-market is the ratio of book value of equity in fiscal year $t - fy$ (CEQ_{t-fy}) to the market value of equity at the end of June in year t (ME_t). The subscript fy assumes the values 1 or 2 if fiscal year-end month is between July 1 and Dec. 31 or between Jan. 1 and June 30, respectively. Chen et al. (2001) find this variable is positively related to skewness, probably because glamor stocks are more crash-prone.

- GO_t . Growth option intensity represents the percentage of firm market value (MV_t) that derives from future growth opportunities (GO_t). It is estimated by subtracting from the current market value of the firm (MV_t) the perpetual discounted stream (at the weighted average cost of capital (WACC)) of firm-operating free cash flows under a no-further-growth policy $FCF_{t-fy}(ng)$ (e.g., see Cao et al. (2008), Trigeorgis and Lambertides (2014)):

$$(4) \quad GO_t = \frac{MV_t - \frac{FCF_{t-fy}(ng)}{WACC_{t-fy}}}{MV_t},$$

where $MV_t = ME_t + LT_{t-fy}$. The weighted average cost of capital ($WACC_{t-fy}$) is estimated as $COST_EQUITY \times (1 - LEV_{t-fy}) + COST_DEBT \times LEV_{t-fy}$, where the cost of equity is obtained from the market model (or capital asset pricing model assuming a market beta equal to 1 for all firms). The market equity premium is estimated as the average stock market excess return (roughly 6%) over the Treasury bill rate. The cost of debt is estimated by applying an annual spread of 2% to the 10-year Treasury bond rate. The results are robust to use of different spreads. $FCF_{t-fy}(ng)$ is free cash flow under no-further-growth, that is, firm “as is” policy.⁹

- $CAPFIX_t = CAPX_{t-fy} / PPENT_{t-fy}$. $CAPFIX$ is used as a proxy for exercising growth options and turning them into assets in place. If capital expenditures capture past exercised growth options, the relation between capital expenditures and future growth options may not be linear (see Goyal, Lehn, and Racic (2002), Cao et al. (2008)). Capital expenditure intensity is measured as the ratio of capital expenditures in fiscal year $t - fy$ ($CAPX_{t-fy}$) over the net value of property, plant, and equipment (PPE) in the same fiscal year ($PPENT_{t-fy}$).
- $RD_t = XRD_{t-fy} / AT_{t-fy}$. Research and development (R&D) intensity is a common real option measure that captures systematic firm efforts to cultivate or develop new multistage growth options. R&D intensity is measured as R&D expenses in fiscal year $t - fy$ (XRD_{t-fy}) over total assets in the same fiscal year (AT_{t-fy}). Missing values in XRD_{t-fy} are replaced by zeros to save observations; relaxing this assumption does not substantially change the main results.
- $TURNOVER_t$. Used as a measure of investor heterogeneity (Chen et al. (2001)), $TURNOVER$ is given by the ratio of average daily volume from July 1 in year $t - 1$ to June 30 in year t , divided by average shares outstanding in same period.

⁹In the previous literature (e.g., Cao et al. (2008), Trigeorgis and Lambertides (2014)) OANCF from Compustat is used as an estimate of $FCF(ng)$. We adhere to a more precise definition of free cash flow used in company valuation, adding back to OANCF the interest and assuming that under a no-growth policy, capital expenditures roughly equal depreciation. This leads to our estimating $FCF_{t-fy}(ng)$ as $OANCF_{t-fy} + XINT_{t-fy} - DPC_{t-fy}$. OANCF is net cash flow from operating activities, XINT is interest and related expense (total), and DPC is depreciation and amortization (cash flow).

- \bar{R}_t and IV_t . This is the average daily firm (asset) return and idiosyncratic volatility from July 1 in year $t - 1$ to June 30 in year t . Campbell and Hentschel (1992) and Harvey and Siddique (1999) show that skewness is a time-varying firm characteristic that can be modeled by autoregressive processes. Blanchard and Watson (1983) suggest that bubbles and subsequent crashes may lead to negatively skewed return distributions. These results suggest that in modeling the determinants of skewness one should control for endogenous market-based variables, especially lagged average returns, volatility, and past skewness.
- $LEV_t = LT_{t-fy} / MV_t$, where $MV_t = ME_t + LT_{t-fy}$. Leverage partly captures the financial flexibility of the firm while it may also proxy for distress. It is calculated as the ratio of total liabilities at fiscal year $t - fy$ (LT_{t-fy}) to the market value of the firm at t , MV_t . The market value of equity (ME_t) is given by stock price times number of shares outstanding at the end of June in year t ($PRICE_t \times SHARE_OUT_t$). The value of debt is approximated by total liabilities LT_{t-fy} .
- $CONCENTRATION_t$. This is measured by the Herfindahl–Hirschman index (HHI) calculated at the 2-digit Standard Industrial Classification (SIC) industry level using sales ($SALE_{t-fy}$). HHI is used as a proxy for the level of competition in an industry and captures how well protected the firm’s competitive advantage is. For firm i in year $t - fy$ we calculate

$$CONCENTRATION_{i,t} = \left(\frac{SALE_{i,t-fy}}{\sum_{i=1}^{N_{SIC}} SALE_{i,t-fy}} \right)^2 \times 100,$$

where N_{SIC} is the total number of firms in the same 2-digit industry.

- $ROA_t = NI_{t-fy} / AT_{t-fy}$. ROA_t is the return on assets in fiscal year t , where NI_t is net income in fiscal year t and AT_t is total assets at the beginning of fiscal year t . ROA is a measure of the firm’s past operating performance.
- $MKT_SENT_t = \bar{RM}_t / \sigma_{m,t}$. This variable proxies for market ups/downs or market sentiment (e.g., pessimism or optimism) in year t . It is given by the ratio of the average return on the market over 1 year (\bar{RM}_t) to the standard deviation of market returns from July in year $t - 1$ to June in year t ($\sigma_{m,t}$). During downmarket or market pessimism periods, this measure declines as lower (or even negative) market rates of return are realized along with higher volatility. This variable captures general economic conditions that affect the firm production level and proxies for demand shocks.

To avoid excessive influence of outliers for BM, GO, CAPFIX, ROA, and RD, we remove the extreme 0.1% of observations in both tails. For comparability, the horizon used to calculate $BETA_t$, $TURNOVER_t$, average firm return (\bar{R}_t), idiosyncratic volatility of daily asset returns (IV_t), and MKT_SENT_t are analogously extended when skewness is calculated over 2, 3, 4, and 5 years. When skewness is calculated on monthly returns, we consider 36 monthly observations (rolled each year) from July 1 in year $t - 3$ to June 30 in year t . To allow for more

observations and enable direct comparison with the previous literature (see Chen et al. (2001)), we use daily skewness calculated over 1 year as our base case. In Section V we include the results obtained for skewness calculated over longer horizons.

To examine the conjecture that investors may be willing to sacrifice mean-variance portfolio efficiency in exchange for enhanced expected idiosyncratic skewness deriving from real options, we also estimate real options-induced expected idiosyncratic skewness, analogous to Boyer et al. (2010). We estimate idiosyncratic skewness (IS_t) using the following series of cross-sectional regressions:

$$(5) \quad IS_t = \alpha_0 + \beta_1 IS_{t-T} + \beta_2 GO_{t-T} + \beta_3 RD_{t-T} + \beta_4 CAPFIX_{t-T} + \beta_5 IV_{t-T} + \beta_6 (IV_{t-T} \times IS_{t-T}^+) + \epsilon_t.$$

We include as key explanatory variables the three main real option determinants plus idiosyncratic volatility. IV (estimated over T years) is included for two reasons: i) IV is a key driver of the value of real options and ii) idiosyncratic volatility and skewness may be codetermined as high firm-specific volatility attracts more active management, which influences asymmetrically the shape of the return distribution while active management simultaneously contains idiosyncratic volatility. The latter justifies use of the interaction term. IS^+ is a binary dummy that equals 1 if past idiosyncratic skewness is positive, and 0 otherwise. As in Boyer et al., the analysis is affected by the choice of horizon used for the skewness expectation. For robustness, we estimate expected idiosyncratic skewness using different lengths of the time window. In particular, IS_t is the idiosyncratic skewness calculated from July 1 in year $t - T$ to June 30 in year t , where $T = 2, 3, 4$ years; GO_{t-T} , RD_{t-T} , $CAPFIX_{t-T}$, and IV_{t-T} are observed on June 30 in year $t - T$; and IS_{t-T} is past (lagged) idiosyncratic skewness calculated from July 1 in $t - 2T$ to June 30 in $t - T$. Expected idiosyncratic skewness (at year t) over future horizon $t + T$ is then estimated as

$$(6) \quad E_t[IS_{t+T}] = \hat{\alpha}_0 + \hat{\beta}_1 IS_t + \hat{\beta}_2 GO_t + \hat{\beta}_3 RD_t + \hat{\beta}_4 CAPFIX_t + \hat{\beta}_5 IV_t + \hat{\beta}_6 (IV_t \times IS_t^+).$$

Expected idiosyncratic skewness over a future horizon (T) calculated as above is then used to test the impact of expectations of idiosyncratic skewness on mean-variance portfolio efficiency and on Sharpe ratios.

IV. Main Empirical Results

We next present basic descriptive statistics for our explanatory variables by skewness deciles. Table 1 shows averages of the explanatory variables in each skewness decile. Explanatory variables are observed in the previous period and are then cross-sectionally averaged depending on their skewness classification in year t . Table 1 shows that positive skewness rises almost linearly with GO and RD but shows potential nonlinearity in CAPFIX. Nonlinearity of skewness

TABLE 1
Basic Descriptive Statistics of Explanatory Variables by Idiosyncratic Skewness Deciles

Table 1 contains the time-series averages of each portfolio built by dividing idiosyncratic skewness in 10 equally spaced deciles. The variables are built using daily data from July 1983 to June 2011. Idiosyncratic skewness, IS_t ; lagged firm-specific volatility, IV_{t-1} ; average rate of return, \bar{R}_{t-1} ; TURNOVER $_{t-1}$; and BETA $_{t-1}$ are calculated from daily data over 1 year. Each year skewness is reclassified in 10 equally spaced deciles, and the lagged values of the covariates are cross-sectionally averaged. RD_{t-1}^* indicates that missing values of the research and development expenses (RD) are dropped. RD_{t-1} is calculated with missing values in RD replaced by zeros. Details on the variable definition and construction are contained in Section III.B.

Decile	\overline{IS}_t	\overline{IS}_{t-1}	\overline{BETA}_{t-1}	\overline{SIZE}_{t-1}	\overline{BM}_{t-1}	\overline{GO}_{t-1}	\overline{RD}_{t-1}	\overline{RD}_{t-1}^*
1	-1.695	0.346	0.899	12.688	0.513	0.786	0.049	0.079
2	-0.280	0.347	0.837	12.703	0.585	0.732	0.037	0.066
3	0.021	0.347	0.803	12.501	0.633	0.722	0.037	0.071
4	0.204	0.427	0.782	12.250	0.657	0.770	0.038	0.073
5	0.364	0.462	0.789	12.095	0.671	0.806	0.045	0.081
6	0.529	0.508	0.788	11.884	0.684	0.843	0.051	0.087
7	0.725	0.560	0.794	11.695	0.704	0.913	0.054	0.092
8	0.999	0.625	0.779	11.510	0.704	0.959	0.060	0.099
9	1.496	0.758	0.768	11.259	0.739	1.020	0.064	0.105
10	3.753	0.835	0.685	10.899	0.841	1.101	0.071	0.118

Decile	\overline{IS}_t	\overline{CAPFIX}_{t-1}	\overline{IV}_{t-1}	$\overline{TURNOVER}_{t-1}$	$\overline{\bar{R}}_{t-1}(\times 100)$	\overline{LEV}_{t-1}	\overline{CONC}_{t-1}	\overline{ROA}_{t-1}
1	-1.695	0.301	0.029	0.073	0.083	0.295	0.459	0.031
2	-0.280	0.268	0.030	0.063	0.083	0.331	0.508	0.036
3	0.021	0.262	0.032	0.058	0.084	0.343	0.426	0.027
4	0.204	0.264	0.035	0.056	0.088	0.345	0.434	0.015
5	0.364	0.271	0.037	0.055	0.082	0.348	0.416	-0.011
6	0.529	0.277	0.039	0.057	0.081	0.344	0.342	-0.014
7	0.725	0.284	0.042	0.056	0.077	0.353	0.259	-0.028
8	0.999	0.290	0.044	0.060	0.082	0.358	0.310	-0.052
9	1.496	0.294	0.047	0.058	0.071	0.365	0.245	-0.073
10	3.753	0.284	0.048	0.057	0.066	0.385	0.247	-0.094

with GO and RD is observed when skewness turns to negative values.¹⁰ Table 1 confirms that idiosyncratic skewness is positively associated with distress (high leverage and high book-to-market ratio) and higher volatility. Size, market beta, and profitability (ROA), conversely, appear to be negatively related to skewness. Generally high idiosyncratic skewness is associated with real option-intensive firms (high GO and RD), high-risk firms (high volatility and distress), and small unprofitable firms (small size, low market beta, and low profitability).

Table 2 shows the results of panel regressions with firm fixed effects and Arellano and Bond (1991) dynamic panel estimators (as extended by Arellano and Bover (1995), Blundell and Bond (1998)) based on daily data at the firm level (equation (3)).¹¹ Standard errors are corrected for heteroskedasticity and cluster correlation by firm (see Petersen (2009)). In line with Chen et al. (2001) and Xu (2007), skewness is negatively related to past average firm returns and size but positively related to past volatility and book-to-market (BM) ratio. In line with a real options view, the positive association between volatility and skewness stems from a positive relation between volatility and growth options (e.g., see Cao et al. (2008), Grullon et al. (2012)). As in Cao et al. (2008), we find that our real option variables are positively related to idiosyncratic volatility. Financial leverage, by providing a second layer of flexibility and convexity, has an enhancing

¹⁰The relation between GO, RD, and skewness is weaker in this case. Table 1 raises an interesting issue on the determinants of negative skewness. Negatively skewed assets become lottery stocks if short sold.

¹¹Results based on monthly return data are similar (not reported, but available from the authors).

TABLE 2
Panel Regressions of Idiosyncratic Skewness Determinants (Daily Data)

Table 2 contains the results of the panel regressions of equation (3) on individual daily idiosyncratic skewness. The dependent variable is daily idiosyncratic skewness (IS_t) calculated from July 1 to June 30 each year. The sample period covers July 1983 to June 2011. Columns 0 and 1 contain the results from standard panel regressions with firm-specific fixed effect (FE) and heteroskedasticity- and cluster-corrected standard errors (see Petersen (2009)). Column 2 contains the Arellano and Bond (1991) (as extended by Arellano and Bover (1995), Blundell and Bond (1998)) (AB) dynamic panel estimators. Missing values in research and development expenses (RD) are replaced by zeros. * and ** indicate significance at the 5% and 1% levels, respectively. MSE is the square root of the mean square errors (residual).

	Dependent Variable: Idiosyncratic Skewness (IS_t)		
	FE	FE	AB
	0	1	2
Constant	0.538** (28.5)	1.931** (11.8)	1.411** (29.5)
IS_{t-1}	—	-0.086** (11.1)	-0.006 (0.98)
$BETA_{t-1}$	—	-0.018 (1.30)	-0.045** (5.36)
$SIZE_{t-1}$	—	-0.147** (12.3)	-0.101** (30.6)
BM_{t-1}	—	0.067** (4.62)	0.051** (7.66)
GO_{t-1}	0.109** (7.32)	0.062** (4.17)	0.094** (13.2)
RD_{t-1}	0.708** (4.65)	0.734** (4.72)	0.665** (11.7)
$CAPFIX_{t-1}$	-0.305** (6.58)	-0.193** (4.03)	-0.129** (4.86)
$TURNOVER_{t-1}$	—	0.349* (2.56)	0.117 (1.79)
IV_{t-1}	—	2.261** (4.06)	4.628** (15.7)
\bar{R}_{t-1}	—	-21.37** (5.27)	-52.74** (23.7)
LEV_{t-1}	—	0.859** (11.9)	0.479** (18.4)
$CONCENTRATION_{t-1}$	—	-0.002 (0.98)	-2.4e-4 (0.17)
ROA_{t-1}	—	-0.076 (1.64)	-0.220** (8.63)
MKT_SENT_{t-1}	—	1.025** (9.15)	0.854** (11.1)
No. of obs.	67,151	66,919	66,919
F	46	110.520	—
Prob > F	0.0000	0.000	—
R^2	0.2212	0.248	—
Root MSE	1.4821	0.146	—

impact on idiosyncratic skewness. In line with previous studies, we find mixed evidence on the impact of turnover on skewness (see Chen et al. (2001), Xu (2007)). The impacts of size (-), volatility (+), and financial leverage (+) are also consistent with the leverage effect noted by Black (1976) and Christie (1982) and the volatility feedback mechanisms of Campbell and Hentschel (1992). Higher market sentiment (+MKT_SENT), given by the ratio of past average market return over market volatility, is positively associated with skewness, in line with Blanchard and Watson (1983). Past profitability measured by ROA is inversely related to skewness. Compared to the univariate analysis in Table 1, all variables maintain their sign, with the exception of past idiosyncratic skewness and turnover, after controlling for all other explanatory variables.

After controlling for all of the above factors, the main real option variables, GO and RD, are seen to be positively and significantly related to skewness. Table 2 confirms that higher growth options (GO) lead to more positively skewed returns, in line with our real options–skewness hypothesis. These results are valid in both daily and monthly return data (unreported). The results are robust to different estimation methodologies and time horizons. Capital expenditure intensity (CAPFIX), related to the past exercise of growth options, has a negative sign. Our overall findings indicate that growth options are not only important determinants of idiosyncratic volatility (see also Cao et al. (2008)), but their presence significantly affects the shape (skewness) of the return distribution.¹²

V. Robustness and Firm Characteristics

We tested the robustness of our results contained in Table 2 when skewness is calculated over longer horizons (from 1 to 5 years). Although GO loses some power as the horizon increases, RD intensity remains important.¹³ Overall, results for longer horizons are qualitatively analogous to those contained in column 2 of Table 2. Table 3 presents various additional robustness test results. Here we examine how results are affected by the estimation methodology and the construction of real option variables. We run different panel estimation methods and use alternative proxies for the main variables in our regression models. Table 3 confirms that fixed effect (column 1), Arellano and Bover (1995)/Blundell and Bond (1998) dynamic panel estimation (column 2), and pooled regressions (column 3) produce qualitatively similar results concerning the main real option variables, GO and RD. To account for the time dynamics of the estimated coefficients, column 4 reports the time-series average coefficients of year-by-year cross-sectional regression slopes (CS). The results confirm that growth option proxies are significant positive determinants of idiosyncratic skewness. Robustness tests employing alternative definitions of our GO variable, namely: i) setting negative GO values to 0 (GO1) in column 5 and ii) using the Cao et al. (2008) measurement approach (GO2) in column 6, produce similar results as in our base case. Overall, over and above all other variables considered in the previous literature, our main real option variables (GO and RD) are significant and robust determinants of idiosyncratic skewness.

All else equal, we expect growth options to be more important determinants of idiosyncratic skewness for more volatile, high-tech, or high-growth firms. We therefore examine the relation between growth options and future idiosyncratic skewness for different groups of firms classified on specific characteristics. If skewness is mainly the result of active management exploiting growth option potential, we should expect real option variables to be more important in

¹²Panel regressions at the portfolio level (using daily data) show similar results. The real option variables, GO, RD, and CAPFIX, explain a significant portion (about 35%) of average portfolio idiosyncratic skewness. The overall model explanatory power at the portfolio level is high ($R^2 = 56\%$).

¹³There are several reasons RD intensity remains important over longer horizons: i) RD investments are long term; ii) RD can generate preemptive or first-mover advantages, which translate into more convex payoffs that enhance skewness; and iii) investment in RD generates future follow-on growth options.

TABLE 3
Robustness Tests of Idiosyncratic Skewness Determinants (Daily)

Table 3 contains robustness results of panel regressions of equation (3) on daily idiosyncratic skewness. The dependent variable is daily idiosyncratic skewness (IS_{*t*}) calculated from July 1 to June 30 each year. The sample period covers July 1983 to June 2011. Standard errors are corrected for heteroskedasticity and cluster correlation by firm (see Petersen (2009)). Columns 1 and 2 contain the fixed effects (FE) base case and the Arellano and Bond (AB) (1991) (as extended by Arellano and Bover (1995), Blundell and Bond (1998)) dynamic panel estimators shown in Table 2, where GO is defined as in equation (4). Column 3 contains the results of pooled estimation, and column 4 contains the coefficients as time-series averages of cross-sectional (CS) year-by-year regression slopes. Column 5 (GO1) contains the results of the pooled regression with GO values bounded below at zero. Column 6 (GO2) contains results using the definition of GO as in Cao et al. (2008). Missing values in research and development (RD) expenses are replaced by zeros. * and ** indicate significance at the 5% and 1% levels, respectively. MSE is the square root of the mean square errors (residual).

	Dependent Variable: Idiosyncratic Skewness (IS _{<i>t</i>})					
	FE	AB	Pooled	CS	GO1	GO2
	1	2	3	4	5	6
Constant	1.931** (11.8)	1.411** (29.5)	1.123** (14.9)	2.107 (1.68)	1.902** (11.6)	2.164** (10.6)
IS _{<i>t-1</i>}	-0.086** (11.1)	-0.006 (0.98)	0.049** (5.91)	0.041** (4.56)	-0.086** (11.1)	-0.084** (10.2)
BETA _{<i>t-1</i>}	-0.018 (1.30)	-0.045** (5.36)	-0.043** (3.87)	-0.040 (1.86)	-0.018 (1.32)	-0.012 (0.72)
SIZE _{<i>t-1</i>}	-0.147** (12.3)	-0.101** (30.6)	-0.078** (15.7)	-0.080** (8.56)	-0.146** (12.1)	-0.164** (11.1)
BM _{<i>t-1</i>}	0.067** (4.62)	0.051** (7.66)	0.031** (2.88)	0.010 (1.12)	0.067** (4.61)	0.096** (5.28)
GO _{<i>t-1</i>}	0.062** (4.17)	0.094** (13.2)	0.075** (6.36)	0.041* (2.23)	0.073** (4.63)	0.016* (2.55)
RD _{<i>t-1</i>}	0.734** (4.72)	0.665** (11.7)	0.443** (5.01)	0.235* (2.40)	0.722** (4.65)	0.939** (4.53)
CAPFIX _{<i>t-1</i>}	-0.193** (4.03)	-0.129** (4.86)	-0.132** (3.57)	-0.133** (3.76)	-0.191** (3.98)	-0.179** (3.07)
TURNOVER _{<i>t-1</i>}	0.349* (2.56)	0.117 (1.79)	0.134 (1.48)	-0.463** (2.68)	0.350* (2.57)	0.525** (3.41)
IV _{<i>t-1</i>}	2.261** (4.06)	4.628** (15.7)	6.375** (12.8)	7.939** (7.40)	2.214** (4.00)	2.901** (4.10)
\bar{R}_{t-1}	-21.37** (5.27)	-52.74** (23.7)	-48.99** (6.64)	-55.74** (7.45)	-21.23** (5.23)	-25.82** (4.94)
LEV _{<i>t-1</i>}	0.859** (11.9)	0.479** (18.4)	0.334** (9.66)	0.315** (6.89)	0.860** (12.0)	0.765** (8.84)
CONCENTRATION _{<i>t-1</i>}	-0.002 (0.98)	-2.4e-4 (0.17)	-0.001 (0.30)	0.000 (0.16)	-0.002 (0.99)	-0.003 (1.06)
ROA _{<i>t-1</i>}	-0.076 (1.64)	-0.220** (8.63)	-0.239** (6.44)	-0.261** (5.12)	-0.072 (1.54)	-0.161** (2.91)
MKT_SENT _{<i>t-1</i>}	1.025** (9.15)	0.854** (11.1)	0.828** (7.95)	-14.41 (1.12)	1.024** (9.15)	1.098** (8.64)
No. of obs.	66,919	66,919	66,919	24	66,919	50,822
<i>F</i>	110.520	—	220.360	—	110.710	86.600
Prob > <i>F</i>	0.000	—	0.000	—	0.000	0.000
<i>R</i> ²	0.248	—	0.062	0.079	0.248	0.248
Root MSE	0.146	—	1.525	—	0.146	0.145

determining idiosyncratic skewness, particularly for smaller and highly volatile firms. Furthermore, firms with higher skewness should exhibit lower average return and less mean-variance efficient (lower Sharpe ratio) portfolios. To examine this, we classify firms in three quantile groups based on each separate characteristic, that is, low = (0, 0.25), medium = (0.25, 0.75), and high = (0.75, 1) quantiles, and run the model of equation (3) for each individual quantile group.

Table 4 contains the estimated panel coefficients with firm-specific fixed effects.¹⁴ In Panel A, GO appears to have a more significant positive impact in determining idiosyncratic skewness for small and medium-size firms (low book value of total

TABLE 4
Panel Regressions of Idiosyncratic Skewness Determinants and Firm Characteristics

Table 4 contains results of the panel regressions with firm-specific fixed effects of equation (3) on individual daily idiosyncratic skewness for different groups of the selected variables. In Panel A, the dependent variable is daily idiosyncratic skewness (IS_t) calculated from July 1 to June 30 each year. Panel B contains the results when the dependent variable is shocks in idiosyncratic skewness (ΔIS_t) measured as first difference of idiosyncratic skewness calculated from July 1 to June 30 each year. Low, Medium, and High are determined by dividing the whole sample in three quantiles (bottom 0.25, middle 0.25–0.75, and upper 0.25 quantiles). The *t*-statistics (reported in parentheses) are corrected for heteroskedasticity and cluster correlation by firm (see Petersen (2009)). The sample period covers July 1983 to June 2011. Missing values in research and development expenses (RD) are replaced by zeros. Size (BVTA) is the book value of total assets. Book-to-Market is the book value of equity divided by market capitalization. Idiosyncratic Volatility is the standard deviation of the equity return's residuals after the market model. Default risk is the negative of the Merton's distance to default. Leverage is the quasi market leverage. * and ** indicate significance at the 5% and 1% levels, respectively.

Panel A. Dependent Variable: Idiosyncratic Skewness (IS_t)

	Size (BVTA)			Book-to-Market			Idiosyncratic Volatility		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
Constant	0.769** (16.0)	0.538** (18.2)	0.518** (11.2)	0.255** (4.26)	0.464** (13.4)	0.779** (18.8)	0.516** (8.45)	0.564** (18.1)	0.768** (16.7)
GO	0.208** (7.23)	0.087** (4.11)	-0.222** (4.45)	0.214** (5.01)	0.077* (2.36)	0.060* (2.12)	-0.094 (1.23)	-0.012 (0.43)	0.170** (7.00)
RD	0.041 (0.17)	1.456** (4.64)	1.841 (1.70)	0.903** (4.27)	1.214* (2.57)	2.760** (2.79)	0.267 (0.18)	0.970** (3.75)	0.365 (1.48)
CAPFIX	-0.163 (1.95)	-0.337** (4.79)	-0.485** (3.90)	-0.249** (2.62)	-0.255** (3.37)	-0.230 (1.81)	-0.574** (3.00)	-0.338** (4.98)	0.034 (0.38)
R^2	0.3005	0.2432	0.1874	0.3732	0.2952	0.3831	0.2962	0.3013	0.3724
<i>N</i>	13,514	33,711	19,926	15,991	34,503	16,657	17,940	33,372	15,839

	Leverage			Default Risk			ROA		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
Constant	0.274** (4.19)	0.545** (17.8)	0.696** (18.5)	0.452** (4.89)	0.511** (15.9)	0.876** (20.3)	0.629** (11.9)	0.629** (20.4)	0.512** (8.06)
GO	0.189** (3.58)	0.045* (2.06)	0.023 (0.71)	-0.141 (1.19)	0.035 (1.17)	0.098** (4.01)	0.223** (8.52)	-0.091** (3.21)	-0.255** (3.57)
RD	0.488* (2.31)	1.117** (3.21)	4.563** (3.17)	0.586 (1.40)	0.668** (3.14)	0.320 (0.62)	0.388 (1.94)	1.154 (1.75)	0.921 (1.23)
CAPFIX	-0.220* (2.56)	-0.265** (3.45)	-0.020 (0.16)	-0.338* (2.37)	-0.243** (3.64)	0.040 (0.37)	-0.145 (1.47)	-0.226** (2.58)	-0.141 (1.38)
R^2	0.3252	0.2994	0.3525	0.3289	0.3136	0.3649	0.3985	0.2693	0.3311
<i>N</i>	15,431	34,841	16,879	15,736	33,616	17,798	16,027	34,346	16,666

	Exchange		Industry		NBER		
	NASDAQ	NYSE/AMEX	High-Tech/ Growth	Other	Peak	Trough	Normal
Constant	0.546** (19.7)	0.563** (21.8)	0.472** (13.6)	0.580** (26.9)	0.476** (9.23)	0.640** (11.8)	0.545** (17.6)
GO	0.152** (8.31)	-0.031 (1.17)	0.180** (7.42)	0.052** (2.87)	0.104* (2.56)	0.064 (1.62)	0.063* (2.47)
RD	0.697** (4.15)	0.546 (1.13)	0.612** (3.66)	0.835* (2.33)	0.765* (2.09)	0.607 (1.21)	0.821** (2.77)
CAPFIX	-0.309** (5.39)	-0.259** (3.21)	-0.269** (3.83)	-0.330** (5.41)	-0.109 (0.90)	-0.418** (2.79)	-0.221** (3.10)
R^2	0.2463	0.2057	0.2273	0.2170	0.4280	0.5090	0.3400
<i>N</i>	37,339	29,812	25,571	41,580	19,259	14,482	33,410

(continued on next page)

¹⁴Results in Table 4 may somewhat differ from those contained in Table 1 because of potential nonlinearities and random sampling errors.

TABLE 4 (continued)
 Panel Regressions of Idiosyncratic Skewness Determinants and Firm Characteristics

Panel B. Dependent Variable: Shocks in Idiosyncratic Skewness ($\Delta I_{i,t}$)

	Size (BVTA)			Book-to-Market			Idiosyncratic Volatility		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
Constant	0.011** (7.33)	0.114** (132)	0.093** (43.0)	-0.215** (77.8)	0.096** (199)	0.377** (117)	0.103** (165)	0.145** (121)	-0.066** (30.9)
ΔGO	0.253** (5.25)	0.117** (2.89)	-0.452** (5.41)	0.308** (5.12)	-0.051 (1.08)	-0.020 (0.40)	-0.397** (3.62)	-0.059 (1.28)	0.300** (6.71)
ΔRD	0.236 (0.67)	1.455** (3.64)	2.686 (1.91)	0.792* (2.51)	0.458 (0.78)	1.015 (0.92)	-1.825 (1.10)	0.709* (2.08)	0.665 (1.55)
$\Delta CAPFIX$	0.051 (0.49)	0.090 (0.94)	0.172 (0.93)	0.063 (0.52)	0.213* (2.34)	0.272 (1.63)	0.129 (0.51)	0.079 (0.92)	0.112 (0.94)
R^2	0.1394	0.1074	0.0841	0.2381	0.1727	0.2523	0.2096	0.1842	0.2380
N	10,897	29,231	18,571	13,673	30,463	14,563	16,600	29,175	12,924
	Leverage			Default Risk			RDA		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
Constant	-0.146** (48.9)	0.113** (147)	0.266** (94.8)	-0.019** (30.3)	0.121** (104)	0.130** (28.0)	0.047** (9.60)	0.111** (65.8)	0.009 (1.08)
ΔGO	0.333** (5.63)	0.020 (0.49)	0.003 (0.06)	-0.574** (3.68)	0.132** (2.95)	0.174** (3.67)	0.394** (8.89)	-0.134* (2.13)	-0.747** (6.29)
ΔRD	0.437 (1.39)	0.289 (0.63)	2.789 (1.13)	0.843 (1.69)	0.541 (1.85)	0.368 (0.32)	0.400 (1.28)	0.649 (0.76)	1.388 (1.54)
$\Delta CAPFIX$	0.154 (1.43)	0.142 (1.47)	0.447* (2.44)	0.075 (0.41)	0.152 (1.70)	0.146 (0.97)	0.096 (0.83)	0.245* (2.15)	-0.117 (0.68)
R^2	0.1713	0.1612	0.2135	0.2373	0.1831	0.2427	0.2802	0.1555	0.2225
N	13,109	30,825	14,765	14,134	29,411	15,153	13,244	30,659	14,713
	Exchange		High-Tech/ Growth	Industry		NBER			
	NASDAQ	NYSE/AMEX		Other	Peak	Trough	Normal		
Constant	0.085** (148)	0.093** (164)	0.070** (109)	0.100** (163)	0.008** (14.3)	0.235** (43.0)	0.074** (127)		
ΔGO	0.245** (7.29)	-0.167** (3.60)	0.272** (6.17)	0.050 (1.43)	0.174* (2.20)	0.114 (1.61)	0.122** (2.88)		
ΔRD	0.665** (2.60)	-0.663 (1.01)	0.559* (2.20)	0.573 (0.94)	0.452 (0.87)	-0.300 (0.34)	0.852* (2.11)		
$\Delta CAPFIX$	0.048 (0.63)	0.196 (1.75)	0.052 (0.59)	0.094 (1.10)	0.248 (1.51)	-0.004 (0.02)	0.117 (1.31)		
R^2	0.1057	0.0652	0.0831	0.0825	0.2504	0.3382	0.2148		
N	31,722	26,977	22,272	36,427	17,203	12,781	28,715		

assets).¹⁵ RD is most significant for medium-size firms. CAPFIX turns growth options into cash-generating assets-in-place, reducing idiosyncratic skewness, more so for medium and bigger firms.

Real option variables (GO, RD and CAPFIX) are more significant drivers of idiosyncratic skewness for more volatile firms and firms exhibiting lower mean-variance efficiency (lower Sharpe ratios). GO is positive and significant for high-volatility firms, whereas CAPFIX is more important (negative) in less volatile firms. The significance of growth options in explaining idiosyncratic skewness is also greater for more distressed firms. CAPFIX is significant in less

¹⁵ A sign reversal of GO (negative GO for larger firms) arises because larger firms tend to be more mature with steadier (larger) cash flow and hence a lower GO component, with lower skewness. Many bigger firms may also have negative skewness, so GO (proxying for growth potential) may not be suitable to explain negative skewness.

distressed firms. Low book-to-market (BM) ratio is positively related to more growth potential (GO), whereas capital expenditures have a negative impact, as they relate to the exercise of past real options. Although skewness is increasing in BM ratio, the marginal contribution of GO is smaller for high book-to-market firms. High GO involving more intangibles is associated with low leverage as measured by traditional debt instruments, consistent with findings by Bartram (2017). RD has a positive impact on idiosyncratic skewness across leverage levels. GO has a significant positive impact on skewness for low ROA, indicating potential for more productivity. RD has a positive impact for low- and medium-ROA firms. Overall, our findings show that the link between real options and idiosyncratic skewness is more significant for firms that are smaller, more volatile, distressed, and have low ROA.

We further examine the impact of the type of industry in explaining idiosyncratic skewness. The highest quartile built on GO has the following industry composition: 16.6% chemical and allied products (SIC code 28), 14.3% business services (SIC code 73), 12% electronic and other electric equipment (SIC code 36), and 10.9% instruments and related products (SIC code 38). We further construct a dummy for high-tech/growth-type industries based on the Fama and French (1997) 49-industry classification.¹⁶ Unreported results confirm that real option-intensive industries have a statistically higher level of idiosyncratic skewness. Panel A of Table 4 shows that the impact of real options in enhancing idiosyncratic skewness is significantly stronger for firms in real option-intensive industries (high-tech/growth) and for firms listed on NASDAQ. Finally, we analyze the time variation of the explanatory power of real options as drivers of idiosyncratic skewness over different macroeconomic cycles based on National Bureau of Economic Research (NBER) peaks, troughs, and normal times. The last tabular in Panel A confirms that growth option variables (GO, RD) have a stronger impact on idiosyncratic skewness around normal and economic peak periods (whereas CAPFIX is significant in troughs). For robustness, we divide the sample into high versus low volatility and into crisis versus normal periods, obtaining qualitatively analogous results. However, the different impact of real options variables in different cycles is less noticeable.¹⁷

The finding that growth options are an important forecasting variable for idiosyncratic skewness raises the question of whether innovations in growth options intensity have good predictive power in forecasting innovations in idiosyncratic skewness. To test this, we regress changes in idiosyncratic skewness (ΔIS_t), measured as first differences in observed skewness, against shocks in real options variables (ΔGO_t , ΔRD_t , and $\Delta CAPFIX_t$). Panel B of Table 4 presents results of panel estimation with firm-specific fixed effects confirming that innovations

¹⁶Following Bhamra and Shim (2015), we classify as high-tech/growth industries those with the following Fama and French (1997) industry codes: 12 (medical equipment), 13 (pharmaceutical products), 22 (electric equipment), 27 (precious metal), 28 (mining), 30 (oil and natural gas), 32 (telecommunications), 35 (computers), 36 (computer software), 37 (electronic equipment), and 38 (measuring and control equipment).

¹⁷High-volatility periods are defined as those where the CBOE volatility index (VIX) crosses from below its past 3-year moving average, and crisis periods are those with market crashes and sovereign and banking crises as defined by Reinhart and Rogoff (2009) and Schularick and Taylor (2012).

in real option variables are generally significant drivers of future changes in idiosyncratic skewness, and that the impact is more significant for firms with lottery-type features and similar characteristics discussed previously. Shocks in growth option variables (ΔGO , ΔRD) are also more significant for firms traded on NASDAQ and for firms operating in high-tech/growth industries.

VI. Diversification Discount and the Role of Financial Flexibility

In previous sections we show that growth opportunities enhance subsequent skewness in equity returns. Mitton and Vorkink (2007) find evidence that higher levels of skewness are associated with lower diversification and portfolio mean-variance efficiency. In our extended mean-variance-skewness framework, investors are willing to accept a lower level of portfolio efficiency in exchange for higher levels of skewness. In this section we relate our results to Mitton and Vorkink, examining whether there is a direct link between growth options, idiosyncratic skewness, and portfolio efficiency. As in Mitton and Vorkink, we measure portfolio efficiency using the Sharpe ratio $(E[r_j] - r_f)/\sigma_j$, where $E[r_j]$ is the average monthly return of portfolio j , σ_j is the standard deviation of monthly returns of portfolio j , and r_f is the risk-free rate.

Table 5 shows the Sharpe ratio for 5 equally spaced portfolios built on GO, RD, and CAPFIX in the previous period, as well as expected idiosyncratic skewness over future horizon $t + T$ calculated based on equation (6). Portfolios are calculated by value weighting individual firm returns in each quintile, classifying firms each year in 5 equally spaced quintiles built on the selected variables. Table 5 contains the (average) Sharpe ratio of each portfolio. We find that higher levels of growth options (GO, RD) are associated with significantly lower Sharpe ratios, confirming that investors are willing to accept less mean-variance efficient portfolios in exchange for a higher expectation of idiosyncratic skewness. Similar results are obtained for CAPFIX.

Following Mitton and Vorkink (2007), we calculate preformation Sharpe ratios for 100 portfolios built on expected idiosyncratic skewness based on equation (6) over 36 months. Figure 2 presents the kernel-estimated relation between actual and expected idiosyncratic skewness at time t ($E_t[IS_{t+T}]$) over 1 year ($T = 1$) and the preformation Sharpe ratios over the previous 36 months. Similar

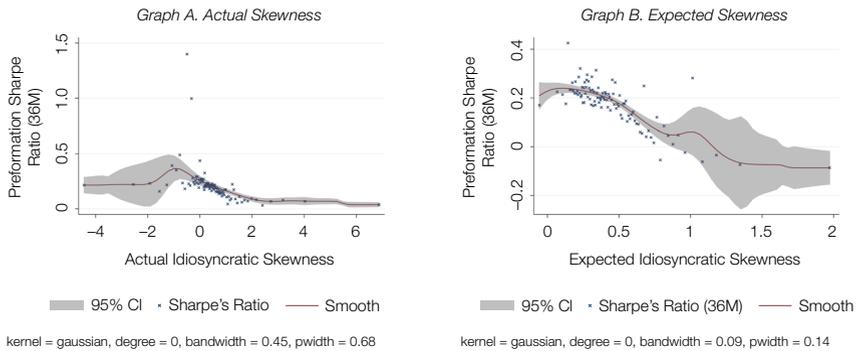
TABLE 5
Mean-Variance Portfolio Efficiency

Table 5 contains the average Sharpe ratio calculated over 12 months in five portfolios obtained by dividing firms into five equally spaced quantiles based on the observed variables indicated in each row. GO is the growth option variable calculated following equation (4); CAPFIX is the capital expenditure intensity measured as the ratio of capital expenditure over the net value of property, plant, and equipment (PPE); RD is research and development (R&D) intensity measured as R&D expenses over total asset; and $E_t[IS_{t+T}]$ is expected idiosyncratic skewness calculated following equations (5) and (6).

Sharpe Ratio _{<i>t</i>}	1 (Low)	2	3	4	5 (High)	High – Low
GO _{<i>t-1</i>}	0.328	0.308	0.213	0.179	0.156	-0.172**
RD _{<i>t-1</i>}	0.258	0.223	0.268	0.198	0.205	-0.052*
CAPFIX _{<i>t-1</i>}	0.294	0.245	0.255	0.218	0.218	-0.076**
$E_t[IS_{t+T}]$	0.284	0.259	0.219	0.245	0.213	-0.070**

FIGURE 2
Idiosyncratic Skewness and Sharpe Ratios

Figure 2 shows the nonparametric kernel estimated relation between expected idiosyncratic skewness based on equations (5) and (6) and preformation Sharpe ratio based on the previous 36 months for 100 equally spaced portfolios built on actual (Graph A) and expected (Graph B) idiosyncratic skewness using local polynomial smooth estimation.



to Mitton and Vorkink, we find that higher levels of subsequent idiosyncratic skewness are associated with lower preformation Sharpe ratios. This is more pronounced when using expected idiosyncratic skewness derived from real options. Graph B shows that higher levels of expected idiosyncratic skewness are associated with lower preformation Sharpe ratios. The above findings confirm that investors are willing to accept less mean-variance efficient portfolios (involving lower average returns) in exchange for higher expected real options-generated idiosyncratic skewness. Our finding that expectations on idiosyncratic skewness are associated with lower preformation Sharpe ratios corroborates similar results in Mitton and Vorkink (2007). It provides further evidence that investors are willing to sacrifice mean-variance efficiency in exchange for greater expected idiosyncratic skewness deriving from real options. If greater skewness was merely a consequence of the failure of investors to diversify, regardless of whether they have a greater preference for skewness, the relation between expected idiosyncratic skewness and preformation Sharpe ratios would not be significant.

We next consider the incremental role and potential interaction between financial flexibility (FIN_FLEX) and real options-driven asset flexibility. Our broader hypothesis is that idiosyncratic skewness is enhanced in firms whose management values or exploits flexibility, be it on the asset side in the form of GO or on the financial side in the form of financial flexibility. However, growth-option-intensive firms have difficulty borrowing via traditional debt-financing channels because of asymmetric information and high proportion of intangible assets that cannot be used as collateral. The issue arises then as to whether high-GO firms use nontraditional borrowing means, such as off-balance-sheet postretirement pension obligations and leasing arrangements, as long-term flexible instruments, and whether these act in a complementary way with real asset flexibility. In this vein, Bartram (2017) examines the relation between real investment and defined-benefit plans, concluding that postretirement plans are particularly attractive for firms with high R&D. These firms must sustain investment but have low leverage due

to difficulties in borrowing through standard channels. Defined-benefit plans can be used as an alternative channel that allows growth-option-intensive firms in effect to borrow from their employees with lower agency and monitoring costs. By contrast, capital expenditures in PPE involve large investments that can serve as collateral and are thus more easily financed via regular debt. Bartram finds that the size of defined-benefit plans is positively related to R&D and negatively related to capital expenditures. Motivated by these findings, we examine whether financial flexibility, measured as the ratio of off-balance-sheet obligations to the market value of the firm, is a reinforcing driver of idiosyncratic skewness. We measure off-balance-sheet obligations by using the last 5 years total of rental commitments (Compustat variable MRCT), the thereafter portion of leases (MRCTA), and the pension-projected benefit obligations (PBPRO). Missing values of off-balance-sheet items are replaced by zeros. All else equal, we expect a positive relation between off-balance-sheet financing and idiosyncratic skewness.

Results in Table 6 show that financial flexibility (FIN_FLEX) is a positive and significant incremental determinant of idiosyncratic skewness after all other controls. This confirms that real option-induced asset flexibility as well as financial flexibility are positive contributors to the idiosyncratic skewness of stock returns. To further examine whether financial flexibility enhances the effect of asset flexibility due to real options, we examine the interaction of financial flexibility with GO. The interaction between financial flexibility and growth options seems

TABLE 6
Panel Regressions of Idiosyncratic Skewness Determinants
with Financial Flexibility (Daily Data)

Table 6 contains the results of the panel regressions of equation (3) on individual daily idiosyncratic skewness, with the addition of off-balance-sheet financial flexibility and/or its interaction with GO. The dependent variable is daily idiosyncratic skewness (IS_t) calculated from July 1 to June 30 each year. The sample period covers July 1983 to June 2011. Column 1 contains the results from standard panel regressions with firm-specific fixed effects (FE) and heteroskedasticity- and cluster-corrected (see Petersen (2009)) standard errors (model 1 in Table 2). Models 2, 3, and 4 contain similar results from standard panel regressions with firm-specific fixed effects when a proxy for financial flexibility (FIN_FLEX_{t-1}) and its interaction with GO is included. Model 5 contains the AB (1991) (as extended by Arellano and Bover (1995), Blundell and Bond (1998)) dynamic panel estimators. * and ** indicate significance at the 5% and 1% levels, respectively. MSE is the square root of the mean square errors (residual).

	Dependent Variable: Idiosyncratic Skewness (IS_t)				
	FE 1	FE 2	FE 3	FE 4	AB 5
Constant	1.931** (11.8)	1.917** (11.7)	1.940** (11.8)	1.923** (11.7)	1.455** (29.6)
IS_{t-1}	-0.086** (11.1)	-0.086** (11.1)	-0.086** (11.1)	-0.086** (11.1)	-0.006 (0.98)
$BETA_{t-1}$	-0.018 (1.30)	-0.018 (1.32)	-0.018 (1.34)	-0.018 (1.34)	-0.044** (5.25)
$SIZE_{t-1}$	-0.147** (12.3)	-0.147** (12.2)	-0.148** (12.3)	-0.147** (12.2)	-0.105** (30.3)
BM_{t-1}	0.067** (4.62)	0.065** (4.47)	0.067** (4.63)	0.065** (4.51)	0.050** (7.63)
GO_{t-1}	0.062** (4.17)	0.062** (4.21)	0.054** (3.61)	0.059** (3.89)	0.089** (11.5)
RD_{t-1}	0.734** (4.72)	0.730** (4.71)	0.732** (4.74)	0.730** (4.72)	0.668** (11.8)
$CAPFIX_{t-1}$	-0.193** (4.03)	-0.190** (3.96)	-0.193** (4.02)	-0.190** (3.97)	-0.116** (4.33)

(continued on next page)

TABLE 6 (continued)
 Panel Regressions of Idiosyncratic Skewness Determinants
 with Financial Flexibility (Daily Data)

	Dependent Variable: Idiosyncratic Skewness (IS _{<i>t</i>})				
	FE	FE	FE	FE	AB
	1	2	3	4	5
TURNOVER _{<i>t-1</i>}	0.349* (2.56)	0.331* (2.44)	0.345* (2.54)	0.332* (2.44)	0.122 (1.86)
IV _{<i>t-1</i>}	2.261** (4.06)	2.230** (4.00)	2.246** (4.03)	2.228** (4.00)	4.713** (16.0)
\bar{R}_{t-1}	-21.37** (5.27)	-21.25** (5.24)	-21.41** (5.27)	-21.29** (5.24)	-53.00** (23.8)
LEV _{<i>t-1</i>}	0.859** (11.9)	0.835** (11.5)	0.844** (11.8)	0.832** (11.5)	0.412** (13.1)
CONCENTRATION _{<i>t-1</i>}	-0.002 (0.98)	-0.002 (0.92)	-0.002 (0.97)	-0.002 (0.93)	-1.8e-4 (0.13)
ROA _{<i>t-1</i>}	-0.076 (1.64)	-0.074 (1.58)	-0.077 (1.64)	-0.074 (1.59)	-0.224** (8.75)
MKT_SENT _{<i>t-1</i>}	1.025** (9.15)	1.033** (9.21)	1.025** (9.15)	1.031** (9.20)	0.855** (11.1)
FIN_FLEX _{<i>t-1</i>}	—	0.339** (3.31)	—	0.283** (2.82)	0.284* (2.40)
FIN_FLEX _{<i>t-1</i>} × GO _{<i>t-1</i>}	—	—	0.218* (2.22)	0.101 (0.92)	0.233* (2.37)
No. of obs.	66,919	66,919	66,919	66,919	66,919
<i>F</i>	111	104	103	98.12	—
Prob > <i>F</i>	0.000	0.000	0.000	0.000	—
<i>R</i> ²	0.2480	0.2482	0.2481	0.2483	—
Root MSE	1.4551	1.4538	1.4539	0.1464	—

to play a relevant role in explaining idiosyncratic skewness. A firm may have more potential to grow if it has excess debt capacity in the form of off-balance sheet financial flexibility, such as flexible, lower cost borrowing from its employees. Naturally, firm growth plans can be restrained if the firm is financially constrained. The impact of the interaction terms (FIN_FLEX × GO) on idiosyncratic skewness in models 3 and 5 of Table 6 appears positive. This is in line with our broader hypothesis that both asset flexibility (GO) and financial flexibility (FIN_FLEX) positively enhance idiosyncratic skewness as a result of active firm management.¹⁸

VII. Conclusions

Firm-specific skewness is known to be priced in the market. This effect has been shown using idiosyncratic skewness (Mitton and Vorkink (2007)), expected idiosyncratic skewness (Boyer et al. (2010)), total skewness (Chen et al. (2001)), and (risk-neutral) skewness implied from options prices (Conrad et al. (2013)). In this article, we examine what drives this economically important asymmetry in stock returns. We show that active management based on real options and the ensuing asset flexibility is a key driver of idiosyncratic skewness. From an in-

¹⁸We examine further the impact that financial flexibility has on idiosyncratic skewness depending on the degree of growth options being low, medium, or high based on groupings using GO or RD. Unreported results confirm that financial flexibility (FIN_FLEX_{*t-1*}) rises in importance with both high GO and RD, suggesting a potential synergistic relation. These findings suggest that off-balance-sheet financial flexibility enhances skewness for high-RD and high-growth firms.

vestor's perspective, this also relates to the trade-off in portfolio diversification between preserving positive skewness and lowering portfolio volatility. The drivers, generation, and preservation of skewness in a portfolio context are relevant in most diversification decisions both by active investors in a portfolio of stocks and by active managers of a portfolio of business activities. Firm-specific skewness is important for both underdiversified investor portfolios and clientele drawn to lottery-type stocks (Bali et al. (2011), Kumar (2009)). We identify firm characteristics, industry, and other situations when real option-driven asset flexibility has a positive and significant impact on idiosyncratic skewness.

More generally, idiosyncratic skewness is enhanced in firms whose management exploits flexibility, be it on the asset side in the form of real options or on the financial side in the form of financial flexibility. We confirm empirically that both real options and financial flexibility positively enhance idiosyncratic skewness. We measure financial flexibility using off-balance-sheet items (see Bartram (2017)) and provide supportive evidence that financial flexibility is an incremental positive determinant of idiosyncratic skewness and that it seems most pronounced when real options (GO and RD) are high.

Real options are also important in asset pricing. Various studies show that real options are priced in the marketplace and have a statistical connection both to stock returns (Anderson and Garcia-Feijóo (2006), Trigeorgis and Lambertides (2014)) and to idiosyncratic volatility (Cao et al. (2008), Grullon et al. (2012)). In this article we enhance these linkages with a theoretical argument and an empirical link that reveal how real options and associated asset flexibility are key drivers of idiosyncratic skewness. In exchange for this enhanced idiosyncratic skewness, we find that investors settle for lower mean-variance portfolio efficiency.

Our analysis of real options variables as key skewness determinants provides added contributions to previous explanatory theories of skewness. In the prior literature, skewness is linked to leverage and volatility feedback mechanisms (Black (1976), Christie (1982), and Campbell and Hentschel (1992)), investor heterogeneity (Hong and Stein (2003), Chen et al. (2001), and Xu (2007)), information blockage (Cao et al. (2002)), and information ambiguity (Epstein and Schneider (2008)). Our findings provide not only a new link between real options and idiosyncratic skewness but also an explanation for why investors in their portfolio of stocks and managers in their portfolio of business projects may be willing to accept lower required returns in exchange for an enhanced skewness profile arising from such real options. The effective creation and exercising of such real options, and the resulting enhancement and preservation of idiosyncratic skewness in a portfolio context, are at the heart of transforming exogenous chance events into exploitative asymmetric investment opportunities for investors or business opportunities for managers.

Based on our theoretical framework of active management leading to asset (and financial) flexibility, we test our posited real options–skewness hypothesis and provide robust empirical evidence that real option variables, specifically growth option (GO) and R&D intensity, are significant key drivers of idiosyncratic skewness, over and above other determinants previously reported. Our overall results confirm this real options–skewness hypothesis while corroborating earlier findings on standard determinants of skewness. Our findings that real option vari-

ables are significant drivers of idiosyncratic skewness are robust to using decile tables and alternative regression models, daily or monthly returns, different time horizons, different estimation methods, and alternative definitions of key variables. These findings reinforce and extend related results by Boyer et al. (2010) and Conrad et al. (2013). We depart from previous authors by showing that this effect is significantly driven by real option variables that affect returns via the channel of skewness.

Our analysis has important implications for portfolio management and diversification efficiency. In managing a portfolio involving several positively skewed assets, less than full diversification can potentially preserve some desirable skewness benefits while attaining low portfolio volatility by carefully selecting assets with low correlations. Empirically, we confirm that higher growth options leading to enhanced idiosyncratic skewness tend to be associated with lower mean-variance efficiency. These findings provide additional evidence on investor willingness to trade off some portfolio efficiency to acquire more skewed, lottery-type investment opportunities. We further examine for what type of firms, industries, and situations the link between real options and idiosyncratic skewness is more significant. Dividing the sample into subsamples based on firm characteristics, we find that the real options impact on skewness is more significant for lottery-type firms that are small, volatile, distressed, and have low profitability and low book-to-market. We further document that firms in volatile industries and in industries with high real option intensity have higher idiosyncratic skewness.

Extending Bartram (2017), we posit that off-balance-sheet financial flexibility is reinforcing real options-based asset flexibility in enhancing idiosyncratic skewness as a result of active management. We confirm empirically that financial flexibility is a positive and significant determinant of firm-specific skewness over and above all other determinants and real option variables. We further show that financial flexibility is more pronounced when real options (GO and RD) are high. These findings confirm our conjecture that both asset flexibility and financial flexibility are significant determinants of idiosyncratic skewness via active management and that they reinforce each other in enhancing skewness.

We conclude that idiosyncratic skewness is an important characteristic for many firms and investors, especially when asymmetric growth option and lottery-type features are preferred over full diversification. We show both theoretically and empirically how real options-driven asset flexibility is a strong determinant of beneficial idiosyncratic skewness. We provide evidence that the growth option impact on skewness is more significant in lottery-type situations, particularly for high-tech/growth industries and for small, volatile, distressed, low-profitability, and low-book-to-market types of firms. We also document that these situations are associated with lower mean-variance portfolio efficiency, in line with our contention that investors may be willing to accept lower average returns (and hence lower Sharpe ratios) in exchange for higher skewness deriving from real growth and contraction options. Finally, we show that off-balance-sheet financial flexibility plays a reinforcing role along with real options-derived asset flexibility in the generation of idiosyncratic skewness as a result of active firm management. The reinforcing impact of financial flexibility is strongest in growth-option-intensive companies and industries.

References

- Amaya, D.; P. Christoffersen; K. Jacobs; and A. Vasquez. "Does Realized Skewness Predict the Cross-Section of Equity Returns?" *Journal of Financial Economics*, 118 (2015), 135–167.
- Anderson, C. W., and L. Garcia-Feijóo. "Empirical Evidence on Capital Investment, Growth Options, and Security Returns." *Journal of Finance*, 61 (2006), 171–194.
- Arellano, M., and S. Bond. "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations." *Review of Economic Studies*, 58 (1991), 277–297.
- Arellano, M., and O. Bover. "Another Look at the Instrumental Variable Estimation of Error-Components Models." *Journal of Econometrics*, 68 (1995), 29–51.
- Bakshi, G.; N. Kapadia; and D. Madan. "Stock Return Characteristics, Skew Laws, and the Differential Pricing of Individual Equity Options." *Review of Financial Studies*, 16 (2003), 101–143.
- Bali, T. G.; N. Cakici; and R. F. Whitelaw. "Maxing Out: Stocks as Lotteries and the Cross-Section of Expected Returns." *Journal of Financial Economics*, 99 (2011), 427–446.
- Barberis, N., and M. Huang. "Stocks as Lotteries: The Implications of Probability Weighting for Security Prices." *American Economic Review*, 98 (2008), 2066–2100.
- Bartram, S. "Corporate Postretirement Benefit Plans and Real Investment." *Management Science*, forthcoming (2017).
- Bhamra, H. S., and K. H. Shim. "Stochastic Idiosyncratic Cash Flow Risk and Real Options: Implications for Stock Returns." *Journal of Economic Theory*, forthcoming (2017).
- Black, F. "Studies of Stock Price Volatility Changes." In *Proceedings of the 1976 Meetings of the American Statistical Association, Business and Economics Statistics Section*, Alexandria, VA: American Statistical Association (1976), 177–181.
- Black, F., and M. Scholes. "The Pricing of Options and Corporate Liabilities." *Journal of Political Economy*, 81 (1973), 637–654.
- Blanchard, O., and M. Watson. "Bubbles, Rational Expectation and Financial Markets." Working Paper No. 945, National Bureau of Economic Research (1983).
- Blundell, R., and S. Bond. "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models." *Journal of Econometrics*, 87 (1998), 115–143.
- Bollerslev, T.; D. Osterrieder; N. Sizova; and G. Tauchen. "Risk and Return: Long-Run Relations, Fractional Cointegration, and Return Predictability." *Journal of Financial Economics*, 108 (2013), 409–424.
- Boyer, B.; T. Mitton; and K. Vorkink. "Expected Idiosyncratic Skewness." *Review of Financial Studies*, 23 (2010), 169–202.
- Brunnermeier, M. K.; C. Gollier; and J. A. Parker. "Optimal Beliefs, Asset Prices, and the Preference for Skewed Returns." *American Economic Review*, 97 (2007), 159–165.
- Campbell, J. Y., and L. Hentschel. "No News Is Good News: An Asymmetric Model of Changing Volatility in Stock Returns." *Journal of Financial Economics*, 31 (1992), 281–318.
- Campbell, J. Y.; J. Hilscher; and J. Szilagyi. "In Search of Distress Risk." *Journal of Finance*, 63 (2008), 2899–2939.
- Cao, C.; T. Simin; and J. Zhao. "Can Growth Options Explain the Trend in Idiosyncratic Risk?" *Review of Financial Studies*, 21 (2008), 2599–2633.
- Cao, H. H.; J. D. Coval; and D. Hirshleifer. "Sidelined Investors, Trading-Generated News, and Security Returns." *Review of Financial Studies*, 15 (2002), 615–648.
- Chan, L. K., and J. Lakonishok. "Are the Reports of Beta's Death Premature?" *Journal of Portfolio Management*, 19 (1993), 51–62.
- Chang, B. Y.; P. Christoffersen; and K. Jacobs. "Market Skewness Risk and the Cross Section of Stock Returns." *Journal of Financial Economics*, 107 (2013), 46–68.
- Chen, J.; H. Hong; and J. C. Stein. "Forecasting Crashes: Trading Volume, Past Returns, and Conditional Skewness in Stock Prices." *Journal of Financial Economics*, 61 (2001), 345–381.
- Christie, A. A. "The Stochastic Behavior of Common Stock Variances: Value, Leverage and Interest Rate Effects." *Journal of Financial Economics*, 10 (1982), 407–432.
- Conine, T., and M. Tamarkin. "On Diversification Given Asymmetry in Returns." *Journal of Finance*, 36 (1981), 1143–1155.
- Conrad, J.; R. F. Dittmar; and E. Ghysels. "Ex Ante Skewness and Expected Stock Returns." *Journal of Finance*, 68 (2013), 85–124.
- Epstein, L., and M. Schneider. "Ambiguity, Information Quality, and Asset Pricing." *Journal of Finance*, 63 (2008), 197–228.
- Fama, E. F., and K. R. French. "Common Risk Factors in the Returns on Stocks and Bonds." *Journal of Financial Economics*, 33 (1993), 3–56.
- Fama, E. F., and K. R. French. "Industry Costs of Equity." *Journal of Financial Economics*, 43 (1997), 153–193.

- Gandhi, P., and H. Lustig. "Size Anomalies in U.S. Bank Stock Returns." *Journal of Finance*, 70 (2015), 733–768.
- Goyal, V. K.; K. Lehn; and S. Racic. "Growth Opportunities and Corporate Debt Policy: The Case of the U.S. Defense Industry." *Journal of Financial Economics*, 64 (2002), 35–59.
- Green, C. T., and B. H. Hwang. "Initial Public Offerings as Lotteries: Skewness Preference and First-Day Returns." *Management Science*, 58 (2012), 432–444.
- Grullon, G.; E. Lyandres; and A. Zhdanov. "Real Options, Volatility, and Stock Returns." *Journal of Finance*, 67 (2012), 1499–1537.
- Harvey, C. R., and A. Siddique. "Autoregressive Conditional Skewness." *Journal of Financial and Quantitative Analysis*, 34 (1999), 465–487.
- Harvey, C. R., and A. Siddique. "Conditional Skewness in Asset Pricing Tests." *Journal of Finance*, 55 (2000), 1263–1295.
- Hong, H., and J. C. Stein. "Differences of Opinion, Short Sales Constraints, and Market Crashes." *Review of Financial Studies*, 16 (2003), 487–525.
- Kapadia, N. "The Next Microsoft? Skewness, Idiosyncratic Volatility, and Expected Returns." Working Paper, Tulane University (2006).
- Kelly, B., and H. Jiang. "Tail Risk and Asset Prices." *Review of Financial Studies*, 27 (2014), 2841–2871.
- Kogan, L., and D. Papanikolaou. "Growth Opportunities, Technology Shocks and Asset Prices." *Journal of Finance*, 69 (2014), 675–718.
- Kraus, A., and R. H. Litzenberger. "Skewness Preference and the Valuation of Risk Assets." *Journal of Finance*, 31 (1976), 1085–1100.
- Kumar, A. "Who Gambles in the Stock Market?" *Journal of Finance*, 64 (2009), 1889–1933.
- Mitton, T., and K. Vorkink. "Equilibrium Underdiversification and the Preference for Skewness." *Review of Financial Studies*, 20 (2007), 1255–1288.
- Nickell, S. "Biases in Dynamic Models with Fixed Effects." *Econometrica*, 49 (1981), 1417–1426.
- Patton, A. J., and K. Sheppard. "Good Volatility, Bad Volatility: Signed Jumps and the Persistence of Volatility." *Review of Economics and Statistics*, 97 (2015), 683–697.
- Petersen, M. A. "Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches." *Review of Financial Studies*, 22 (2009), 435–480.
- Reinhart, C. M., and K. S. Rogoff. *This Time Is different: Eight Centuries of Financial Folly*. Princeton, NJ: Princeton University Press (2009).
- Schularick, M., and A. M. Taylor. "Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870–2008." *American Economic Review*, 102 (2012), 1029–1061.
- Trigeorgis, L., and N. Lambertides. "The Role of Growth Options in Explaining Stock Returns." *Journal of Financial and Quantitative Analysis*, 49 (2014), 749–771.
- van Zwet, W. "Convex Transformations: A New Approach to Skewness and Kurtosis." *Statistica Neerlandica*, 18 (1964), 433–441.
- Xu, J. "Price Convexity and Skewness." *Journal of Finance*, 62 (2007), 2521–2552.
- Xu, Y., and B. G. Malkiel. "Investigating the Behavior of Idiosyncratic Volatility." *Journal of Business*, 76 (2003), 613–645.