What Does Skewness of Firm Fundamentals Tell Us about Firm Growth, Profitability, and Stock Return

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This paper investigates whether the skewness of firm fundamentals is informative about future firm performance and stock return. We present two distinct preference-free theoretical models of firm fundamentals, both of which imply a positive relation between the skewness of firm fundamentals and expected stock return. Consistent with this implication, we show empirically that the skewness measures of firm fundamentals positively predicts cross-sectional stock returns. Further supporting both models, we find that higher fundamental skewness implies not only higher future firm growth option but also higher future firm profitability. Our results cannot be explained by existing risk factors and return predictors including the levels of firm fundamentals and the skewness of stock returns.

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Abstract

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JEL Classification: G12

Keyword: Skewness, fundamental, growth option, profitability, earnings, stock return

1 Introduction

There is overwhelming evidence in the finance literature that firm fundamentals predict cross-sectional stock returns.[1] However, little is known whether the higher moments of firm fundamentals are related to stock returns. In this paper, we shed light on this research question by providing two distinct theoretical models, both of which generate a positive relation between the skewness of firm fundamentals and stock returns. We further empirically test the implications of the models and find supporting evidence for both models. Our results cannot be explained by existing risk factors and return predictors including the levels of firm fundamentals and the skewness of stock returns.

Our first model is motivated by the line of research on firm growth opportunities (e.g., Berk, Green, and Naik (1999), Carlson, Fisher, and Giammarino (2004), and Bernardo, Chowdhry, and Goyal (2007)). In this framework, a firm has growth opportunities, which are treated and valued as real options on the firm assets-in-place. But previous studies assume (log) normal distribution for the firm assets-in-place so that the classical option pricing models can be applied to value the growth opportunities. We specifically extend the model of Bernardo, Chowdhry, and Goyal (2007) by allowing the distribution of the firm assets-in-place to have non-zero skewness. Using the recent developments in the option pricing theory, we are able to derive the value and risk of the firm growth option. Under very general conditions, the model yields two main implications: (1) the value of the growth option increases with the skewness; and (2) the risk and return of the total firm value increase with the skewness. Two insights are helpful in understanding the model. First, as argued by Bernardo, Chowdhry, and Goyal (2007), firm growth opportunities have higher risk because of the implicit leverage of options and therefore higher returns relative to the

[1] Examples of firm fundamentals that predict returns are ROE, profitability, investment, and asset growth. Recent studies documenting the evidence include Cohen, Gompers, and Vuolteenaho (2002), Fairfield, Whisenant, and Yohn (2003), Titman, Wei, and Xie (2004), Fama and French (2006, 2008), Aharoni, Grundy, and Zeng (2013), Novy-Marx (2013), and Hou, Xue, and Zhang (2015). Beyond the level, a small number of papers have examined whether the second moment of firm fundamentals can predict stock returns and firm performance (e.g., Dichev and Tang (2009) and Gow and Taylor (2009)).

firm assets-in-place. Second, the asymmetry in option payoffs implies that higher skewness of the underlying process raises the expected payoff of a call option.

Our second model is rooted in the basic stock valuation equation, a mathematical identity that relates firm cash flows and stock returns (e.g., Miller and Modigaliani (1961), Campbell and Shiller (1988), and Vuolteenaho (2002)). According to one common interpretation of the equation, higher expected growth rate of firm cash flows implies higher expected stock return if the book-to-market ratio is fixed. Fama and French (2006, 2008) emphasize that most stock return anomalies, no matter whether they are rational or irrational, are consistent with the valuation equation. In order to apply the equation, we present a novel interpretation of the conditional sample skewness of firm cash flows. The key ingredient of our argument is a link between the skewness and the sampling properties of the growth rate process. We demonstrate analytically and numerically that, for very general data-generating specifications, the conditional sample skewness is positively correlated with the expected growth rate of firm cash flows and therefore the expected stock return via the basic stock valuation equation.

Our model-implied positive relation between the skewness of firm fundamentals and stock returns highlights one major dichotomy between this paper and previous studies on the return predictability of stock return skewness, in which the stock return skewness is generally shown to be negatively related to stock returns.[2] To explain the negative return predictability, researchers assume that investors prefer positive skewness. In contrast, the models in this paper are preference-free.

To empirically test the model implications, we use two skewness measures: SK_{GP}, skewness of gross profitability (GP) of Novy-Marx (2013), and SK_{EPS}, skewness of earnings per

[2] The literature on the relation between stock return (co)skewness and expected stock return dates back to the seminal work of Kraus and Litzenberger (1976). Recent papers include Harvey and Siddique (2000), Dittmar (2002), Barone-Adesi, Gagliardini, and Urga (2004), Chung, Johnson, and Schill (2006), Mitton and Vorkink (2007), Boyer, Mitton, and Vorkink (2010), Engle (2011), Chang, Christoffersen, and Jacobs (2013), Conrad, Dittmar, and Ghysels (2013), and Chabi-Yo, Leisen, and Renault (2014).

share.[3] Strongly supporting the main implication of the two models, both skewness measures are significantly positive in predicting cross-sectional stock returns. For example, when stocks are sorted on SK_{GP} into decile portfolios, the equal-weighted average next-quarter portfolio return increases from decile 1 to decile 10. The H-L spread between deciles 10 and 1 is 1.55% per quarter and statistically significant at the 1% level. Value-weighting stock returns and adjusting returns by the conventional risk factors do not change the results. The evidence is corroborated by the estimates of Fama-MacBeth regressions, even in the presence of other return predictors including the level of GP.

To identify which of the two models drives the return predictability, we further test whether the skewness measures positively predict some widely accepted proxies of firm growth option and firm profitability. In particular, we measure growth option by market-asset-to-book-asset ratio ($MABA$) and Tobin's q, and profitability by ROE and GP. Interestingly, the evidence supports both models. The two skewness measures positively predict not only the proxies of firm growth option but also the proxies of firm profitability. The results suggest that the skewness of firm fundamentals is a powerful statistic as it captures different factors driving the firm value. Moreover, the return and firm performance predictability of skewness seems to hold in the long run.

Between the two skewness measures, SK_{GP} dominates SK_{EPS} in that the return predictability of SK_{EPS} is significantly reduced when SK_{GP} is simultaneously used as a predictor. This is consistent with the evidence in Novy-Marx (2013) that GP is a superior measure of firm profitability. To address the concern whether our findings are consequences of the existing evidence in the literature that the stock return skewness predicts stock returns, we conduct robustness checks by incorporating some widely used measures of stock return skewness (e.g., Harvey and Siddique (2000), Boyer, Mitton, and Vorkink (2010), and Bali, Cakici, and Whitelaw (2011)). We do not find any changes in our results after controlling

[3] We have also considered alternative firm fundamental measures such as ROE (return on equity) and various versions of earnings surprises. The results for the alternative measures are very similar and available upon request.

for the skewness of stock returns.

In spite of a large body of research on higher moments of stock returns, to our knowledge, this paper is the first to examine the information content of higher moments of firm fundamentals. A paper related to ours is Scherbina (2008) who examines the relation between a non-parametric skewness measure of analysts' earnings forecasts and stock returns. There are two main differences between the two papers. First, the skewness of cross-sectional analysts' forecasts is not directly linked to the skewness of firm fundamentals. Second but more importantly, Scherbina (2008) finds a negative relation between her skewness measure and stock returns, opposite to our results.[4] At the aggregate market level, Colacito, Ghysels, and Meng (2013) show evidence that the skewness of forecasts on the GDP growth rate made by professional forecasters is related to stock market returns. In a separate study, we consider the skewness of aggregate market earnings and find that it predicts stock market returns.

The rest of the paper is organized as following. In Section 2, we present the theoretical models and their implications. We describe the data and econometric methodology in Section 3. Section 4 discusses the empirical evidence. Section 5 concludes.

2 Theoretical Models

The first model is based on the recent developments in the option pricing theory for non-normally distributed underlying processes and the premise that the firm value contains a growth opportunity component. In the second model, we provide an econometric approach of inferring the expected growth rate of firm cash flows from the conditional sample skewness. The argument, together with the basic stock valuation equation, implies the positive return predictability.

[4] In a separate study, we use the standard skewness measure of analysts' forecasts and find that it positively predicts stock returns. However, the theoretical models in this paper do not apply to the skewness of analysts' forecasts. In fact, the skewness of analyst's forecasts is uncorrelated with the skewness measures in this paper.

2.1 Model 1: Growth Option

We follow the approach of Bernardo, Chowdhry, and Goyal (2007) in modeling the growth option of a firm.[5] The value of the firm at time t, $V_t = A_t + G_t$, is decomposed into two components: the value of assets-in-place, A_t, and the present value of a growth opportunity, G_t, which is treated as a European call option on A_t with time-to-expiration T and strike price I, regarded as an investment to undertake the opportunity. Bernardo, Chowdhry, and Goyal (2007) assume that A_t follows a Geometric Brownian motion and consequently the value of G_t is given by the Black-Scholes formula. Skewness has no role in their setting because the distribution of the assets-in-place is log normal.

We extend the model of Bernardo, Chowdhry, and Goyal (2007) by allowing the distribution of $\log A_T$ to have non-zero skewness. In the option pricing literature, one popular approach of generating non-zero skewness in the underlying stock price or foreign exchange rate process is using the jump-diffusion processes (e.g., Bakshi, Cao, and Chen (1997)). But there is no empirical evidence whether jump-diffusion specifications are suitable for firm fundamentals, which are infrequently observed with noises. Therefore, we use the model-free approach of Backus, Foresi, and Wu (2004) to incorporate non-zero skewness. In addition to skewness, Backus, Foresi, and Wu (2004) consider the impact of non-zero excess kurtosis to option pricing. Because our focus is skewness, we assume zero excess kurtosis to simplify our presentation.

Let γ denote the skewness of $\log A_T$. Proposition 1 of Backus, Foresi, and Wu (2004) implies the following approximation of the option value:[6]

$$G_t \approx A_t\Phi(d) - Ie^{-rT}\Phi(d - \sigma\sqrt{T}) + \frac{1}{6}A_t\phi(d)\sigma\sqrt{T}(2\sigma\sqrt{T} - d)\gamma, \qquad (1)$$

[5] It is also feasible to consider other models of growth options in the literature (e.g., Berk, Green, and Naik (1999) and Carlson, Fisher, and Giammarino (2004)). The parsimonious approach of Bernardo, Chowdhry, and Goyal (2007) is especially convenient to motivate our empirical analysis.

[6] The formula in Backus, Foresi, and Wu (2004) is for a call option on foreign exchange rate. But it is straight forward to modify it for the call option on the assets-in-place with the assumption that the dividend yield on A_t is zero. Bakshi, Kapadia, and Madan (2003) also provide a similar analysis.

where r is the risk-free interest rate, σ is the annualized standard deviation of $\log A_T$, $\Phi(.)$ and $\phi(.)$ are the probability and density functions of the standard normal distribution, and d is defined by:

$$d = \frac{\log(A_t/I) + (r + \sigma^2/2)T}{\sigma\sqrt{T}}. \tag{2}$$

When the skewness is zero, equation (1) becomes the Black-Scholes formula. With non-zero skewness, the sign of the last term of equation (1) is determined by the sign of $2\sigma\sqrt{T} - d$. It is plausible to treat the growth opportunity as an out-of-the-money call option because otherwise the firm would have exercised it.[7] That is, we assume $A_t < I$. Then it can be shown that $2\sigma\sqrt{T} - d > 0$ if the risk-free rate, r, is not very high. Even for high value of r, $2\sigma\sqrt{T} - d > 0$ holds if A_t is sufficiently lower than I, that is, the option is deep out-of-the-money. Consequently, we obtain the following proposition.

Proposition 1: If the firm's growth opportunity is an (deep) out-of-the-money call option, then G_t is monotonically increasing in the skewness of the log assets-in-place distribution.

The above result is very intuitive because a higher skewness increases the chance of an out-of-the-money call option to be in-the-money in the future. Backus, Foresi, and Wu (2004) also provide the formula for the call option delta:

$$\Delta_t = \Phi(d) + \frac{1}{6}\phi(d)(d^2 - 3d\sigma\sqrt{T} + 2\sigma^2 T - 1)\gamma. \tag{3}$$

For zero skewness, equation (3) becomes $\Phi(d)$ which is the delta formula in the Black-Scholes model. For non-zero skewness, the second term in equation (3) can be either positive or negative. But when the option is deep out-of-the-money, $A_t \ll I$, or for large value of $\sigma\sqrt{T}$, it can be shown easily that the sign of the coefficient of γ is positive. In other words, the option delta is positively related to the skewness. Again, this makes sense as the option

[7] Note that we assume the growth option to be of European style for analytical tractability. American options are more appropriate in describing growth opportunities in practice. Our approach can be regarded as an approximation, which should be relatively accurate for short-term out-of-the-money options because of low probability of early exercise.

writer needs to hedge more since the option is more likely to be in-the-money in the future.

We next follow the argument of Bernardo, Chowdhry, and Goyal (2007) to link the fundamental skewness to expected stock returns. We assume that the risk and return of any financial asset in the economy is captured by its β relative to the stochastic discount factor. As an example, in the CAPM framework, β is just the market beta. A higher value of β implies a higher value of the expected return. Let β_t^A and β_t^G denote the betas of the assets-in-place and growth option. It is straight forward to see that

$$\begin{aligned}\beta_t^G &= \frac{dG_t/dA_t}{G_t/A_t}\beta_t^A \\ &= \frac{\Delta_t}{G_t/A_t}\beta_t^A. \qquad (4)\end{aligned}$$

One can plug in the formulae of G_t and Δ_t into equation (4) and show that $\beta^G > \beta^A$. The conclusion can be obtained without using the pricing formulae but by noting that G_t is a convex function of A_t. Intuitively, the growth option is riskier than the underlying because the option is implicitly a leveraged position. We can write the beta of the firm value as:

$$\begin{aligned}\beta_t &= \frac{A_t}{A_t+G_t}\beta_t^A + \frac{G_t}{A_t+G_t}\beta_t^G \\ &= \frac{1+\Delta_t}{1+G_t/A_t}\beta_t^A. \qquad (5)\end{aligned}$$

To understand the relation between β_t and the skewness, γ, we consider the dependence of $\frac{1+\Delta_t}{1+G_t/A_t}$ on γ. The problem is a little complicated because both the numerator and denominator are increasing in γ for deep out-of-the-money options from our earlier results. Note, however, that the term in the numerator containing γ is $\frac{1}{6}\phi(d)(d^2 - 3d\sigma\sqrt{T} + 2\sigma^2 T - 1)\gamma$ and the term in the denominator containing γ is $\frac{1}{6}\phi(d)\sigma\sqrt{T}(2\sigma\sqrt{T} - d)\gamma$. It can be shown easily that for $d \ll 0$, the numerator term dominates the denominator term. We summarize the result in the next proposition.

Proposition 2: If the firm's growth opportunity is a deep out-of-the-money call option, then the β of firm's total value is monotonically increasing in the skewness of the log assets-in-place distribution. Therefore, higher value of skewness implies higher value of expected stock return.

One caveat about this model is that the option pricing formulae are based on the risk-neutral probability distribution but we can only estimate skewness using the realized data. The probability transformation between the objective and risk-neutral probability measures is unobserved. However, this problem is not very critical to our empirical analysis on cross-sectional stock returns. Because the same probability transformation is applied to all stocks at the same time, any cross-sectional property under the risk-neutral probability measure should hold under the real probability measure if the biases are about the same size across the stocks.

2.2 Model 2: Conditional Skewness of Small Samples

In contrast to the real option approach in the first model, our second model takes an econometric approach. The insight is a new way of interpreting the sample skewness of time series processes in small samples. Let x_t denote the time series process of some measure of firm cash flows such as earnings per share. Using the past sample of size n, $\{x_{t-n+1}, ..., x_t\}$, we estimate the conditional skewness, $\hat{b}$, with the standard formula:

$$\hat{b} = \frac{m_3}{s^3} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_{t-n+i} - \bar{x})^3}{\left[\frac{1}{n-1}\sum_{i=1}^{n}(x_{t-n+i} - \bar{x})^2\right]^{3/2}}, \tag{6}$$

where $\bar{x}$ is the sample mean, s is the sample standard deviation, and m_3 is the sample third central moment. We show next that $\hat{b}$ is informative about the order of the sample observations of the change of x, defined as $\Delta x_t = x_t - x_{t-1}$. For presentation purpose, assume zero initial value, $x_{t-n} = 0$. Using the identity $x_t = \sum_{i=1}^{n} \Delta x_{t-n+i}$, we can express the first three sample moments as:

$$\begin{aligned}
\bar{x} &= \frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{i}\Delta x_{t-n+j} \\
&= \frac{1}{n}\sum_{i=1}^{n}(n-i+1)\Delta x_{t-n+i}, \qquad (7) \\
s^2 &= \frac{1}{n-1}\sum_{i=1}^{n}\left(\sum_{j=1}^{i}\Delta x_{t-n+j}-\bar{x}\right)^2 \\
&= \frac{1}{n-1}\sum_{i=1}^{n}\left(\sum_{j=1}^{i}\frac{j-1}{n}\Delta x_{t-n+j}-\sum_{j=i+1}^{n}\left(1-\frac{j-1}{n}\right)\Delta x_{t-n+j}\right)^2, \qquad (8) \\
m_3 &= \frac{1}{n}\sum_{i=1}^{n}\left(\sum_{j=1}^{i}\Delta x_{t-n+j}-\bar{x}\right)^3 \\
&= \frac{1}{n}\sum_{i=1}^{n}\left(\sum_{j=1}^{i}\frac{j-1}{n}\Delta x_{t-n+j}-\sum_{j=i+1}^{n}\left(1-\frac{j-1}{n}\right)\Delta x_{t-n+j}\right)^3. \qquad (9)
\end{aligned}$$

In the sample mean, $\bar{x}$, earlier observations of Δx_{t-n+i} are clearly over-weighed than later observations. To see how the location of an observation affects its weight in s^2 and m_3, we consider two examples. For $n = 3$, simple calculations show:

$$\begin{aligned}
s^2 &= \frac{2}{3}\left(\Delta x_2^2+\Delta x_2\Delta x_3+\Delta x_3^2\right), \\
m_3 &= \frac{1}{9}(\Delta x_3-\Delta x_2)\left(2\Delta x_2^2+3\Delta x_2\Delta x_3+2\Delta x_3^2\right).
\end{aligned}$$

In this case, s^2 is symmetric with respect to Δx_2 and Δx_3 while m_3 is monotonically increasing in $\Delta x_3 - \Delta x_2$. For $n = 4$, we can write:

$$\begin{aligned}
s^2 &= \frac{1}{4}\left(3\Delta x_2^2+\Delta x_3^2+3\Delta x_4^2+4\Delta x_2\Delta x_3+2\Delta x_2\Delta x_4+4\Delta x_3\Delta x_4\right), \\
m_3 &= \frac{3}{8}(\Delta x_4-\Delta x_2)\left(\Delta x_2^2+\Delta x_4^2+2\Delta x_2\Delta x_3+2\Delta x_2\Delta x_4+2\Delta x_3\Delta x_4\right).
\end{aligned}$$

In this case, s^2 is symmetric with respect to Δx_2 and Δx_4. m_3 is monotonically increasing in $\Delta x_4 - \Delta x_2$ if the second part of m_3 is positive, which is the case when $\Delta x_3 = 0$. These two examples suggest that the sign and magnitude of m_3 depend on the order of observations $\{\Delta x_i\}_{i=1}^n$ but it is not the case for s^2. So a high value of $\hat{b}$ suggests high (low) values for more recent (earlier) observations of Δx_t.

It is messy to extend the above examples to general settings without specifying the underlying data-generating process. In the following, we consider the class of AR(1) processes:

$$x_t = \rho x_{t-1} + u_t, \tag{10}$$

where $\rho \leq 1$ is a constant and u_t is an *iid* standard white noise process. Note that x_t is a random walk when $\rho = 1$. The initial value x_0 is set to be zero for simplicity. There is no constant term on the right-hand side although including one does not change the results.

Instead of providing analytical proofs, we conduct the following numerical exercise. To be consistent with our later empirical work, we consider n = 8, 12, 16, and 20 and ρ = 0.9, 0.95, and 1.[8] To take into account of sampling errors, we use the Monte Carlo simulation method to examine the correlations between the conditional sample skewness and cross-sections of sample observations of Δx_t. The detailed steps are as following.

- Step 1: For fixed n and ρ, independently generate $N = 1,000,000$ paths of x_t according to equation (10). Denote the observations of the *ith* path by $\{x_{it}\}_{t=0}^n$.
- Step 2: For the *ith* path, compute the sample skewness $\hat{b}_i$.
- Step 3: For each value of $t = 2, ..., n$, compute the correlation of $\hat{b}_i$ and Δx_{it} across the N sample paths and denote it by $c(t)$.

Figure 1 shows the plots of $c(t)$ as a function of t for different values of n and ρ. Several interesting patterns emerge. First, for every (n, ρ) pair, the value of $c(t)$ is negative during the first half of the sample but positive during the second half of the sample. Second, $c(t)$

[8] The small sample sizes are appropriate when we consider low-frequency financial accounting data such as the quarterly earnings. Using larger sample sizes to estimate the conditional skewness is problematic if the underlying data-generating mechanism is time-varying and non-stable. The near-unit-root or unit-root specification for x is also reasonable as most financial accounting variables are highly persistent.

is monotonically increasing in t for the cases of $n = 8$, from less than -0.2 to over 0.2 when $\rho = 1$. For the cases of $n = 12, 16, 20$, $c(t)$ is monotonically increasing except for the two ends of the sample. In these cases, the minimum and maximum of $c(t)$ still occur near the beginning and ending of the sample, respectively. Third, when n is fixed, the increasing pattern of $c(t)$ becomes more significant as ρ increases to 1. Fourth, when ρ is fixed, the shape of $c(t)$ becomes flatter as n increases. The minimum and maximum of $c(t)$ are located further away from the first and last observations. These correlation patterns of $c(t)$ are not sensitive to the *iid* assumption for u_t as we have checked various heteroscedastic specifications for u_t. We have also considered numerous alternative ARMA(p,q) specifications for x_t and find qualitatively similar results. The following proposition summarize our findings.

Proposition 3: If the firm cash flow process, x_t, is persistent, then the conditional sample skewness, $\hat{b}$, is informative about the order of observations of Δx_t at least for small sample size up to 20. A high positive value of $\hat{b}$ suggests that the recent growth rates are likely high while the earlier growth rates are likely low. A low negative value of $\hat{b}$ suggests the opposite.

Although $\hat{b}$ is related to the past growth rates of x, an important open question is: What does $\hat{b}$ tell us about the expected future growth rate of x. If Δx_t is *iid* over time, the above results are not useful for forecasting purpose because knowing $\hat{b}$ and therefore the order of the past observations of Δx_t does not provide useful information about future Δx_t. For firm cash flows, however, Δx_t is likely non-*iid*, and $\hat{b}$ can be informative about the expected growth of x. As an example, consider the following process for the growth rate of x:

$$\Delta x_t = u_t + \varepsilon_t \tag{11}$$

$$u_t = \mu + \theta u_{t-1} + e_t \tag{12}$$

where μ and $0 < \theta < 1$ are constants, and ε_t and e_t are *iid* standard white noise processes. In this model, u_t is the expected growth rate of x and follows an AR(1) process which is unobserved. A high value of Δx_t implies a high value of u_t and consequently a higher future growths of x due to the persistence of the growth rate process.

This type of models are typically estimated with methods such as the Kalman filters. But there are some practical challenges to the parametric approach. First, accurate estimates of such models require long time-series data, which are not available. Second, the models are very likely unstable over time. This can happen, for example, when there are structural breaks in the underlying data-generating process. Third, the models are possibly misspecified. Alternative ARMA specifications or regime-switching models can provide similar fit of the same data.

Using the conditional sample skewness $\hat{b}$ to imply the expected growth rate of x circumvents these problems. It doesn't need long time series to estimate. More importantly, it doesn't rely on any parametric models. It allows many different types of model specifications. We summarize our argument in the following proposition.

Proposition 4: If the growth rate of x_t is positively autocorrelated, then a high value of conditional sample skewness for small samples, $\hat{b}$, implies that the future growth rate of x_t is likely high.

Proposition 4 has a direct implication about stock returns. According to the basic stock valuation equation (e.g., Fama and French (2006)), when everything else is fixed, a higher expected growth rate of firm cash flows implies higher stock return. Combining this argument with Proposition 4, we obtain the following result.

Proposition 5: For relatively small time-series samples, higher value of the conditional sample skewness of firm fundamentals, $\hat{b}$, implies higher value of the expected stock return.

In spite of different modeling approaches, both models generate the same positive relation between the skewness of firm fundamentals and stock returns. Because the two models are not mutually exclusive, which one of them drives the skewness and return relation is an empirical issue. In our empirical analysis next, after we first test the positive return predictability, we will investigate the validity of both models by testing the model-specific implications.

3 Data and Methodology

In this section, we first define the skewness measures of firm fundamentals. We then describe the data. Finally, we discuss the econometric methods.

3.1 Definition of Skewness Measures

We consider two measures of firm fundamentals: gross profitability GP and earnings per share EPS. GP is motivated by the significant evidence that it positively predicts returns (e.g., Novy-Marx (2013)) while earnings has been widely accepted as a measure of firm cash flows. At the end of quarter t, we define skewness of GP and EPS as the standard skewness coefficient of lagged observations during the rolling window of quarters $t-n$ to $t-1$:[9]

$$SK_{GP,t} = \frac{n}{(n-1)(n-2)} \sum_{\tau=t-n}^{t-1} \left(\frac{GP_\tau - \mu_{GP}}{s_{GP}} \right)^3, \tag{13}$$

$$SK_{EPS,t} = \frac{n}{(n-1)(n-2)} \sum_{\tau=t-n}^{t-1} \left(\frac{EPS_\tau - \mu_{EPS}}{s_{EPS}} \right)^3, \tag{14}$$

where $\mu_{GP}(\mu_{EPS})$ and $s_{GP}(s_{EPS})$ are, respectively, the sample average and standard deviation of $GP(EPS)$. In the benchmark case reported in the paper, we fix $n = 8$. The results for n up to 20 are similar and available upon request. It should be pointed out that GP is scaled by firm total asset but EPS is not scaled. This, however, is not a problem for our econometric analysis because the skewness of either variable is unit free by definition.

Note that we don't use the GP and EPS of quarter t in constructing the skewness measures at the end of quarter t because they are not reported until quarter $t+1$. When examining whether the skewness of earnings skewness up to quarter t predicts the stock returns in quarter $t+1$, using future information that is available in quarter $t+1$ but not in quarter t biases the statistical inference. We in fact have conducted our analysis without skipping quarter t and have found even stronger but biased results.

[9] This definition, for example, is used by Gu and Wu (2003).

3.2 Data Descriptions

Stock return and accounting data are obtained from the CRSP and COMPUSTAT. We consider all NYSE, AMEX and NASDAQ firms in the CRSP monthly stock return files up to December, 2013 except financial stocks (four digit SIC codes between 6000 and 6999) and stocks with end-of-quarter share price less than $5. We further require a firm to have at least 16 quarters of gross profitability or earnings data during 1971–2013 to be included in the sample of that skewness measure. The construction of each observation of skewness measure needs observations of 8 consecutive quarters. Because the first 2 years of data are used to construct the skewness measures, the portfolio and regression analysis begin in 1973. For each quarter, the accounting variables are defined as follows.

- GP: Following Novy-Marx (2013), gross profitability is quarterly revenue minus quarterly cost of goods sold scaled by quarterly asset total.

- EPS: Quarterly earnings per share before extraordinary items.

- MC: Market capitalization is the quarter-end shares outstanding multiplied by the stock price.

- BM: Book-to-market ratio is the ratio of quarterly book equity to quarter-end market capitalization. Quarterly book equity is constructed by following Hou, Xue, and Zhang (2015) (footnote 9), which is basically a quarterly version of book equity of Davis, Fama, and French (2000).

- $MABA$: Market-asset-to-book-asset ratio is defined as [Total Asset−Total Book Common Equity+Market Equity]/Total Assets.

- Tobin's q: It is defined as [Market Equity+Preferred Stock+Current Liabilities−Current Assets Total+Long-Term Debt]/Total Assets.

- ROE: Return on equity is defined as income before extraordinary items (IBQ) divided by 1-quarter-lagged book equity.

Firm size and book-to-market ratio are standard control variables in asset pricing studies. $MABA$ and Tobin's q are often regarded as proxies of firm growth options in the literature (e.g., Cao, Simin, and Zhao (2008)). ROE is a popular measure of firm cash flows other than GP and has been shown to predict stock returns (e.g., Hou, Xue, and Zhang (2015)). The variables related to stock returns are defined in the following.

- MOM: Momentum for month t is defined as the cumulative return between months $t-6$ and $t-1$. We follow the convention in the literature by skipping month t when MOM is used to predict returns in month $t+1$. We have also used the cumulative return between months $t-11$ and $t-1$ and obtained similar results.

- $Idvol$: Idiosyncratic volatility is, following Jiang, Xu, and Yao (2009), the standard deviation of the residuals of the Fama and French (1993) 3-factor model using daily returns in the quarter.

- $Idskew$: Following Harvey and Siddique (2000) and Bali, Cakici, and Whitelaw (2011), it is defined as the skewness of the regression residuals of the market model augmented by the squared market excess return. We use daily returns in the quarter to estimate the regression.

- $Prskew$: It is predicted idiosyncratic skewness defined in Boyer, Mitton, and Vorkink (2010). We obtain the $Prskew$ data from Brian Boyer's website.

- MAX: Following Bali, Cakici, and Whitelaw (2011), it is the average of the three highest daily returns in quarter t. Note that we use quarterly frequency instead of monthly frequency.

We use $Idvol$ as a control because a number of studies have documented that it predicts returns (e.g., Ang, Hodrick, Xing, and Zhang (2006)). The skewness measures of stock returns, $Idskew$, $Prskew$, and MAX are good controls to evaluate additional return explanatory power of firm fundamental skewness. We have also considered total return skewness of daily stock returns in the quarter and obtained similar results. We winsorize all the variables except the stock return at 1% and 99% levels although the results do not change significantly without winsorizing or winsorizing at 0.5% and 99.5% levels.

There are 350,050 and 384,402 firm-quarter observations for SK_{GP} and SK_{EPS}, respectively. Panel A of Table 1 shows the summary statistics of SK_{GP} and SK_{EPS}. On average, both SK_{GP} and SK_{EPS} are negative while SK_{GP} is more negative than SK_{GP}. The large standard deviations and extreme percentile values indicate significant cross-sectional variation of fundamental skewness across stocks. Both skewness measures are positively autocorrelated but the first-order autocorrelation coefficients (ρ_1) are low (0.14 and 0.13). The relatively low values of ρ_1 is an artifact of our estimation method of using non-overlapping samples. That is, we first use non-overlapping samples to construct the skewness measures and then estimate an AR(1) regression to get ρ_1.

Panel B reports the average contemporaneous cross-sectional correlations of the skewness measures and the control variables. SK_{GP} and SK_{EPS} are mildly correlated with the correlation coefficient of 0.31, suggesting that the two measures may capture different aspects of firm cash flows. SK_{GP} is mildly correlated with MOM and GP but uncorrelated with other controls. SK_{EPS} seems to be slightly correlated with all the control variables but none of the correlation coefficients is above 0.2. These low correlations give us confidence that the skewness measures are not proxies of the control variables.

3.3 Econometric Methods

We rely mostly on the portfolio sorts and cross-sectional regressions of Fama and MacBeth (1973) for our empirical tests. In single portfolio sorts, we rank stocks on a skewness measure of firm fundamentals into decile portfolios and then consider both equally-weighted and value-weighted portfolio returns. If the skewness is positively related to stock returns, we expect an increasing pattern of portfolio returns from decile 1 to decile 10. In double portfolio sorts, we first rank stocks into quintiles by a control variable such as MC and then further sort stocks within each portfolio into quintiles by the skewness measure. If the control variable can explain the predictability of skewness, we expect the increasing pattern of returns in skewness to be much less significant in each quintile of the control variable. To compute t-statistics of average portfolio returns, we use the Newey-West adjusted standard errors because of the persistence in the portfolio compositions.[10]

For the Fama-MacBeth regressions, we expect the average estimated coefficient of a skewness measure to be positive and significant. The cross-sectional regressions allow us to examine the marginal effect of the skewness measure when controlling for other variables known to predict stock returns. In the most general specification, we include all the control variables in the regression. If the skewness measure captures information about expected stock returns beyond that in other variables, the coefficient of the skewness measure should be significant even in the presence of all the control variables.

We also use the Fama-MacBeth regression approach to compare the explanatory power of different skewness measures. To do so, we include the two skewness measures in one regression. If the coefficient of one skewness measure is no longer significant in the presence of the other, it indicates that the later skewness measure dominates the first measure in the sense that it subsumes the explanatory power of the first measure.

4 Empirical Evidence

In this section, we show the results of portfolio sorts first and then the estimates of Fama-MacBeth regressions. We next present further evidence validating the theoretical models. We conduct robustness checks at the end.

[10] We use six lags in the Newey-West standard errors. Using more lags does not change the results.

4.1 Single Portfolio Sorts

Table 2 reports the average returns and characteristics of the decile portfolios formed by sorting stocks on the two skewness measures. When sorted on SK_{GP} as in panel A, the average equal-weighted quarterly return increases from decile 1 (2.99%) to decile 10 (4.54%). The average H-L spread is 1.55% per quarter (or 6.20% per year) and highly significant ($t = 5.67$). To make sure that the significant H-L spread is not driven by higher stock risk, we estimate the risk-adjusted α using either the 3-factor model of Fama and French (1996) or the 5-factor model of Fama and French (2015).[11] The risk-adjusted H-L spreads are even higher at 1.69% and 1.61%. The value-weighted H-L spreads are very similar to but slightly smaller than the equal-weighted H-L spreads, indicating that the results are not dominated by small stocks.

Next, we look at the characteristics of the equal-weighted decile portfolios. Low-SK_{GP} stocks have low past return, GP, and ROE but slightly higher book-to-market ratio and idiosyncratic volatility. These patterns are not surprising because low-SK_{GP} stocks are past under-performers in terms of profitability. To make sure that the return predictability of SK_{GP} is not driven by the firm characteristics, we will perform double portfolio sorts and Fama-MacBeth regressions.

The results of portfolios sorts on SK_{EPS} in panel B are very close to those for SK_{GP}. The unadjusted and adjusted H-L spreads for SK_{EPS} are actually slightly higher than those for SK_{GP}. The average unadjusted H-L spread is 1.66% per quarter (or 6.64% per year) and highly significant ($t = 4.20$). The firm characteristics of the decile portfolios also exhibit similar patterns as those in panel A.

Overall, we find a positive relation between the skewness of firm fundamentals and future stock returns, consistent with the main prediction of both theoretical models. The results are robust regardless whether the returns are equal-weighted or value-weighted, and unadjusted

[11]We have also used the 4-factor model of Carhart (1997). The results are similar and available upon request.

or risk-adjusted. The question that which model drives the return predictability will be examined later.

4.2 Double Portfolio Sorts

We now investigate whether the predictability of the skewness measures are results of firm characteristics. We use the double portfolio sorts by first sorting stocks on firm characteristics and then sorting on the skewness measures. Table 3 reports the average equal-weighted returns of double-sorted portfolios for the six characteristics reported in Table 2. The results for value-weighted returns are very similar and unreported for brevity. We have also examined a number of other control variables and those results are available upon requests.

We first consider the results for SK_{GP} in panel A. When stocks are initially ranked by MC, the H-L spreads of the skewness quintiles show a decreasing pattern from MC quintile 1 (2.51%) to MC quintile 5 (0.58%), suggesting that the predictability of SK_{GP} is stronger for small stocks. Among the other characteristics, the predictability of SK_{GP} is stronger for high MOM, GP, and $Idvol$ stocks but there is no clear pattern for BM and ROE. No matter which firm characteristic is considered, all H-L spreads remain positive and most of them are statistically significant. The evidence indicates that the return predictive power of SK_{GP} cannot be explained the firm characteristics.

The results for SK_{EPS} in panel B are generally similar to those for SK_{GP} but with some differences. The predictability of SK_{EPS} is stronger for low BM and high ROE stocks. The H-L spreads for GP quintiles exhibit a U-shape pattern. In sum, the double sorts evidence for SK_{EPS} is not as robust as for SK_{GP} in the presence of control variables. The predictability of SK_{EPS} is particularly weaker for MOM, GP, and ROE quintiles as the average H-L spreads across the quintiles are smaller in magnitude than that in single portfolio sorts. In particular, the H-L spread is significant only for the highest ROE quintile. Some loss of statistical significance can be attributed to the higher standard errors due to the smaller sample size of the 5×5 portfolios. Close inspection of the ROE quintiles reveals non-linear interactions among stock return, SK_{EPS}, and ROE. We will look at this issue from another perspective by the Fama-MacBeth regressions where multiple control variables are jointly considered.

4.3 Fama-MacBeth Regressions

We now examine the return predictability of the skewness measures with the Fama-MacBeth regressions, which allow us to control for multiple return predictors simultaneously. The results are reported in Table 4. We estimate eight regression models. The first one uses a skewness measure as the only explanatory variable. Models (2)-(7) examines the six control variables, one at a time. Because of different sample sizes for the two skewness measures, we reestimate these models for each skewness measure. Model (8) includes the skewness measure and all six control variables.

First, we consider the results for SK_{GP} in panel A. The average coefficient of SK_{GP} in model (1) is positive and significant at the 1% level (0.24 and $t = 6.18$). Every control variable but MC is significant when it is used alone to forecast returns. The signs of the coefficients for the control variables except MC are consistent with those documented in the literature (e.g., Fama and French (1992), Jegadeesh and Titman (1993), Ang, Hodrick, Xing, and Zhang (2006), Novy-Marx (2013), and Hou, Xue, and Zhang (2015)). In model (8) where all controls are incorporated, the average coefficient of SK_{GP} is smaller in magnitude than that in model (1) but still significant at the 1% level (0.11 and $t = 3.87$). Interestingly, the average coefficient for MC is now significant at the 10% level and has the same negative sign as that documented in the literature.

Next, as shown in panel B, the estimation results for SK_{EPS} are very similar to those for SK_{GP}. By itself, SK_{EPS} positively predicts stock returns in model (1). The average coefficient is 0.25 and significant at the 1% level ($t = 4.73$). When all the control variables are included in model (8), the average coefficient of SK_{EPS} remains positive and significant at the 5% level (0.09 and $t = 2.37$). In sum, the results of Fama-MacBeth regressions are consistent with those of portfolio sorts. Both skewness measures of firm fundamentals positively predict stock returns. While in the presence of control variables the evidence is not as significant as when they are absent, the overall return predictability by the fundamental skewness cannot be explained by other predictors.

4.4 Skewness and Firm Growth Option

We now test the firm growth option model by checking whether the skewness of firm fundamentals is positively related to future firm growth opportunities. We use two popular measures of firm growth option in the literature: $MABA$ and Tobin's q (e.g., Cao, Simin, and Zhao (2008)). We present evidence of both portfolio sorts and Fama-MacBeth regressions.

Table 5 reports the average equal-weighted future $MABA$ and Tobin's q for the next four quarters of the decile portfolios formed by sorting stocks on the skewness measures. Value-weighted results are very similar and not reported for brevity. The results support our argument that a higher value of skewness implies higher growth opportunities. For both skewness measures, the H-L spreads in $MABA$ and Tobin's q are all positive and significant at the 1% level for all four future quarters. The magnitude of the H-L spreads is higher for SK_{EPS} than for SK_{GP}. The slow decaying of the H-L spreads indicates that the impact of the skewness on firm growth option is persistent.

In Table 6, we present the estimates of Fama-MacBeth regressions where the dependent variable is the next-quarter $MABA$ or Tobin's q. Again, the results for the two proxies of firm growth options are very similar. When a skewness measure is the only predictor, its estimated coefficient is positive and significant at the 1%. Next, we consider the estimation results with all the control variables. Because both $MABA$ and Tobin's q are persistent, we include their lagged values as additional control variables in the corresponding regressions. The coefficients on the skewness measures with the controls included are much smaller but still significant at the 5% level. The coefficient for SK_{EPS} is always higher than the coefficient for SK_{GP}, consistent with the results of portfolio sorts. Taken together, the evidence of portfolio sorts and Fama-MacBeth regressions support our model implication that firms with higher fundamental skewness have higher growth options.

4.5 Skewness and Firm Profitability

We turn attention to testing the second model by examining whether the skewness of firm fundamentals is positively related to future profitability or growth of firm fundamentals. We proxy firm profitability by two widely used measures in the literature: ROE and GP.

Table 7 reports the average equal-weighted future ROE and GP for the next four quarters of the decile portfolios formed by sorting stocks on the skewness measures. The results for both SK_{GP} and SK_{EPS} indicate that high-skewness stocks have higher profitability in the next four quarters. The H-L spreads of both ROE and GP are positive and significant at the 1% level for all four quarters. The H-L spreads decline gradually as horizon increases, suggesting mean reversion. But the slow reversion indicates the impact of the skewness on firm profitability is persistent. There is an interesting pattern between the two panels: The H-L spreads in ROE in panel B are larger than those in panel A but the H-L spreads in GP in panel B are smaller than those in panel A. This is not surprising as the skewness of earnings should be more significant in predicting ROE while the skewness of GP should be more significant in predicting GP.

Table 8 reports the estimation results of the Fama-MacBeth regressions where the dependent variable is the next-quarter ROE or GP. The regressions evidence is mostly consistent with the portfolio sorts evidence. Both skewness measures positively predict future ROE and GP even in the presence of the control variables including lagged ROE and GP. The only insignificant coefficient is that of SK_{EPS} when all controls are included but it is still positive.

Overall, the above evidence supports our second model. Together with the evidence in the previous section, our findings are consistent with both models. That is, higher skewness of firm fundamental implies higher firm growth option as well as higher firm profitability.

4.6 Comparison of Alternative Skewness Measures

It is interesting to compare the return predictive power of the two skewness measures. To do this, we estimate Fama-MacBeth regressions with both skewness measures as explanatory variables. The first regression contains no control variables while the second regression includes all control variables. The estimation results are reported in Table 10.

Without control variables, the average coefficient of SK_{GP} is 0.19 and significant at the 1% level ($t = 5.67$) while the average coefficient of SK_{EPS} is 0.13 and only significant at the 10% level ($t = 1.93$), indicating that the predictability of SK_{GP} dominates that of SK_{EPS}. When all the control variables are incorporated, the average coefficients of SK_{GP} (0.11) remains significant at the 1% level but the average coefficient of SK_{EPS} is insignificant albeit positive (0.02). The evidence suggests that the predictability of SK_{EPS} is subsumed by SK_{GP} and the control variables. Our findings support the claim of Novy-Marx (2013) that GP is one of the best accounting measures of firm performance.

4.7 Robustness Checks

4.7.1 Long Horizons

We have shown earlier that the fundamental skewness predicts long-run firm growth option and profitability. We now investigate if the return predictability holds for long horizons. We estimate Fama-MacBeth regressions for returns in quarters $t + 2$, ..., $t + 5$ and report the results in Table 10. We only consider two regression specifications. In model (1), the skewness is the only explanatory variable while model (2) also contains all the control variables.

The results show that the skewness of fundamentals, particularly SK_{GP}, can predict long-run returns. The coefficient on SK_G in model (1) is positive and significant at least at the 10% up to quarter $t + 5$. Even in the presence of the control variables in model (2), it is significant up to quarter $t+3$. The coefficient on SK_{EPS} is always positive but becomes insignificant beyond quarter $t+2$. As a whole, the return predictability holds at least up to the third quarter after portfolio formation. Note that if we use the cumulative returns as the dependent variables, then all the coefficients will become significant. Among the control variables, GP is the strongest return predictor as its coefficient is positive and significant up to quarter $t+5$, consistent with the findings of Novy-Marx (2013).

4.7.2 Controlling for Return Skewness

One concern about our empirical results is whether the return predictability of the fundamental skewness is related to the return predictability of the return skewness documented in the literature. We address this issue by incorporating three popular return skewness measures (MAX, $Idskew$, and $Prskew$) in the Fama-MacBeth regressions of the fundamental skewness measures. Table 11 reports the estimation results.

In models (1)–(3), we only use one of the three return skewness measures. MAX and $Prskew$ are significant but $Idskew$ is insignificant in predicting returns. However, the average coefficient for MAX changes signs between the samples of SK_{GP} and SK_{EPS}. Model (4) use all three return skewness measures. MAX and $Idskew$ are significant in the sample of SK_{GP} while $Prskew$ is significant in the sample of SK_{EPS}. It seems that the return skewness measures do not consistently predict stock returns.

We next combine the skewness of fundamentals with the return skewness measures in models (5) an (6). In model (5), we do not use any control variables. The average coefficients of SK_{GP} and SK_{EPS} are positive and significant at the 1% level. Among the skewness measures of returns, only MAX is significant at the 1% level for the SK_{GP} sample and $Prskew$ is significant at the 10% level in the SK_{EPS}. We now include all the control variables in model (6). MAX and $Prskew$ are marginally significant in the sample of SK_{EPS}. Most importantly, the average coefficients SK_{GP} and SK_{EPS} are still significant at the 1% level. The evidence indicates that our findings cannot be explained by the skewness of stock returns.

4.7.3 Additional Tests

We perform more robustness checks and report the results in Table 12. For brevity, we only consider two regression specifications. Model (1) only contains the skewness measure as the explanatory variable while model (2) also contains all the control variables.

First, we estimate panel regressions instead of Fama-MacBeth regressions and compute t-statistics using two-way clustered standard errors. The coefficients on SK_{GPS} and SK_{EPS} are similar to those of the Fama-MacBeth regressions in Table 4. As expected, the t-statistics are smaller but remain significant at the 1% level for SK_{GP} and 10% level for SK_{EPS}.

Next, we extend the panel regressions by adding the time fixed effect to take care of the potential seasonality in the data. The estimates with the time fixed effect are almost identical to those without the time fixed effect.

Thirdly, we estimate Fama-MacBeth regressions with the industry fixed effect. The coefficients on SK_{GPS} and SK_{EPS} are comparable to those reported in Table 4 without the industry fixed effect.

Finally, we estimate the basic Fama-MacBeth regressions for the skewness measures that are constructed using the data of last 12 quarters instead of 8 quarters. The results, particularly of model (2), are very close to those reported in Table 4 for the benchmark case. Taken together, the results of these additional tests provide further support to our main model implication that the skewness of firm fundamentals is positively related to stock returns.

5 Conclusions

We present two distinct models that relate the skewness of firm fundamentals to stock returns. The first model hinges on the premise that the firm value contains a growth option component and the fundamental skewness affects the option value. The second model relies on the interpretation of the sample skewness of firm fundamentals as a proxy of the expected growth rate of firm cash flows. Both models imply a positive relation between the fundamental skewness and expected stock return.

Using two skewness measures, one for firm gross profitability and the other for earnings per share, we find strong evidence supporting both models. The skewness measures positively predict not only cross-sectional stock returns but also future firm growth option and profitability. The evidence cannot be explained by the existing risk models and other return predictors including the skewness of stock returns.

Because our models are based on the real option theory and the basic stock valuation equation, we are, in the spirit of Fama and French (2006, 2008), agnostic about whether the return predictability of the skewness measures is rational or irrational. Given the strong evidence of skewness in firm cash flows, our results highlight the importance of incorporating the skewness measures of firm fundamentals in asset pricing research.

References

Aharoni, Gil, Bruce Grundy, and Qi Zeng, 2013, Stock returns and the Miller Modigliani valuation formula: Revisiting the Fama French analysis, *Journal of Financial Economics* 110, 347–357.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The cross-section of volatility and expected returns, *Journal of Finance* 61, 259–299.

Backus, David, Silverio Foresi, and Liuren Wu, 2004, Accounting for biases in Black-Scholes, New York University Woring Paper.

Bakshi, Gurdip, Charles Cao, and Zhiwu Chen, 1997, Empirical performance of alternative option pricing models, *Journal of Finance* 52, 2003–2049.

Bakshi, Gurdip, Nikunj Kapadia, and Dilip Madan, 2003, Stock returns characteristics, skew laws, and the differential pricing of individual equity options, *Review of Financial Studies* 16, 101–143.

Bali, Turan G, Nusret Cakici, and Robert F. Whitelaw, 2011, Maxing out: Stocks as lotteries and the cross-section of expected returns, *Journal of Financial Economics* 99, 427–446.

Barone-Adesi, Giovanni, Patrick Gagliardini, and Givanni Urga, 2004, Testing asset pricing models with coskewness, *Journal of Business & Economic Statistics* 22, 474–485.

Berk, Jonathan B, Richard C Green, and Vasant Naik, 1999, Optimal investment, growth options, and security returns, *Journal of Finance* 54, 1553–1607.

Bernardo, Antonio E, Bhagwan Chowdhry, and Amit Goyal, 2007, Growth options, beta, and the cost of capital, *Financial Management* 36, 1–13.

Boyer, Brian, Todd Mitton, and Keith Vorkink, 2010, Expected idiosyncratic skewness, *Review of Financial Studies* 23, 169–202.

Campbell, John Y., and Robert J. Shiller, 1988, Stock prices, earnings, and expected dividends, *Journal of Finance* 43, 661–676.

Cao, Charles, Tim Simin, and Jing Zhao, 2008, Can growth options explain the trend in idiosyncratic risk?, *Review of Financial Studies* 21, 2599–2633.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.

Carlson, Murray, Adlai Fisher, and Ron Giammarino, 2004, Corporate investment and asset price dynamics: Implications for the cross-section of returns, *Journal of Finance* 59, 2577–2603.

Chabi-Yo, Fousseni, Dietmar P.J. Leisen, and Eric Renault, 2014, Aggregation of preferences for skewed asset returns, *Journal of Economic Theory* 154, 453–489.

Chang, Bo Young, Peter Christoffersen, and Kris Jacobs, 2013, Market skewness risk and the cross section of stock returns, *Journal of Financial Economics* 107, 46–68.

Chung, Y. Peter, Herb Johnson, and Michael J. Schill, 2006, Asset pricing when returns are nonnormal: Fama-French factors versus higher-order systematic comoments, *Journal of Business* 79, 923–940.

Cohen, Randolph B., Paul A. Gompers, and Tuomo Vuolteenaho, 2002, Who underreacts to cash-flow news? Evidence from trading between individuals and institutions, *Journal of Financial Economics* 57, 409–462.

Colacito, Riccardo, Eric Ghysels, and Jianghan Meng, 2013, Skewness in expected macro fundamentals and the predictability of equity returns: Evidence and theory, University of North Carolina Working Paper.

Conrad, Jennifer, Robert F. Dittmar, and Eric Ghysels, 2013, Ex ante skewness and expected stock returns, *Journal of Finance* 61, 85–124.

Davis, James L., Eugene F. Fama, and Kenneth R. French, 2000, Characteristics, covariances, and average returns: 1929 to 1997, *Journal of Finance* 55, 389–406.

Dichev, Ilia D., and Vicki Wei Tang, 2009, Earnings volatility and earnings predictability, *Journal of Accounting and Economics* 47, 160–181.

Dittmar, Robert F., 2002, Nonlinear pricing kernels, kurtosis preference, and evidenc from the cross section of equity returns, *Journal of Finance* 57, 369–403.

Engle, Robert, 2011, Long-term skewness and systemic risk, *Journal of Financial Econometrics* 9, 437–468.

Fairfield, Patricia M., Scott Whisenant, and Terry Lombardi Yohn, 2003, Accrued earnings and growth: Implications for future profitability and market mispricing, *The Accounting Review* 78, 353–371.

Fama, Eugene F., and Kenneth R. French, 1992, The cross section of expected stock returns, *Journal of Finance* 47, 427–465.

———, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

———, 1996, Multifactor explanations of asset pricing anomalies, *Journal of Finance* 51, 55–84.

———, 2006, Profitability, investment, and average returns, *Journal of Financial Economics* 82, 491–518.

———, 2008, Dissecting anomalies, *Journal of Finance* 63, 1653–1678.

———, 2015, A five-factor asset pricing model, *Journal of Financial Economics* 116, 1–22.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607–636.

Gow, Ian D., and Daniel Taylor, 2009, Earnings volatility and the cross-section of returns, Northwestern University Working Paper.

Gu, Zhaoyang, and Joanna Shuang Wu, 2003, Earnings skewness and analyst forecast bias, *Journal of Accounting and Economics* 35, 5–29.

Harvey, Campbell R., and Akhtar Siddique, 2000, Conditional skewness in asset pricing tests, *Journal of Finance* 55, 1263–1295.

Hou, Kewei, Chen Xue, and Lu Zhang, 2015, Digesting anomalies: An investment approach, *Review of Financial Studies* 28, 650–705.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *The Journal of Finance* 48, 65–91.

Jiang, George J., Danielle Xu, and Tong Yao, 2009, The information content of idiosyncratic volatility, *Journal of Financial and Quantitative Analysis* 44, 1–28.

Kraus, Alan, and Robert Litzenberger, 1976, Skewness preference and the valuation of risk assets, *Journal of Finance* 31, 1085–1100.

Miller, Merton, and Franco Modigaliani, 1961, Dividend policy, growth, and the valuation of shares, *Journal of Business* 34, 411–433.

Mitton, Todd, and Keith Vorkink, 2007, Equilibrium underdiversification and the preference for skewness, *Review of Financial Studies* 20, 1255–1288.

Novy-Marx, Robert, 2013, The other side of value: The gross profitability premium, *Journal of Financial Economics* 108, 1–28.

Scherbina, Anna, 2008, Suppressed negative information and future underperformance, *Review of Finance* 12, 533–565.

Titman, Sheridan, K. C. John Wei, and Feixue Xie, 2004, Capital investments and stock returns, *Journal of Financial and Quantitative Analysis* 39, 677–700.

Vuolteenaho, Tuomo, 2002, What drives firm-level stock returns?, *Journal of Finance* 57, 233–264.

Figure 1: Correlations of Sample Skewness and Changes of Sample Observations

This figure presents the plots of the correlations of estimated sample skewness and changes of sample observations. The data-generating process is $x_t = \rho x_{t-1} + u_t$, where $\rho \leq 1$ is a constant and u_t is an *iid* standard white noise process. The initial value x_0 is set to be zero. In step 1, we independently generate $N = 1,000,000$ paths of x_t. Denote the observations of the ith path by $\{x_{it}\}_{t=0}^{n}$. In step 2, we compute, for the ith path, the sample skewness $\hat{b}_i$ for the ith path. In the last step 3, for each value of $t = 2, ..., n$, we compute the cross-sectional correlation of $\hat{b}_i$ and Δx_{it} and denote it by $c(t)$. The four rows of the panels correspond to $n = 8$, 12, 16, and 20, respectively while the three columns of the panels correspond to $\rho =$ 0.9, 0.95, and 1, respectively.

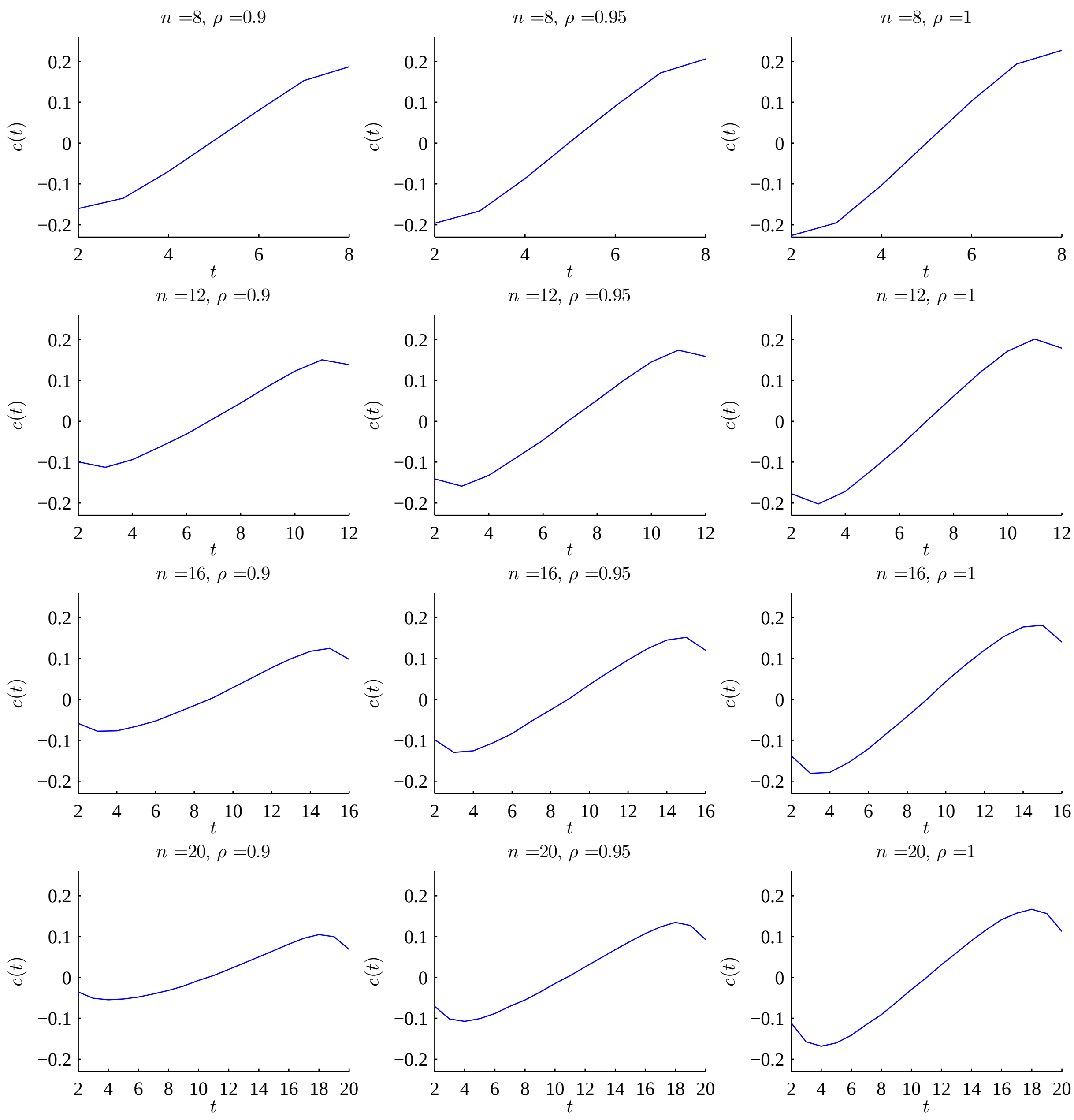

Table 1: Data Description

Panel A shows the summary statistics of the two measures of skewness of firm fundamentals: SK_{GP}–the skewness of gross profitability and SK_{EPS}–the skewness of earnings per share. In addition to mean, median, and standard deviation, we report the 10th, 25th, 75th, and 95th percentiles as well as the average first order autocorrelation coefficient, ρ_1. To get ρ_1 for each stock, we use non-overlapping 8-quarter samples to construct the skewness and then estimate an AR(1) regression. Panel B reports the average contemporaneous cross-section correlations of the skewness measures and control variables. MC is the market capitalization, BM is the book-to-market ratio, MOM is the cumulative return from month $t-6$ to $t-1$, GP is the gross profitability, ROE is the return on equity, $Idvol$ is the idiosyncratic volatility, The detailed definitions of the variables are shown in Section 3. The sample period is $Q1, 1973 - Q4, 2013$. Panel B reports the average contemporaneous cross-section correlations of quarterly skewness measures and the control variables.

Panel A: Summary Statistics

				Percentile				
	Mean	Median	Std. Dev.	10	25	75	90	ρ_1
SK_{GP}	-0.05	0.02	1.02	-1.40	-0.62	0.60	1.19	0.14
SK_{EPS}	-0.13	-0.05	1.22	-1.89	-0.89	0.67	1.38	0.13

Panel B: Correlations

	SK_{GP}	SK_{EPS}	MC	BM	MOM	GP	ROE	$Idvol$
SK_{GP}	1							
SK_{EPS}	0.31	1						
MC	0.04	0.08	1					
BM	-0.07	-0.13	-0.16	1				
MOM	0.15	0.17	0.10	-0.13	1			
GP	0.21	0.15	-0.01	-0.11	0.12	1		
ROE	0.05	0.13	0.05	-0.04	0.13	0.15	1	
$Idvol$	-0.02	-0.09	-0.36	-0.04	-0.05	-0.04	-0.05	1

Table 2: Returns and Characteristics of Decile Portfolios Sorted on Fundamental Skewness
This table reports the average next-quarter returns and firm characteristics of decile portfolios formed by sorting stocks on the skewness measures. Panels A and B are for SK_{GP} and SK_{EPS}, respectively. EW and VW mean equal-weight and value-weight, respectively. Ret is the raw quarterly return and α is the risk-adjusted return. We use two models for risk adjustment: the 3-factor model of Fama and French (1996) and the 5-factor model of Fama and French (2015). The row H-L reports the differences of average returns between decile 10 and decile 1, with the corresponding Newey-West t-statistics shown in the last row. The firm characteristics of the decile portfolios are equal-weighted. The unadjusted and adjusted returns, MOM, and $Idvol$ are reported in percentage while MC is in \$ billion.

Panel A: SK_{GP}

Decile	EW Ret	EW FF3-α	EW FF5-α	VW Ret	VW FF3-α	VW FF5-α	SK_{GP}	MC	BM	MOM	GP	ROE	$Idvol$
Low	2.99	0.16	0.36	3.11	0.31	0.39	-3.63	5.60	0.91	9.39	0.07	0.01	11.06
2	3.10	0.61	0.68	3.14	0.67	0.73	-2.20	5.58	0.89	12.23	0.09	0.02	10.64
3	3.03	0.39	0.41	3.01	0.41	0.44	-1.39	5.51	0.94	13.08	0.09	0.02	10.60
4	3.40	0.43	0.62	3.43	0.51	0.63	-0.76	5.53	0.87	15.13	0.09	0.02	10.52
5	3.41	0.81	0.93	3.44	0.87	0.99	-0.20	5.54	0.86	15.95	0.10	0.03	10.48
6	3.84	0.94	1.58	3.82	0.97	1.59	0.29	5.54	0.89	19.03	0.10	0.03	10.48
7	4.38	1.33	1.63	4.27	1.30	1.57	0.79	5.56	0.88	20.03	0.10	0.03	10.43
8	4.11	1.48	1.68	4.01	1.45	1.61	1.38	5.60	0.87	23.57	0.11	0.03	10.40
9	4.17	1.67	1.71	4.07	1.64	1.64	2.15	5.59	0.78	26.67	0.11	0.03	10.57
High	4.54	1.85	1.97	4.41	1.76	1.87	3.67	5.64	0.72	30.85	0.12	0.04	10.88
H-L	1.55	1.69	1.61	1.30	1.45	1.48							
t-stat.	5.67	5.14	5.49	4.85	4.17	4.47							

Panel B: SK_{EPS}

Decile	EW Ret	EW FF3-α	EW FF5-α	VW Ret	VW FF3-α	VW FF5-α	SK_{EPS}	MC	BM	MOM	GP	ROE	$Idvol$
Low	2.43	-0.27	0.40	2.62	-0.14	0.53	-3.45	5.19	0.97	6.14	0.06	-0.02	11.94
2	3.09	0.52	0.77	3.09	0.51	0.77	-1.93	5.34	0.95	10.02	0.06	0.01	11.07
3	3.01	0.51	0.89	3.00	0.54	0.92	-1.13	5.34	0.93	11.33	0.07	0.01	10.96
4	3.18	0.70	1.03	3.24	0.81	1.10	-0.51	5.37	0.91	12.87	0.07	0.02	10.68
5	3.22	0.79	1.14	3.23	0.86	1.17	0.01	5.39	0.89	14.56	0.08	0.02	10.59
6	3.37	0.98	1.13	3.39	1.01	1.20	0.47	5.39	0.87	17.09	0.08	0.03	10.43
7	3.58	1.26	1.45	3.51	1.26	1.45	0.95	5.49	0.81	19.10	0.08	0.04	10.38
8	3.64	1.16	1.45	3.57	1.19	1.44	1.53	5.56	0.78	21.49	0.09	0.04	10.28
9	3.96	1.56	1.83	3.81	1.49	1.78	2.30	5.60	0.73	23.88	0.10	0.05	10.34
High	4.09	1.63	2.01	3.98	1.62	2.01	3.85	5.64	0.66	30.14	0.11	0.06	10.63
H-L	1.66	1.89	1.61	1.36	1.75	1.47							
t-stat.	4.20	3.97	3.78	3.44	3.61	3.51							

Table 3: Double Portfolio Sorts of Fundamental Skewness and Firm Characteristics

This table reports the equal-weighted average next-quarter returns of portfolios formed by double sorting stocks on the skewness measures and firm characteristics. Panels A and B are for SK_{GP} and SK_{EPS}, respectively. For each firm characteristic, we first sort stocks into quintiles using the characteristic, and then within each quintile, we further sort stocks into quintiles based on the skewness measure of interest. The row H-L shows the differences of average returns between quintile 5 and quintile 1, with the corresponding Newey-West t-statistics shown below.

Panel A: SK_{GP}

SK_{GP}	MC Quintile					BM Quintile				
Quintile	Low	2	3	4	High	Low	2	3	4	High
Low	2.40	3.07	3.31	3.29	3.16	2.00	2.54	2.77	3.66	4.23
2	2.67	3.04	3.24	3.45	3.16	2.17	2.83	3.21	3.75	4.17
3	3.45	3.58	4.14	3.75	3.53	2.35	3.43	4.21	4.02	3.92
4	4.19	4.29	4.06	3.84	3.54	2.95	3.51	4.15	4.60	4.94
High	4.91	4.64	4.63	4.44	3.74	3.42	3.91	4.34	5.05	5.27
H-L	2.51	1.56	1.32	1.14	0.58	1.42	1.37	1.58	1.39	1.04
t-stat.	3.04	4.41	3.40	3.07	1.96	4.01	5.21	4.17	3.07	2.71
SK_{GP}	MOM Quintile					GP Quintile				
Quintile	Low	2	3	4	High	Low	2	3	4	High
Low	2.23	2.74	3.61	3.83	4.21	1.96	3.07	3.46	3.80	4.17
2	1.52	3.26	3.39	3.62	4.35	2.09	2.85	3.15	3.68	4.39
3	1.96	2.99	3.83	4.07	4.76	2.52	3.20	3.41	4.42	4.46
4	2.43	3.91	4.13	4.38	5.14	2.56	3.59	4.61	4.08	5.05
High	2.73	3.49	3.87	4.62	5.21	2.67	3.58	4.01	4.45	5.58
H-L	0.49	0.74	0.26	0.80	1.00	0.71	0.51	0.56	0.65	1.42
t-stat.	1.08	2.76	1.32	2.72	3.36	2.02	1.37	1.56	1.96	4.55
SK_{GP}	ROE Quintile					$Idvol$ Quintile				
Quintile	Low	2	3	4	High	Low	2	3	4	High
Low	1.58	3.24	3.66	3.72	3.65	3.29	3.22	3.67	3.19	1.50
2	1.37	3.26	3.17	4.12	3.67	3.44	3.64	3.27	2.96	1.34
3	1.81	3.52	3.94	4.23	4.46	3.67	3.83	4.26	3.47	2.54
4	1.61	3.72	4.56	4.55	4.93	3.99	4.17	4.43	3.89	2.19
High	3.16	3.89	4.64	4.60	4.65	4.16	4.32	5.01	4.88	3.58
H-L	1.58	0.65	0.98	0.88	1.00	0.87	1.09	1.34	1.69	2.07
t-stat.	1.78	2.27	3.19	3.65	3.30	3.34	4.76	3.41	3.39	2.72

Table 3 – Continued

Panel B: SK_{EPS}

SK_{EPS}	MC Quintile					BM Quintile				
Quintile	Low	2	3	4	High	Low	2	3	4	High
Low	1.83	2.54	3.11	3.20	2.76	1.02	2.39	2.73	3.27	3.90
2	2.66	2.83	3.26	3.40	2.98	1.64	2.65	3.14	3.81	3.92
3	2.85	3.29	3.52	3.50	3.15	2.35	2.79	3.63	3.84	4.05
4	3.52	3.57	3.87	3.40	3.37	2.38	3.32	3.65	4.14	4.33
High	4.31	4.37	4.29	4.14	3.27	3.22	3.42	4.19	4.64	4.99
H-L	2.49	1.82	1.18	0.94	0.51	2.20	1.03	1.46	1.36	1.09
t-stat.	5.50	3.67	2.77	2.23	1.70	5.53	2.73	3.47	3.36	2.52

SK_{EPS}	MOM Quintile					GP Quintile				
Quintile	Low	2	3	4	High	Low	2	3	4	High
Low	1.72	3.09	3.17	3.40	4.28	1.31	2.77	3.02	4.04	4.00
2	1.81	2.91	3.33	3.66	4.51	1.79	2.64	3.37	3.65	4.33
3	2.01	3.05	3.29	3.81	4.33	2.15	2.77	3.28	3.31	4.40
4	1.78	3.13	3.82	4.22	4.31	2.46	2.90	3.29	3.80	4.61
High	1.84	3.12	3.66	4.05	5.06	2.70	3.02	3.39	3.98	4.95
H-L	0.13	0.03	0.49	0.65	0.78	1.38	0.25	0.37	-0.06	0.96
t-stat.	0.27	0.08	1.44	2.24	2.38	2.48	0.56	1.07	-0.18	2.64

SK_{EPS}	ROE Quintile					$Idvol$ Quintile				
Quintile	Low	2	3	4	High	Low	2	3	4	High
Low	1.41	3.34	3.92	4.03	4.00	3.07	3.21	3.48	2.77	0.91
2	1.83	3.67	3.75	3.96	4.19	3.46	3.24	3.30	3.02	1.50
3	1.45	3.46	3.92	4.03	4.59	3.44	3.66	3.92	3.27	1.79
4	1.96	3.45	3.91	4.41	4.10	3.48	3.60	4.11	3.85	1.92
High	1.76	3.44	4.30	4.02	4.94	3.66	4.38	4.38	4.14	2.09
H-L	0.35	0.11	0.39	-0.01	0.95	0.60	1.17	0.90	1.38	1.18
t-stat.	0.78	0.02	1.31	-0.05	2.82	2.48	3.86	2.34	2.70	2.02

Table 4: Fama-MacBeth Regressions

This table reports the average estimated coefficients and corresponding t-statistics of Fama-MacBeth regressions for the skewness measures of firm fundamentals. Panels A and B are for SK_{GP} and SK_{EPS}, respectively. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. The dependent variable of the regressions is the next-quarter stock return. For each of models (1)–(7), there is only one independent variable. Model (8) includes all variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: SK_{GP}								
SK_{GP}	0.24***							0.11***
	(6.18)							(3.87)
MC		0.23						-0.26*
		(0.90)						(-1.76)
BM			0.93***					1.42***
			(2.85)					(4.32)
MOM				1.98***				0.10***
				(3.01)				(3.36)
GP					9.05***			8.34***
					(4.01)			(4.07)
ROE						5.80**		3.64**
						(2.36)		(2.24)
$Idvol$							-0.16***	-0.19***
							(-2.72)	(-3.22)
Panel B: SK_{EPS}								
SK_{EPS}	0.25***							0.09**
	(4.73)							(2.37)
MC		0.03						-0.26**
		(0.33)						(-2.41)
BM			0.88***					1.02***
			(2.74)					(3.63)
MOM				2.03***				0.92**
				(3.15)				(2.45)
GP					10.24***			8.57***
					(5.27)			(5.75)
ROE						3.75***		5.80***
						(3.36)		(3.96)
$Idvol$							-0.16***	-0.18***
							(-3.13)	(-3.71)

Table 5: Future Firm Growth Option of Decile Portfolios Sorted on Skewness Measures
This table reports the average equal-weighted future firm growth option, measured by $MABA$ and Tobin's q, of decile portfolios formed by sorting stocks on the skewness measures. Panels A and B are for SK_{GP} and SK_{EPS}, respectively. We consider four future quarters ($t+1, ..., t+4$). All numbers are reported in percentage. The row H-L reports the differences of firm growth option between decile 10 and decile 1, with the corresponding Newey-West t-statistics shown in the last row.

	Quarterly $MABA$				Quarterly Tobin's q			
Decile	t+1	t+2	t+3	t+4	t+1	t+2	t+3	t+4
				Panel A: SK_{GP}				
Low	1.89	1.87	1.85	1.83	1.31	1.29	1.27	1.25
2	1.84	1.83	1.80	1.78	1.26	1.25	1.22	1.20
3	1.84	1.83	1.80	1.78	1.26	1.25	1.22	1.20
4	1.88	1.85	1.82	1.80	1.29	1.27	1.24	1.21
5	1.90	1.89	1.86	1.83	1.32	1.30	1.27	1.24
6	1.93	1.92	1.88	1.84	1.34	1.32	1.29	1.25
7	1.92	1.93	1.88	1.85	1.32	1.93	1.28	1.25
8	1.95	1.94	1.97	1.95	1.36	1.35	1.95	1.94
9	2.06	2.03	1.99	1.96	1.46	1.43	1.39	1.36
High	2.30	2.27	2.22	2.17	1.72	1.69	1.63	1.59
H-L	0.41	0.40	0.36	0.34	0.41	0.40	0.36	0.34
t-stat.	8.51	8.35	8.07	7.66	7.88	7.74	7.50	7.15
				Panel B: SK_{EPS}				
Low	1.80	1.79	1.77	1.75	1.22	1.20	1.18	1.16
2	1.78	1.78	1.75	1.73	1.20	1.20	1.17	1.14
3	1.86	1.83	1.81	1.78	1.28	1.25	1.22	1.19
4	1.85	1.83	1.79	1.77	1.27	1.24	1.21	1.18
5	1.89	1.86	1.83	1.80	1.30	1.27	1.25	1.21
6	1.90	1.88	1.85	1.83	1.31	1.29	1.27	1.24
7	1.99	1.95	1.91	1.88	1.40	1.36	1.32	1.29
8	2.05	2.01	1.97	1.92	1.45	1.42	1.37	1.33
9	2.15	2.11	2.06	2.02	1.55	1.52	1.46	1.43
High	2.41	2.34	2.27	2.19	1.82	1.76	1.68	1.61
H-L	0.61	0.56	0.50	0.44	0.60	0.56	0.50	0.45
t-stat.	10.22	9.57	9.33	9.21	9.72	9.69	9.25	8.79

Table 6: Fama-MacBeth Regressions of Future Firm Growth Option

This table reports the average estimated coefficients and corresponding t-statistics of Fama-MacBeth regressions of future firm growth option on the skewness measures of firm fundamentals. Panels A and B consider $MABA$ and Tobin's q, respectively. For each skewness measure, the first regression only uses the skewness measure while the second regression contains all control variables, including the lagged value of the firm growth option proxy. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A: $MABA$

SK_{GP}	MC	BM	MOM	GP	ROE	$Idvol$	Lagged $MABA$
0.048***							
(11.17)							
0.012**	0.019***	-0.097***	0.230***	0.310**	-0.027	0.001	0.870***
(2.32)	(3.23)	(-4.36)	(8.79)	(2.09)	(-0.73)	(0.72)	(44.84)
SK_{EPS}							
0.076***							
(8.33)							
0.010**	0.021***	-0.034***	0.231***	0.32**	-0.31	0.009*	0.916***
(1.99)	(3.37)	(-3.41)	(7.54)	(2.21)	(-0.91)	(1.75)	(12.76)

Panel B: Tobin's q

SK_{GP}	MC	BM	MOM	GP	ROE	$Idvol$	Lagged Tobin's q
0.045***							
(10.02)							
0.010**	0.022***	-0.057***	0.228***	0.082	-0.171***	0.001	0.868***
(2.13)	(3.47)	(-2.65)	(8.47)	(1.00)	(-3.76)	(0.62)	(43.77)
SK_{EPS}							
0.073***							
(7.69)							
0.014**	0.030***	-0.034***	0.438***	0.003	-0.124**	0.002	0.847***
(2.06)	(4.00)	(-3.70)	(8.24)	(0.04)	(-2.21)	(1.38)	(23.47)

Table 7: Future Firm Profitability of Decile Portfolios Sorted on Skewness Measures
This table reports the average equal-weighted future firm profitability, measured by ROE and GP, of decile portfolios formed by sorting stocks on the skewness measures. Panels A and B are for SK_{GP} and SK_{EPS}, respectively. We consider four future quarters ($t+1, ..., t+4$). All numbers are reported in percentage. The row H-L reports the differences of firm profitability between decile 10 and decile 1, with the corresponding Newey-West t-statistics shown in the last row.

	Quarterly ROE				Quarterly GP			
Decile	t+1	t+2	t+3	t+4	t+1	t+2	t+3	t+4
Panel A: SK_{GP}								
Low	-0.06	-0.14	-0.18	-0.24	7.59	7.66	7.66	7.83
2	0.49	0.43	0.37	0.32	8.66	8.70	8.67	8.73
3	0.57	0.53	0.46	0.36	9.04	9.02	8.98	9.02
4	0.70	0.59	0.52	0.43	9.30	9.24	9.17	9.20
5	0.73	0.63	0.55	0.45	9.64	9.53	9.51	9.50
6	0.76	0.69	0.60	0.51	9.92	9.82	9.72	9.67
7	0.84	0.74	0.67	0.54	10.25	10.17	10.06	9.98
8	0.97	0.87	0.79	0.66	10.83	10.71	10.61	10.46
9	1.04	0.93	0.84	0.69	10.94	10.79	10.66	10.57
High	1.14	1.03	0.92	0.80	11.34	11.12	10.91	10.75
H-L	1.20	1.16	1.11	1.03	3.76	3.46	3.25	2.92
t-stat.	11.54	10.34	9.08	8.26	18.87	17.42	18.48	14.94
Panel B: SK_{EPS}								
Low	-0.70	-0.73	-0.74	-0.70	6.77	6.81	6.88	6.93
2	0.15	0.12	0.08	0.06	7.55	7.47	7.48	7.54
3	0.36	0.29	0.24	0.22	7.84	7.83	7.71	7.81
4	0.56	0.49	0.43	0.41	8.16	8.00	7.92	7.93
5	0.66	0.54	0.45	0.43	8.39	8.23	8.19	8.11
6	0.80	0.69	0.60	0.55	8.66	8.43	8.29	8.26
7	1.02	0.92	0.80	0.71	9.04	9.09	8.84	8.67
8	1.24	1.12	1.05	0.95	9.44	9.34	9.22	9.08
9	1.43	1.32	1.21	1.11	9.51	9.28	9.20	9.11
High	1.85	1.72	1.57	1.43	9.73	9.47	9.26	9.16
H-L	2.55	2.45	2.31	2.13	2.96	2.65	2.38	2.23
t-stat.	11.75	11.44	10.68	9.71	4.42	3.73	3.55	3.14

Table 8: Fama-MacBeth Regressions of Future Firm Profitability

This table reports the average estimated coefficients and corresponding t-statistics of Fama-MacBeth regressions of future firm profitability on the skewness measures of firm fundamentals. Panels A and B consider ROE and GP, respectively. For each skewness measure, the first regression only uses the skewness measure while the second regression includes all control variables. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A: ROE

SK_{GP}	MC	BM	MOM	GP	ROE	$Idvol$
0.004***						
(15.17)						
0.002***	0.002***	0.061***	0.009***	0.123***	0.061***	-0.001***
(8.42)	(8.97)	(3.05)	(14.70)	(10.50)	(10.48)	(-7.34)
SK_{EPS}						
0.004***						
(17.86)						
0.002***	0.001***	0.001**	0.009***	0.106***	0.058***	-0.001***
(14.31)	(10.35)	(2.20)	(13.67)	(9.70)	(9.46)	(-10.69)

Panel B: GP

SK_{GP}	MC	BM	MOM	GP	ROE	$Idvol$
0.006***						
(21.78)						
0.001***	-0.001	-0.003***	0.010***	0.707***	0.039***	-0.001***
(6.63)	(-0.91)	(-8.03)	(8.55)	(28.03)	(3.58)	(-7.16)
SK_{EPS}						
0.005***						
(3.14)						
0.001	-0.001***	-0.003***	0.008***	0.684***	0.054***	-0.001***
(0.82)	(-4.86)	(-9.84)	(4.61)	(19.56)	(3.22)	(-4.07)

Table 9: Comparing Return Predictability of Alternative Skewness Measures

This table reports the average estimated coefficients and corresponding t-statistics of Fama-MacBeth regressions with both skewness measures. The dependent variable of the regressions is the next-quarter stock return. The first model does not use any control variables while the second includes all the control variables. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

SK_{GP}	SK_{EPS}	MC	BM	MOM	GP	ROE	$Idvol$
0.19***	0.13*						
(5.67)	(1.93)						
0.11***	0.02	-0.33**	0.63***	1.73***	6.40***	3.93**	-0.22***
(3.94)	(0.39)	(-2.27)	(3.23)	(2.65)	(3.44)	(2.33)	(-3.50)

Table 10: Long-Run Return Predictability

This table reports the average estimated coefficients and corresponding t-statistics of Fama-MacBeth regressions of future stock returns on the skewness measures of firm fundamentals. Panels A and B are for SK_{GP} and SK_{EPS}, respectively. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. The dependent variables of the regressions are the stock returns in quarter $t+2$, ..., $t+5$. Model (1) only contains the skewness as the explanatory variable while model (2) also contains all the control variables.

	R_{t+2}		R_{t+3}		R_{t+4}		R_{t+5}	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
				Panel A: SK_{GP}				
SK_{GP}	0.18***	0.13***	0.12***	0.08**	0.11*	0.03	0.08*	0.03
	(4.37)	(2.89)	(2.79)	(2.24)	(1.93)	(0.86)	(1.82)	(0.63)
MC		-0.28**		-0.22*		-0.25*		-0.19
		(-2.25)		(-1.74)		(-1.78)		(-1.44)
BM		0.34*		0.26		0.19		0.31*
		(1.96)		(1.41)		(1.09)		(1.84)
MOM		1.04*		0.41		-0.04		-0.07
		(1.87)		(1.32)		(-0.14)		(-0.27)
GP		4.62*		6.87***		4.89***		3.71**
		(1.82)		(3.11)		(2.92)		(2.17)
ROE		0.93		1.29		0.21		1.70*
		(0.72)		(0.62)		(0.13)		(1.90)
$Idvol$		-0.17***		-0.134**		-0.09		-0.06
		(-3.21)		(-2.42)		(-1.59)		(-1.13)
				Panel B: SK_{EPS}				
SK_{EPS}	0.10**	0.09*	0.03	0.06	0.01	0.05	0.02	0.06
	(2.47)	(2.12)	(0.53)	(1.22)	(0.51)	(1.33)	(0.32)	(1.39)
MC		-0.35***		-0.281**		-0.22*		-0.22*
		(-2.76)		(-2.20)		(-1.79)		(-1.68)
BM		0.14		0.073		0.1		0.17
		(1.28)		(0.59)		(0.90)		(1.49)
MOM		1.20**		0.537		-0.05		-0.10
		(2.03)		(1.52)		(-0.18)		(-0.39)
GP		3.89*		5.13***		3.32**		3.16**
		(1.77)		(2.95)		(2.45)		(2.08)
ROE		1.04		1.761		0.62		1.90
		(0.92)		(1.12)		(0.52)		(1.56)
$Idvol$		-0.18***		-0.13**		-0.08		-0.22*
		(-3.52)		(-2.38)		(-1.36)		(-1.68)

Table 11: Controlling for Return Skewness

This table reports the average estimated coefficients and corresponding t-statistics of Fama-MacBeth regressions of future returns on the skewness measures of firm fundamentals and stock returns. Panels A and B are for SK_{GP} and SK_{EPS}, respectively. The three skewness measures of stock returns are MAX, $Idskew$, and $Prskew$. The dependent variable in all regressions is the next-quarter stock return. Models (1)–(5) do not use any control variables while model (6) include all the control variables in Table 4. The estimates for the control variables are not reported. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: SK_{GP}						
MAX	-0.23***			-0.28***	-0.26***	0.05
	(-6.09)			(-6.23)	(-5.64)	(0.02)
$Idskew$		0.03		0.15**	-0.11	0.04
		(0.26)		(2.07)	(-0.40)	(0.68)
$Prskew$			-0.81*	0.11	-0.54	-0.42
			(-1.69)	(0.19)	(-0.69)	(-0.84)
SK_{GP}					0.24***	0.12***
					(6.05)	(3.12)
Controls	No	No	No	No	No	Yes
Panel B: SK_{EPS}						
MAX	0.06***			0.04	0.03	0.05*
	(2.61)			(1.38)	(1.26)	(1.74)
$Idskew$		0.02		0.02	0.03	0.09
		(0.21)		(0.20)	(0.25)	(1.28)
$Prskew$			-0.73*	-0.75*	-0.65*	-0.81*
			(-1.83)	(-1.88)	(-1.71)	(-1.77)
SK_{EPS}					0.25***	0.09***
					(4.12)	(2.88)
Controls	No	No	No	No	No	Yes

Table 12: Additional Robustness Checks

This table reports the results of four additional robustness checks: panel regression with two-way clustered standard errors, panel regression with time fixed effect, Fama-MacBeth regression with industry fixed effect, and Fama-MacBeth regressions with the skewness measures constructed using 12 quarter data. Panels A and B are for SK_{GP} and SK_{EPS}, respectively. The dependent variable in all regressions is the next-quarter stock return. Model (1) only contains the skewness as the explanatory variable while model (2) also contains all the control variables. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

	Panel Regression				Fama-MacBeth Regression			
	Clust. Std. Errors		Time Fixed Effect		Industry Fixed Effect		12-Quarter SK_{GP}	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
				Panel A: SK_{GP}				
SK_{GP}	0.25***	0.15***	0.25***	0.15***	0.24***	0.12***	0.19***	0.012***
	(5.28)	(2.95)	(5.31)	(2.88)	(7.01)	(4.85)	(4.56)	(2.68)
MC		-0.41		-0.40		-0.25		-0.21
		(-1.33)		(-1.31)		(-1.33)		(-0.96)
BM		0.49**		0.49**		0.72***		0.63***
		(2.31)		(2.33)		(4.15)		(3.19)
MOM		0.02		-0.04		1.39**		1.82***
		(0.17)		(-0.37)		(2.34)		(2.82)
GP		9.19***		9.24***		7.10***		6.51***
		(4.62)		(4.65)		(4.70)		(3.49)
ROE		3.18*		3.22*		6.40*		2.96**
		(1.89)		(1.92)		(1.94)		(2.13)
$Idvol$		-0.20		-0.20		-0.22***		-0.21***
		(-1.19)		(-1.21)		(-3.68)		(-3.27)

Panel B: SK_{EPS}

							12-Quarter SK_{GP}	
SK_{EPS}	0.20**	0.14*	0.20**	0.14*	0.13*	0.09**	0.17***	0.10**
	(2.25)	(1.83)	(2.32)	(1.91)	(1.77)	(2.56)	(3.93)	(2.02)
MC		-0.47		-0.47		-0.47***		-0.46***
		(-1.46)		(-1.49)		(-3.72)		(-3.59)
BM		0.29*		0.29*		0.38***		0.29***
		(1.80)		(1.81)		(4.10)		(2.67)
MOM		0.15		0.14		1.66***		2.01***
		(0.14)		(0.13)		(2.96)		(3.15)
GP		7.22***		7.29***		6.45***		6.33***
		(3.43)		(3.44)		(5.21)		(3.89)
ROE		3.31*		3.36*		4.81***		3.84**
		(1.82)		(1.85)		(3.93)		(2.56)
$Idvol$		-0.21		-0.21		-0.27***		-0.26***
		(-1.26)		(-1.30)		(-5.82)		(-4.44)