Essays on the Skewness of Firm Fundamentals and Stock Returns

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Abstract: This dissertation investigates whether the skewness of firm fundamentals is related to future firm performance and stock returns. Essay one discusses the recent research on the relation between higher-order moments of fundamentals and stock returns. Essay two discusses fundamental skewness and cross-sectional stock returns. I present two distinct theoretical models of firm fundamentals with non-zero skewness. Both models imply a positive relation between the skewness of firm fundamentals and expected stock return. Consistent with the implication, I show that the skewness measures of firm fundamentals positively predicts cross-sectional stock returns. I further find evidence supporting both models. That is, higher fundamental skewness implies not only higher future firm growth option but also higher future firm profitability. The results cannot be explained by existing risk factors and return predictors including the skewness of stock returns. The third essay documents that the conditional skewness of aggregate corporate earnings negatively predicts the stock market returns for horizons beyond six months and up to eight years. The evidence is robust to controlling for existing predictors such as the book-to-market ratio, interest term spread, credit spread, and *cay*. I present a theoretical model that is consistent with the empirical evidence. The interaction of the two key ingredients of the model, path dependence and non-Gaussian innovations in the aggregate corporate earnings process, implies the negative impact of productivity-enhancing technology spillover on the stock market returns.

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CHAPTER 1

Introduction and Motivation

Firm fundamentals are underlying factors which can capture or affect actual business operations and the future prospects of a firm. In general, variables such as profitability, earnings, asset and their growth are considered firm fundamentals. It is well documented in theory that the firm fundamentals can predict stock returns. For aggregate stock market returns, a price change can be decomposed into earnings[1] news and discount rate news[2]. The cross-sectional stock returns can be linked to firm fundamentals through general equilibrium production economy by directly modeling or specifying a stochastic discount factor with the firm fundamentals. Empirical research confirms the predicting power of the firm fundamentals[3] on the cross section of stock returns and the time series of aggregate stock market returns[4]. These studies find that the individual stock return is high when asset growth is low, gross profitability is high, and return on equity is high [5]. These studies also find that the aggregate stock market return in excess of short-term interest rate is high when dividend-price ratio and earnings-price ratio are high.

The documented relationship between the firm fundamentals and stock returns is far from perfect. Previous research confirms that the distribution of the firm

[1]Ball, Sadka and Sadka (2009) argue that earning related variables are better than dividend as proxy for firm cash flows.

[2]See Campbell and Shiller (1988)

[3]Belo and Lin (2011), Cooper, Gulen and Schill (2008), Hirshleifer, Hou, Teoh and Zhang (2004), Hou, Xue and Zhang (2015), Novy-Marx (2013), Titman, Wei and Xie (2004), Lyandres, Sun and Zhang (2008), Xing (2008)

[4]Firm fundamentals related predictors of aggregate stock market return include dividend growth, dividend price ratio, earning price ratio, earnings

[5]the fundamentals-related individual stock return predictors are summarized in table 1

fundamentals is time-varying (Givoly and Hayn (2000)) and highly negatively skewed (Ball, Gerakos, Linnainmaa and Nikolaev (2015), Basu (1997), Givoly and Hayn (2000), Gu and Wu (2003)). This time-varying skewness indicates the existence of jumps in the firm fundamentals. If we consider a firm as a portfolio of projects, jumps in the firm fundamentals can be caused by high sensitivity of the firm project portfolio to certain economic shocks, including rare disaster shocks, small economic shocks and upward trend shocks[6]. Firms have different exposures to the same economic shocks if they have different portfolios of projects. If a firm's investment in projects is irreversible[7], the exposure of firm's project portfolio to economic shocks is persistent. In this way, previous jumps (skewness) in the firm fundamentals contain information on the exposure of the firm fundamentals to future economic shocks and future stock returns.

Surprisingly, the information contained in the time-varying skewness of the firm fundamentals regarding future stock returns is not addressed in the current literature. Production-based asset pricing models assume shocks to the firm fundamentals are all standard normal shocks with no skewness. The time-varying skewness of firm fundamentals is also not embedded in the cash flow news of present-value equations. Without considering the skewness of the firm fundamentals, previous models can ignore important information contained in the firm fundamentals. In this dissertation, two questions related to the skewness of the firm fundamentals are addressed: (1) How is the skewness of the firm fundamentals related to stock returns? and (2) How can the skewness of the firm fundamentals be measured?

To address the first question, I extend the framework of Lettau and Wachter (2011) and allow shocks with a time-varying skewness to impact the firm fundamentals. This

[6]Similar to my argument, to capture the sensitivity of aggregate corporate cash flows to economic shocks, Longstaff and Piazessi (2004) use exponential-affine jump-diffusion processes to model corporate earnings.

[7]The irreversibility of firm investment is discussed in a sequence of paper such as Leahy (1993), Abel and Eberly (1996), Kogan (2001) and Lu Zhang (2005).

allows stock price function to contain a component of the time-varying skewness of the firm fundamentals. To answer the second question and explore my model implications, I construct measures of skewness of firm fundamentals at firm level and market level using historical information[8]. I find the skewness of market-level firm fundamentals can negatively predict the stock market returns. In contrast, the skewness of the firm fundamentals at the firm level can positively predict future stock returns. The opposite predictive relationships of the skewness of the firm fundamentals at the firm level and market level require a unified theory taking into consideration the firm-level heterogeneity and more empirical tests. My dissertation proposal proceeds as follows.

Chapter 2 surveys the literature on the fundamental higher-order moments, exploring their existence, formation, and implications on financial market and macroeconomics. This literature review highlights the tension and limitations in recent research on the higher-order moments. Papers discussing the predictive power of fundamental moments on asset prices ignore the microfoundation of fundamental higher-order moments. Research on the information contents of higher order moments mostly uses static models without implications on future asset prices and economic growth. Chapter 3 and chapter 4, on one hand, provide novel measures of higher-order moments of fundamentals which can predict future stock returns. On the other hand, these two chapters are the first group of papers providing theoretical foundation to the return predictive power of fundamental higher-order moments.

In chapter 3, I explore the relationship between the skewness of the firm fundamentals and cross-sectional stock returns. I document a significantly positive predictive relation between the skewness of the firm fundamentals and the cross-sectional stock returns. The evidence is robust to alternative measures of the skewness of the firm fundamentals and cannot be explained by existing return predictors. The findings are consistent with my model of the firm fundamentals where the skewness of the firm

[8] I construct historical skewness of firm fundamentals following the methodology of Gu and Wu (2003).

fundamentals contains information about the firm growth option.

Chapter 4 examines the predictive power of the skewness of market-level firm fundamentals on aggregate stock market excess returns. The skewness measures of market-level firm fundamentals strongly negatively predict aggregate stock market returns in excess of short-term interest rate; skewness of the firm fundamentals has a positive relationship with the short-term/long-term bond yields. Using skewness of the firm fundamentals, I can also decompose government bond yields into two opposite components: the cash flow component which negatively predicts stock returns and discount rate component which positively predicts stock returns.

The predictive signs of skewness of the firm fundamentals on cross-sectional stock returns and the aggregate stock market returns are opposite. This is not surprising since when individual stock measures are aggregated into stock market measures, the correlations between individual stocks dominate the relationship[9].

In general, this dissertation proposal shows that skewness is embedded in the firm fundamentals including measures such as gross profitability, earnings, standardized unexpected earnings and return on equity. The skewness of firm fundamentals can strongly predict cross-sectional stock returns and aggregate market returns because it can extract unique information on the timing of jumps in the firm fundamentals, the skewness risk in a firm's growth option, and the correlation of firms' fundamentals (cash flows) which can not be captured by other measures.

[9]This argument is in line with the return skewness predictability on firm versus aggregate returns in Albuquerque (2012).

CHAPTER 2

Higher-Order Moments of Fundamentals: Existence, Information Contents and Their Implications on Macroeconomics and Financial Markets

2.1 Introduction and Motivation

Fundamentals are considered as the qualitative and quantitative information that contributes to the economic well-being and the subsequent financial valuation of a company, security or currency. At the macro-level, variables which are benchmarks of the whole economy such as consumption, GDP growth and aggregate earnings are considered as macroeconomic fundamentals. At the micro-level, firm fundamentals are underlying factors which can capture or affect actual business operations and the future prospects of a firm. Variables such as firm profitability, earnings, asset and their growth are considered firm fundamentals. It is well documented in theory that fundamentals at both macro and micro levels contain information on the economy and thus the stock prices. For aggregate stock market returns, a price change can be decomposed into earnings[1] news and discount rate[2] news. Macroeconomic fundamentals can predict market returns since the fundamentals are related to earnings news. The cross-sectional stock returns can be linked to firm fundamentals through general equilibrium production economy by directly modeling or specifying a stochastic discount factor with the firm fundamentals. Empirical research confirms the predicting power of the firm fundamentals on the cross section of stock returns and the time

[1] Ball, Sadka and Sadka (2009) argue that earning related variables are better than dividend as proxy for firm cash flows.

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series of aggregate stock market returns. These studies find that the individual stock return is high when asset growth is low, gross profitability is high, and return on equity is high.[3] These studies also find that the aggregate stock market return in excess of short-term interest rate is high when dividend-price ratio and earnings-price ratio are high.[4]

The documented relationship between the level of fundamentals and stock returns is far from complete. Recent research confirms that the level of macroeconomic fundamentals contains jumps, indicating that the fundamental volatility is persistent and time-varying (Acemoglu, Mostagir, and Ozdaglar (2013), Bansal, Kiku, Shaliastovich, and Yaron (2014), Segal, Shaliastovich and Yaron (2015), Piazzesi and Longstaff (2004)). The time-varying volatility contains information on the fluctuation of the economy, thus on the stock market returns. Moreover, if the good and bad jumps in aggregate fundamentals are asymmetric, the fundamental skewness is also priced in the aggregate stock market (Guo, Wang, and Zhou (2015), Jia and Yan (2016)). On the other hand, recent literature documents that at the micro-level, the volatility and skewness of firm fundamentals contain information on firms future growth option (Jia and Yan (2016)) and have asset pricing implications (Dichev and Tang (2008), Huang (2009), Jia and Yan (2016b)).

In this paper, I review this new fast-growing literature on the macroeconomic and financial market implications of higher-order moments of fundamentals. I start with the empirical evidence documenting that fundamentals, at both firm-level and aggregate-level, contain time-varying volatility, non-Gaussian shocks, and skewness. This is followed by a survey of the theory and models rationalizing the information content of the higher-order moments. I then move on to the theoretical framework and empirical results for the predictive power of higher-order moments of fundamentals on macroeconomic quantity variables and asset prices. The last section concludes and

[3] The fundamentals-related individual stock return predictors are summarized in Table 2.1.

[4] The fundamental related market return predictors are summarized in Table 2.2.

points out future directions for research in this area.

2.2 The Existence and Variation of Fundamental Higher-Order Moments

In this part, I summarize the evidence and measures, from both theoretical and empirical works, documenting the dynamics of the higher-order moments of fundamentals. For an economic quantity variable to be meaningful, it should be persistent and have sufficient variation (cross-sectional and time series). Fundamental higher-order moments satisfy all these conditions.

For fundamentals at the macro level, I first survey the literature and use additional results to show that at the macro-level, not only returns but all kinds of fundamentals are highly volatile. Moreover, the volatility of fundamentals is time-varying. I then summarize previous literature to demonstrate the existence of non-Gaussian shocks. The non-Gaussian shocks section is followed by a survey of the skewness and lumpiness of aggregate fundamentals.[5].These measures of higher-order moments are related to economic states and business cycle. For fundamentals at the micro level, I summarize different measures extracting the firm fundamental fluctuations and find these measures have large time series and cross sectional variations. Table 2.3 and 2.4 summarize representative papers documenting the existence of the fundamental higher-order moments.

2.2.1 Higher-Order Moments of Fundamentals at the Macro Level

Recent literature starts to pay attention to the information contained in the distribution of aggregate fundamentals. This section documents the properties and measures

[5]My concept of higher-order moments of fundamentals at the macro-level refers to the time series higher moments (volatility and skewness) of shocks to economic quantity variables of interest. This is distinct from the other uncertainty measures, such as parameter uncertainty, learning, robust-control, and ambiguity.

regarding the empirical distribution used in theoretical and empirical works. The fundamentals such as industrial production, earnings, consumption growth, and earnings surprises have time-varying volatility and jumps (non-Gaussian shocks). The two empirical regularities, non-Gaussian shocks and persistency of fundamentals, lead to the time-varying skewness of fundamentals. On the other hand, the investment and R&Ds at the aggregate level are lumpy, with infrequent and not persistent spikes in certain periods. All the dynamics of the fundamental higher-order moments cannot be captured by the level of fundamentals.

The Time-Varying Volatility of Fundamentals

The time-varying volatility of fundamentals first comes to the sight of researchers from the model setting of the benchmark paper Bansal and Yaron (2004). They specify the consumption growth process as:

$$x_t = \rho x_t + \phi_e \sigma_t e_{t+1}, \tag{2.1}$$

$$\sigma_{t+1}^2 = \sigma^2 + \nu_1(\sigma_t^2 - \sigma^2) + \sigma_w w_{t+1}, \tag{2.2}$$

where x_t is the consumption growth process; the consumption growth σ_t is time-varying; and σ_t represents the time-varying economic uncertainty incorporated in consumption growth rate x_t. The time-varying consumption growth fluctuation, together with "a small long-run predictable component" can help to justify the equity premium puzzle. The time-varying consumption growth fluctuation is confirmed by empirical evidence in Lettau and Wachter (2007) and Yang (2011). Lettau and Wachter (2007) find evidence to support a shift to low consumption growth volatility at the beginning of 1990s. In other words, consumption growth volatility has different regimes. Yang (2011) uses graphical and empirical tests to show that the volatility of both durable and non-durable consumption growth is time-varying. In the time series, the consumption growth tends to be low (high) during recessions (expansions). The consumption growth tends to decrease consecutively during recessions, and to increase consecutively during expansions. Thus, the consumption growth volatility increases when regime-switching happens.

The time-varying volatility also exists in the model setting with fundamentals related to production. Longstaff and Piazzesi (2004) document that corporate cash flows are highly volatile and the corporate earnings volatility is time-varying. Jia and Li (2016) and Segal, Shaliastovich and Yaron (2015) document that industrial production is highly volatile with regime-switching. Jia and Yan (2016b) find that not only corporate earnings, but also earnings surprises have time-varying volatility. Figure 2.1, as an example, shows that earnings surprises volatility rises up and is clustered in certain periods such as the years around 2010 and the years around 2000.

However, the next question is why fundamental volatility is time-varying? The answer is that the fundamental volatility contains non-Gaussian shocks (jumps). The next section surveys the literature to demonstrate the existence of jumps in the fundamentals.

Non-Gaussian Shocks to Fundamentals

The non-Gaussian shocks to consumption are emphasized in recent theoretical works (Drechsler and Yaron (2011), Gourio (2012), Gourio (2015), Longstaff and Piazzessi (2004), and Tsai and Wachter (2016)). In these settings, consumption can encounter rare events with both positive and negative jumps. The non-Gaussian shocks in consumption are confirmed by empirical tests. Empirical evidence suggests that consumption (both durable and non-durable) displays infrequent large movements which are too big to be Gaussian shocks (Yang (2011)).

On the other hand, non-Gaussian shocks also impact production-related fundamentals (Jia and Li (2016), Jia and Yan (2016b), and Segal, Shaliastovich and Yaron (2015)). Non Guassian shocks exist in industrial production and corporate cash flows at the aggregate level. Fig. 2.1 replicates part of the results in Jia and Yan (2016b) and shows the path of quarterly aggregate earnings surprises to illustrate the existence of non-Gaussian shocks in production-related fundamentals. We can find occasional large spikes exist in the series. Largest downward spike happens in the most recent financial crisis. In contrast, the largest upward spike appears after the recession. For further evidence on large movements in fundamentals, Jia and Yan (2016b) apply non-parametric jump-detection methods (Barndorff-Nielsen and Shephard (2006), Bansal and Shaliastovich (2011)) to test whether jumps exist in fundamentals. The test significantly rejects the null hypothesis of no jumps. Since volatility contains the information on fundamental jumps, the existence of jumps in fundamentals sheds light on the importance of incorporating fundamental volatility in models for economic variables and asset prices.

Fundamental Skewness

The time-varying skewness of fundamentals is well documented in different branches of literature. Time-varying skewness exists in both consumption and durable consumption data. Drechsler and Yaron (2011) document the dynamics of consumption growth skewness. This group of papers divides shocks to consumption into two components which capture positive and negative growth innovations. The asymmetry of positive and negative innovations generates time-varying fundamental skewness. Yang (2011) documents that the empirical distribution of durable consumption is negatively skewed. He shows that the performance of long-run risk models incorporating this empirical feature is significantly improved.

The time-varying skewness also shows up in firm fundamentals (industrial production, profitability, earnings and earnings surprise) at the aggregate level. In accounting literature, Basu (1997) and Givoly and Hayn (2000) among others report that the profitability and corporate earnings at the market level have time-varying volatility and are negatively skewed. Specifically, they use negative skewness of corporate earnings as a measure of reporting conservativism. However, the skewness of fundamentals in accounting literature is documented without considering its implication on asset prices. In contrast, finance literature takes the empirical distribution of fundamentals as given to generate implications. Segal, Shaliastovich and Yaron (2015) implicitly discuss the implication of asymmetric good and bad fundamental uncertainties on asset prices. Jia and Li (2016) and Jia and Yan (2016b) document that skewness of industrial production and that of corporate earnings surprise are long-horizon stock market return predictors. Skewness even appears in the expected fundamentals and contains information on aggregate market. Colacito, Ghysels, Meng and Siwasarit (2015) document the skewness in the distribution of professional forecasters expected GDP growth can predict future equity excess returns.

Lumpiness of Fundamentals

This section discusses the higher-order moments of another type of aggregate fundamentals, the aggregate investment, which has a different pattern from consumption or production related fundamentals. A large group of the literature (e.g. Caballero, Engel, and Haltiwanger (1995), Caballero and Engel (1999), Cooper, Hailtwanger and Power (1999), and Doms and Dunne (1998)) finds that a large fraction of the total investment expenditure is concentrated in a single large episode. The likelihood of an investment spike increases with the time since the last primary spike. The dynamics of lumpy investment can also be captured by investment skewness. However, the dynamics of investment is very different from other fundamental measures such as consumption growth, earnings, and industrial production. The aggregate investment is not persistent, with spikes interrupted by periods of smooth periods. In contrast to other fundamentals, the magnitude of upward jumps in investment is larger than that of downward jumps. Because of these two empirical regularities, lumpy investment is closely related to business cycle but have less implications on asset prices.

In sum, the empirical evidence suggests that fundamentals at the aggregate level are persistent with time-varying volatility and skewness. On the other hand, aggregate investment is lumpy, with infrequent spikes but is not persistent. The volatility and skewness of fundamentals contain information on the size, magnitude and the direction of the jumps. Investment at the aggregate level also contains information on economic well-being. Recent literature extracts information in the higher-order moments (volatility, skewness, and lumpiness) of fundamentals to generate macroeconomic and asset pricing implications.

2.2.2 Higher-Order Moments of Fundamentals at the Micro Level

The fundamentals at the micro-level in this section refer to firm fundamentals such as firm profitability, earnings and operating cash flows. The level of firm fundamentals captures a firm's one-period productivity and competition in the production market. However, the level of firm fundamentals is not the full picture. Firm fundamentals, like their counterparts at the aggregate level, contain jumps (skewness) (Ball, Gerakos, Linnainmaa, and Nikolaev (2015), Gu and Wu (2003), Jia and Yan (2016a)) since "Firms have ups and downs in the flow of their performance due to swings in their own competitive positions" (Akbas, Jiang, and Koch (2015)). There are multiple ways to capture the ups and downs in the firm fundamentals.

The fundamental skewness in Jia and Yan (2016), among others, is one efficient way (model-free) to capture the firm fundamental fluctuation. Their measures of fundamental skewness are coefficients of skewness as follows:

$$SK_{GP,t} = \frac{n}{(n-1)(n-2)} \sum_{\tau=t-n}^{t-1} \left(\frac{GP_\tau - \mu_{GP}}{s_{GP}} \right)^3, \quad (2.3)$$

$$SK_{EPS,t} = \frac{n}{(n-1)(n-2)} \sum_{\tau=t-n}^{t-1} \left(\frac{EPS_\tau - \mu_{EPS}}{s_{EPS}} \right)^3, \quad (2.4)$$

where μ_{GP} (μ_{EPS}) and s_{GP} (s_{EPS}) are, respectively, the sample average and standard deviation of $GP(EPS)$. GP and EPS are firm gross profitability and earnings per share, respectively.

Table 2 reports the time-series skewness of gross profitability and earnings per share using data of 8 consecutive quarters. The average fundamental skewness across firms is close to zero. However, for individual firms, the skewness varies from -1.40 for gross profitability skewness at 10 percentile to 1.19 for gross profitability skewness at 90 percentile. The skewness measures are persistent with the first-order autocorrelation of 0.14 (0.13). The fundamental skewness is also time-varying. Specifically, the gross profitability is negatively skewed in the early 1970s, but the profitability skewness comes close to zero after 2000. The persistency, cross-sectional and time-series variation indicate that the higher-order moments of fundamentals have implications on both the future level of fundamentals and asset prices.

In addition to fundamental skewness, Akbas, Jiang and Koch (2015) use the recent trajectory of corporate gross profitability to measure the higher-order moments of fundamentals. Specifically, Akbas, Jiang and Koch (2015) generate the profitability trajectory by running the following trend regression:

$$GPQ_{iq} = \alpha_{iq} + \beta_{iq} t + \lambda_1 D_1 + \lambda_2 D_2 + \lambda_3 D_3 + \lambda_4 D_4 + \epsilon_{iq}, \quad (2.5)$$

where GPQ stands for the gross profit; and $t = 1, 2, ..., 8$, and represents a deterministic time trend covering quarters $q - 7$ through q; and $D_1 - D_3$= quarterly dummy variables to account for potential seasonality in gross profits. The coefficient β_{iq} stands for the trajectory of profitability. When exercising their growth opportunity, firms, especially small firms, can significantly increase their profits, thus generating an upward trend. In contrast, the profit from firms in financial distress may shrink, generating a downward trend. The trajectory measure in Akbas, Jiang, and Koch (2015) can capture the firm expansion and shrinkage dynamics.

Interestingly, even though the skewness and trajectory of fundamentals are all measures of fundamental higher-order moments, they have different information contents since they have a correlation as low as 0.09. The low correlation between the two measures also indicates the complexity of the "ups and downs in the flow of their performance".

Moreover, a branch of literature focuses on the volatility of fundamentals (Dichev and Tang (2009), Huang (2009), Jayaraman (2008), Minton and Schrand (1999)). The literature documents that the volatility of firm-level stock returns and cash flows highly varies over time (Lee and Engle (1993)) and across firms (Black (1976), Christie (1982), and Davis, Haltiwanger, Jarmin, and Miranda (2007), and Koren and Tenreyro (2006)). This group of literature uses firm-level time series volatility to measure the fundamental variation. Acemoglu (2005), among others, finds that even cash flows of large firms are highly volatile. In recent finance literature, papers assign economic meaning to the cash flow volatility. The volatility of fundamentals, in finance literature (Dichev and Tang (2009), Huang (2009), Jayaraman (2008), Minton and Schrand (1999)) captures the cash flow shortfalls of the firm.

In sum, the literature on firm-level fundamental moments documents that the firm fundamentals have persistent time-varying higher-order moments. The implications of the higher-order moments will be discussed in detail in the next several sections.

2.3 The Origin (Formation) of the Fundamental Higher-Order Moments

This section aims at discussing the theoretical foundation of fundamental higher-order moments. I first discuss the three information channels of the fundamental higher-order moments at the macro-level. The second part of this section explores the information contained in the firm-level fundamental higher-order moments.

2.3.1 Fundamental Higher-Order Moments at the Macro Level

Three branches of literature discuss the information contents of macro-level higher-order moments. One branch of the literature does simple decomposition of fundamental uncertainties into positive and negative uncertainties. However, this uncertainties decomposition is too ad hoc to provide a full picture of fundamental higher-order moments. The other two branches of the literature provide the microfoundation by proposing that idiosyncratic firm-level or sectoral-level shocks can explain market-level fundamental uncertainty. The mechanism is that idiosyncratic shocks can affect not only the company itself but also its neighbor companies through the input-output linkages. Table 2.5 summarizes the branches of literature related to the formation of fundamental higher-order moments.

Fundamental Uncertainty Decomposition

The direction and magnitude of jumps in fundamentals vary across economic states. In recessions, fundamentals such as capital stock, productivity and earnings are highly likely to encounter crash risk (Rietz (1988), Barro (2006), Gabaix (2011a), Gourio (2012), and Gourio (2015)). In contrast, fundamentals can significantly jump during boom periods (Segal, Shaliastovich and Yaron (2015), Tsai and Wachter (2016)). In the economy, there are “good“ and “bad“ jumps which are correspondent to booms and recessions, respectively. Consequently, separate volatility measures incorporating good and bad jumps contains different information on financial market and the economy.

Barndorff-Nielsen and Shephard (2010), Guo, Wang, and Zhou (2015), and Segal, Shaliastovich and Yaron (2015), among others, decompose the overall shocks to fundamentals into two separate uncertainties (jumps) which are volatilities correspondent to positive and negative growth innovations. They find the good and bad uncertainties have different directions in predicting economic growth and asset prices. Moreover, based on their model settings, the skewness of fundamentals is the difference between the good and bad uncertainties, capturing the asymmetry of good and bad jumps.

"Good and bad" decomposition provides a way to understand the information contained in the higher-order moments of fundamentals. However, the decomposition is still at the macro-level without considering the relationship between firm-level shocks and aggregate uncertainty. In other words, the model with good and bad decomposition is a "top-down" method, incorporating (modeling) empirical regularities at the market level but leaving cross-sectional interactions untouched. This "top-down" approach to model economic uncertainty is widely used in finance and economics literature (Bansal, Kiku, Shaliastovich, and Yaron (2014), Bansal and Yaron (2004), Drechsler and Yaron (2011), Gourio (2012), Gourio (2015), Kaltenbrunner and Lochstoer (2010), Fernandez-Villaverde, Guerron-Quintana, Rubio-Ramirez, and Uribe (2011), Yang (2011)). However, the "top-down" approach could lose significant implications on the microfoundation of fundamental moments if individual firm risks are inter-connected and non-diversifiable.

Two groups of recent papers, in contrast to Segal, Shaliastovich and Yaron (2015), use "bottom-up" approach by modeling firm-level interactions to explain the formation of the volatility and skewness of fundamentals.

The Granular Origins of Higher-Order Moments

The "diversification argument" in Lucas (1977) demonstrates that when we aggregate individual variables, idiosyncratic shocks would average out, and would only have negligible aggregate effects. The first strong challenge on the diversification argument is from Horvath (1998, 2000). Horvath argues, because of strong synchronization mechanism among sectoral shocks, sectoral shocks themselves can generate aggregate fluctuation. Dupor (1999) refutes Horvath by demonstrating Horvath can only generate large fluctuation based on a moderate number of sectors (N=36). More finely disaggregated sectors can diversify sector specific shocks.

Gabaix (2011) ends the debate between Horvath and Dupor. Gabaix shows that Dupor's reasoning holds only in a world of small firms because the central limit theorem can apply to the aggregation. Horvath's argument holds when the economy contains sufficiently many large firms. Gabaix (2011) shows that the diversification argument breaks down because the distribution of firm sizes is fat-tailed which is supported by the empirical evidence (Axtell (2001)). Gabaix finds that "the idiosyncratic movements of the largest 100 firms in the United States appear to explain about one-third of variation in output growth". Economic fluctuations are attributable to the "incompressible grains of economic activity, the large firms". In other words, the dynamics of higher-order moments of fundamentals can be summarized by the behavior of large firms. This is the "granular" hypothesis.

Specifically, Axtell (2001) and Gabaix (2009) find that the size distribution of U.S. firms follows the Zipf distribution with exponent $\zeta = 1$. Gabaix (2011) proves that an economy with N firms whose growth rate volatility is σ and whose size $S_1, ..., S_N$ are drawn from a power law distribution $P(S > x) = ax^{-\zeta}$ which is a fat-tailed distribution, the $\zeta = 1$. As the number of firm N goes to infinity, the GDP volatility σ_{GDP} converges to $\frac{\nu_\zeta}{lnN}\sigma$, where ν_ζ is a random variable with a distribution independent of N and σ. When firm distribution follows Zipf's law, GDP volatility decays like $1/lnN$

rather than $1/\sqrt{N}$. In sum, the volatility of fundamental higher-order moments can be captured by the dynamics of large firms.

However, Gabaix (2011), among others, emphasizes the "granular" origin of the fundamental higher-order moments but ignores the synchronization mechanism among sectors and firms (Horvath (1998)). The other group of papers, utilizing the input-output linkage among sectors, generates the network origins of fundamental higher-order moments.

The Network Origins of Higher-Order Moments

Firms, in one economy, can reinforce each other through the inter-firm linkages. If two agents (firms) can mutually reinforce (offset) one another, they are called strategic complements (strategic substitutes) (Bulow, Geanakoplos, and Klemperer (1985)).

Jovanovic (1987) presents that with strategic complements, any amount of aggregate shocks (jumps) can be generated by games in which shocks to players are independent. Durlauf (1993, 1994) show that strong strategic complements lead to path dependence of aggregate fundamentals, i.e. the realized history affects the future outcomes. As stated in Durlauf (1993), the path dependence means that "there will be an especially strong relationship between the probability density of shocks and the aggregate dynamics of the model as realizations in the tails of the density determine whether the economy shifts across regimes". Specifically, when it comes to aggregate fundamentals such as industrial productivity, profitability and earnings, Durlauf's statement indicates the non-Gaussian shocks in the path dependent fundamentals can capture the information in the tails to determine whether regime-switch appears in the economy. In summary, firm strategic complementarity leads to regime switch of fundamentals, thus to the aggregate fundamental fluctuation.

Comparing with Jovanovic (1987) and Durlauf (1993), Bak, Chen, Scheinkman and Woodford (1993) specify the resources of strategic complementarity as the supply chains. They illustrate that because firms have input-output linkages, independent shocks to individual sectors cannot be canceled out in the aggregate.

The master piece of work discussing the network origin of aggregate volatility is Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012). It provides a more general and tractable framework to analyze input-output linkages than the above papers. Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) demonstrate that "in the presence of intersectoral input-output linkages, idiosyncratic shocks lead to aggregate fluctuations". Through the input-output linkages, shocks to suppliers can not only affect their immediate customers (first-order interconnections), but also affect the sequence of sectors interconnected to one another (higher-order interconnections), creating a "cascade effect". This cascade effect is especially large when one sector is the supplier of multiple sectors.

Specifically, Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) define a matrix of weighted degree to capture the share of one sector's output in the input supply of the other sector. In the competitive equilibrium, the aggregate volatility of the economy can be represented by the following expression:

$$(Vary_n)^{1/2} = \Omega(\frac{1}{\sqrt{n}} + \frac{CV_n}{\sqrt{n}} + \frac{\sqrt{\tau_2(W_n)}}{n}), \tag{2.6}$$

where $\tau_2(W_n)$ captures the second-order inter-connectivity. The formula indicates that the aggregate volatility is affected by the second-order inter-connections. The second-order inter-connections stand for the shocks to one sector impact its immediate customers' customers. The cascade effect is embedded in the aggregate volatility equation. The model by Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) is also extended to incorporating even higher degrees (larger than 2) of interconnections.

$$(Vary_n)^{1/2} = \Omega(\frac{1}{\sqrt{n}} + \frac{CV_n}{\sqrt{n}} + \frac{\sqrt{\tau_2(W_n)}}{n} + ... + \frac{\sqrt{\tau_m(W_n)}}{n}). \tag{2.7}$$

In sum, the input-output linkages which are modeled by the network structure are the origin of aggregate fluctuations. The "network origin" argument has both similarity and huge differences with the "granular origin" argument. On one hand, the shocks to sectors that are in more central positions in the network structure have a much higher impact on aggregate output than shocks to marginal sectors. The input-output linkage network structure plays the same role as the size distribution in the "granular hypothesis". On the other hand, the network origin argument focuses on the input-output linkages. But the granular origin argument focuses on the asymmetric impact of large firms on the aggregate fluctuations rather than that of small firms. Moreover, the input-output linkages leads to sectoral comovement but granular hypothesis cannot. Consequently, the dynamics of aggregate fluctuations generated by network origin and granular origin can be very different. But both arguments give rise to the microfoundation of aggregate higher-order moments for fundamentals.

2.3.2 Fundamental Higher-Order Moments at the Micro Level

Motivated by the granular argument and network argument for aggregate fundamental volatility, Kelly, Lustig and Van Nieuwerburgh (2014) use similar arguments to build up the foundation for firm-level fundamental volatility. They model the firm volatility in which "the customers' growth rate shocks influence the growth rate of their suppliers, larger suppliers have more customers, and the strength of a customer-supplier link depends on the size of the customer firm". They find the network model can reproduce firm-level dynamics and size distribution dynamics. In the cross section, larger firms and firms with less concentrated customer networks display lower volatility.

Specifically, they define firm size $S_{i,t}$ with growth rate as $g_{i,t+1}$, where

$$S_{i,t+1} = S_{i,t} exp(g_{i,t+1}). \tag{2.8}$$

They model the inter-firm relationship by assuming that supplier i's growth rates depend on its own idiosyncratic shock and a weighted average of the growth rates of its customer j:

$$g_{i,t+1} = \mu_g + \gamma \sum \omega_{i,j,t} g_{j,t+1} + \epsilon_{i,t+1}. \tag{2.9}$$

The weight $\omega_{i,j,t}$ determines how strongly the supplier's growth rate depends on the growth rate of its customers. Kelly, Lustig and Van Nieuwerburgh (2014) combine both the insights of network structure in Acemoglu (2012) and the insights of limited diversification of large firm influence in Gabaix (2011).

In sum, the origin of both macro and micro level higher-order fundamental moments lies on two dimensions: the network structure of heterogeneous firms; and the non-diversifiable influence of large firms.

2.4 The Theoretical Framework for the Return Predictability of the Fundamental Higher-Order Moments

Previous sections survey the literature on the properties regarding fundamental higher-order moments. At both macro and micro level, fundamental higher-order moments are persistent, time-varying and related to business cycle; moreover, the variation (formation) of fundamental higher-order moments lies in the granular networks of heterogeneous firms. The overwhelming purpose of exploring the properties and formation of fundamental higher-order moments is to extract the information contained in these moments on future asset prices and macroeconomic quantity variables. This section discusses the theoretical foundation on why the higher-order moments of fundamentals can predict future economic well-being (at the macro-level), future firm fundamentals (at the micro-level), and asset prices (at both macro and micro levels).

2.4.1 Return Predictability of the Higher-Order Moments of Firm Fundamentals: Theoretical Framework

Based on previous literature, this section answers the question why, in theory, higher-order moments of firm fundamentals can predict future cross-sectional stock returns and future firm fundamentals. Two frameworks based on the production-based asset pricing theory imply the return predictive power of firm fundamental higher-order moments. The first framework is proposed by Jia and Yan (2016a), which can accommodate the return predictability of all measures of firm fundamental higher-order moments. The second framework is based on the networks in production (Herskovic (2015), Kelly, Lustig, and Van Nieuwerburgh (2013)).

Fundamental Higher-Order Moments and Growth Option

The production-based asset pricing model, in a nutshell, decomposes the value of the firm at time t into two components: the value of assets-in-place, A_t, and the present value of the firm growth option, G_t.

$$V_t = A_t + G_t. \tag{2.10}$$

Specifically, the growth option G_t is modeled as an European call option written on A_t with expiration time T and a strike price of I, as the investment to undertake the potential projects (Berk, Green, and Naik (1999), Bernardo, Chowdhry, and Goyal (2007)). Previous literature assumes that the assets-in-place process A_t follows the Geometric Brownian Motion.

$$dA_t = \mu dt + \sigma dz_t. \tag{2.11}$$

Consequently, the growth option is given by the Black-Scholes formula as follows.

$$G_t = N(d_1)A_t - N(d_2)Ie^{-rT} \tag{2.12}$$

"Skewness has no role in this setting because the distribution of the assets-in-place is log-normal" (Jia and Yan (2016a)). The Geometric Brownian Motion assumption of assets-in-place is contradicted by the properties of the empirical distribution I documented in section 2. The firm fundamentals have large time-series & cross-sectional volatility and skewness. Moreover, the firm fundamentals have certain trajectories. In order to close the gap between theoretical models and empirical evidence, Jia and Yan (2016a) extend production models such as Bernardo, Chowdhry, and Goyal (2007) by allowing the distribution of $\log A_t$ to have non-zero skewness. Considering the ups and downs in the firm fundamentals, one can think of the fundamental process as a jump-diffusion process (Bakshi, Cao, and Chen (1997) or Backus, Foresi, and Wu (2004)). Since the growth option is written on the skewed assets-in-place process, the skewness of firm fundamentals is priced in the value of growth option, thus the stock returns (Jia and Yan (2016a)).

The skewed assets-in-place process does not need to be generated by a jump-diffusion process. It can also be generated through a process for assets-in-place similar to the Heston Volatility Model (Heston (1993)). The non-zero correlation between the mean and volatility of fundamentals leads to a priced fundamental skewness risk in the growth option value.

The framework of Jia and Yan (2016a) can accommodate the return predictive power of other measures of fundamental higher-order moments. Since the volatility of fundamentals is time-varying, the Geometric Brownian Motion hypothesis for assets-in-place contradicts the empirical fact. One can extend the assets-in-place process to be a process with time-varying volatility. Specifically, the process can be stated as: $dA_t = \mu dt + \sigma_t dz_t$. Following the similar argument as in Jia and Yan (2016a), the time-varying fundamental volatility risk is then embedded in the value of growth option. The above argument indicates that the cash flow volatility can predict future cross-sectional stock returns, which is confirmed by Huang (2009).

Firm fundamentals, as documented by Akbas, Jiang, and Koch (2015), have trajectories (i.e. upward trend or downward trend). The trend in fundamentals again obviously refutes the Geometric Brownian Motion of assets-in-place. To incorporate the trajectory feature of fundamentals into the assets-in-place process, one can revise the assets-in-place process to be path dependent, which means history of fundamentals matters. One can also revise the growth option written on the fundamental process to be a path dependent option instead of an European style option.

In sum, the higher-order moments of fundamentals can predict cross-sectional stock returns because it captures the fundamental higher-order moment risk embedded in the growth option written on fundamentals.

Granular Networks in Production

The granular origin and network origin embedded in a production model can also generate implications of fundamental higher-order moments on cross-sectional stock returns.

As discussed in Section 2, Kelly, Lustig, and Van Nieuwerburgh (2014) find that firm-level cash flow volatility is driven by customer-supplier linkages. Herskovic (2015), among others, examines asset pricing in a multisector model with sectors connected through an input-output network. He documents that network concentration and network sparsity for individual stocks are priced factors. Specifically, network concentration factor is the "average of firm's log output share weighted by their own output share. The network sparsity factor measures the thickness and scarcity of network linkages. An economy with high network concentration has few large sectors with low return to input investment due to decreasing returns to scale. Because of the network linkages, the lower productivity of large sectors spreads to relatively small sectors. The aggregate output and aggregate consumption both decrease. On the other hand, when sparsity is high, the input-output linkages change, causing aggregate consumption to increase.

When combining Kelly, Lustig, and Van Nieuwerburgh (2014) and Herskovic (2015), one can map out the microfoundation for the relationship between fundamental higher-order moments and cross-sectional stock returns: the variation of network concentration and sparsity leads to the change in fundamental higher-order moments and the change in cross-sectional stock returns.

However, no direct research uses network or granular origins as the predictive power of fundamental higher-order moments on cross-sectional stock returns.[6] This is the limitation of this line of the research which needs future efforts.

2.4.2 Return Predictability of the Higher-Order Moments of Aggregate Fundamentals: Theoretical Framework

There are two branches of literature discussing the theoretical foundation for the return predictive power of fundamental higher-order moments. The first group of literature explores the return predictive power of fundamentals by incorporating fundamental jumps in the long-run risk framework. The second group of literature employs the granular network among firms to provide microfoundation for the predictive power of fundamental higher-order moments.

[6]Kelly, Lustig, and Van Nieuwerburgh (2014) provide linkage between granular network and firm fundamental volatility but have no linkage between firm fundamental volatility and returns. In contrast, Herskovic (2015) discusses the relationship between networks and cross-sectional stock returns.

Long-Run Risk Framework with Jumps

The original long-run risk framework in Bansal and Yaron (2004) incorporates time-varying dividend growth volatility[7] to capture the higher-order moments of fundamentals. However, the time-varying volatility generated by an AR(1) process can capture none of the fundamental jumps, fundamental leverage effect, or skewness in fundamentals which are documented in previous literature (discussed in Section 2). Thus, the time-varying fundamental higher-order moments in the original long-run risk framework have only second-order effects on aggregate equity returns. A large group of papers incorporates the non-Gaussian shocks (or skewness) to explain the relationship between fundamental higher-order moments and aggregate market returns.

Drechsler and Yaron (2011), motivated by the empirical evidence in fundamentals, revise the long-run risk framework by specifying the state vector of the economy is driven by Poisson jump shocks. Benzoni, Dufresne, and Goldstein (2005) and Eraker and Shaliastovich (2008) model fundamental jumps within the long-run risk framework to explain index option return dynamics.

Yang (2011) documents that the empirical distribution of durable consumption growth is negatively skewed. To incorporate the empirical distribution, Yang (2011) specifies a time-varying long-run component in the volatility of durable consumption growth. This specification captures the negative skewed consumption growth dynamics and improves the performance of the original long-run risk model. Segal, Shaliastovich and Yaron (2015) and Guo, Wang, and Zhou (2015) specify positive and negative Poisson jumps in the long-run risk framework to explain the predictive power of fundamental higher-order moments on aggregate returns. Specifically, Segal, Shaliastovich and Yaron (2015) find that good uncertainty associated with good jumps predicts an increase in future economic activity and is positively related to

[7] The time-varying volatility is generated by an AR(1) process.

future market returns. But the bad uncertainty associated with bad jumps has an opposite effect on economic activity and market returns.

Incorporating non-Gaussian shocks is not restricted to long-run risk models. Gourio (2012), Gourio (2015), and Longstaff and Piazzessi (2004) embed jumps or skewness in slightly different model settings and find that incorporating higher-order moments of fundamentals can explain the equity premium puzzle, business cycle, and credit spreads.

However, all the above models follow the "top-down" method that directly incorporates empirical evidence such as time-varying volatility and skewness in the model. This group of models did not pay attention to the microfoundation of the fundamental higher-order moments. In other words, the network and granular origins are not embedded in the higher-order moments. A "bottom-up" method, building the aggregate fundamental higher-order moments from granular network origin, can be very useful in inspecting the mechanism and generating new implications for the fundamental higher-order moments.

Granular Networks and Market Returns

Jia and Li (2016) and Jia and Yan (2016b) set up the framework to incorporate network origin and granular origin in asset pricing models. In contrast to Herskovic (2015), Jia and Li (2016) recover a firm stochastic discount factor with production networks from the firm's first-order condition.[8] Jia and Yan (2016b) derive their firm stochastic discount factor with non-diversifiable large firm influence.

Specifically, non-diversifiable jumps of large firms spread the shocks to other firms, leading to the path dependence of fundamentals. Higher-order moments can capture the path dependence of fundamentals. If the fundamental path is shifted to another path (can be either riskier or safer), the fundamental moments change, and the risk of

[8]Herskovic (2015)'s stochastic discount factor is derived from investor's utility regarding consumption.

the representative investor who holds the market portfolio is changed. Consequently, the required return for the market portfolio is different.

2.5 What Can Fundamental Higher-Order Moments Predict? Empirical Evidence

This section discusses the financial market and macroeconomic implications of the fundamental higher-order moments. At both macro and micro levels, the fundamental higher-order moments can predict not only asset prices but also a wide range of fundamental variables. The predictive power of fundamental higher-order moments has different information content than that of higher-order moments of returns at both micro and macro levels.

2.5.1 Micro Level Predictability

It is well documented that measures of fundamental higher-order moments can predict cross-sectional stock returns. Huang (2009) documents that historical cash flow volatility is negatively related to future cross-sectional stock returns. Consistent with Huang (2009), Allayannis, Rountree, and Weston (2008) find that cash flow volatility is negatively valued by investors, causing a decrease in future firm value. Jia and Yan (2016a) find that historical skewness of firm fundamentals, such as skewness of gross profitability and earnings per share, can positively predict cross-sectional stock returns. Both Huang (2009) and Jia and Yan (2016a) report that the effect of fundamental higher-order moments cannot be driven out by the higher-order moments of returns. Akbas, Jiang, and Koch (2015) find a positive relationship between firm recent trajectory of gross profitability and cross-sectional stock returns. Both fundamental skewness and profit trajectory measures have long-horizon predictability. Among the three measures (volatility, skewness, and trajectory), the predictability of fundamental volatility and trajectory is relatively a phenomenon in small capitalization stocks. In contrast, the fundamental skewness can predict stock returns even for samples of large stocks.

The predictability of fundamental higher-order moments on returns is largely considered to be consistent with rational asset pricing models because fundamental higher-order moments can predict a large group of fundamental variables. Cash flow volatility has a positive relationship with a firm's precautionary cash holdings (Han and Qiu (2007)) since cash flow volatility can be viewed as a measure of cash flow shortfalls. Earnings volatility has a strong predictive power on both short-term and long-term earnings. The skewness of the firm fundamentals can positively predict future gross profitability, return on equity, market to book ratio, and Tobin's q (Jia and Yan (2016a)). The profitability trajectory is strongly correlated with future gross profitability and standardized unexpected earnings (Akbas, Jiang, and Koch (2015)).

2.5.2 Macro Level Predictability

At the aggregate level, the higher-order moments of fundamentals still have strong predictive power on market returns and macroeconomic quantity variables.

Regarding the predictive power on macroeconomic quantity variables, Bloom (2009) finds that fundamental volatility backed out from VIX index can negatively predict future consumption and output growth rate because of delayed firms' investment decisions. Jia and Yan (2016b) find that aggregate earnings skewness can predict industrial production, bond yields, and the level of earnings. Segal, Shaliastovich, and Yaron (2015) find that good and bad uncertainty have opposite influence on consumption, output, and investment. Good uncertainty indicates an increase in the level of fundamentals. In contrast, bad uncertainty forecasts a decline in fundamentals.

In terms of asset prices, Bansal and Yaron (2004) find that economic uncertainty is a priced risk and is negatively related to price-dividend ratio. Bansal, Kiku, Shaliastovich, and Yaron (2014) develop a dynamic capital asset pricing model incorporating a fundamental volatility factor. The model calibration results indicate a negative relationship between fundamental uncertainty and market risk premia. Segal, Shaliastovich, and Yaron (2015) find good and bad uncertainties can predict the price-dividend ratio up to three-year horizon. As to the fundamental skewness, Jia and Li (2016) and Jia and Yan (2016b) find that skewness of industrial production and earnings can strongly negatively predict stock market excess returns from six-month horizon to eight years horizon.

2.6 Conclusions

This paper outlines the major progress in the research of the fundamental higher-order moments. I survey the existence, the formation, and the financial market and macroeconomics implications for the higher-order moments. The time-varying volatility and the non-Gaussian shocks widely exist in all measures of fundamentals at both micro and macro levels. According to the literature, the granular network among firms is the origin of the fundamental higher-order moments. The fundamental higher-order moments have strong predictive power on asset prices and macroeconomic quantity variables.

From this survey article, we can see that one compelling motivation to survey this literature is the differences in approaches between finance and economics research on the higher-order moments of fundamentals. Finance literature, in general, inputs time-varying volatility and non-Gaussian shocks in the asset pricing model to predict asset prices and economic growth but ignores the microfoundation of fundamental higher-order moments. In contrast, economics literature focuses on the mechanism of higher-order moments, investigating the origin of the fundamental higher-order moments but ignores the implications on the macroeconomics and asset prices. Only the most recent research starts to bridge the inter-firm origin of fundamental higher-order moments and asset prices. The relationship between the microfoundation of fundamental higher-order moments and asset prices & macroeconomics urgently calls for more future research.

Table 2.1: Firm Fundamentals and the Cross-Sectional Stock Returns

Predictor	Definition	Literature
ROE	Quarterly income before extraordinary items divided by one-quarter-lagged book equity	Hou, Xue and Zhang (2015)
ROA	Quarterly income before extraordinary items divided by one-quarter-lagged total assets	Hou, Xue and Zhang (2015)
RNOA	Return on net operating assets	Soliman (2008)
PM	Profit margin	Soliman (2008)
ATO	Asset turnover	Soliman (2008)
Gross Profitability	Total revenue minuses cost of goods sold divided by total assets	Novy-Marx (2013)
Asset Growth	Year-on-year percentage changes in total assets	Cooper, Gulen and Schill (2008)
Net Operating Assets	Opertaing assets minus debt included in current liabilities	Hirshleifer, Hou, Teoh and Zhang (2004)
Inventory Growth	Year-on-year percentage changes in inventory	Belo and Lin (2011)
Failure Probability	Measure of corporate failure based on accounting and market-based measures	Campbell, Hilscher and Szilagyi (2008)

Table 2.2: Firm Fundamentals and Aggregated Stock Market Returns

Predictor	Definition	Literature
Term Spread	Difference between the long term yield on government bond and the treasury-bill	Campbell (1987)
Default Premium	Difference between yields of AAA corporate bonds and BBB corporate bonds	Fama and French (1992)
Skewness in Expected Macro Fundamentals	The third moments of cross-section of GDP forecast	Colacito, Ghysels and Meng (2013)
Consumption, Wealth and Income Ratio	The deviation from conumption, labor income and asset holdings	Lettau and Ludvigson (2001)
Investment to Capital Ratio	The ratio of aggregate investment to aggregate capital for the whole economy	Cochrane (1991)
Dividend Price Ratio	The difference between the log of dividends and the log of lagged price	Campbell and Shiller(1988a)
Dividend Payout Ratio	The difference between the log of dividends and the log of earnings	Campbell and Shiller (1988a)
Earnings Price Ratio	The ratio of operating earnings (before depreciation) in the previous fiscal year to market equity in the previous month	Fama and Schwert (1977)
Book to Market Ratio	The ratio of book equity for the previous fiscal year to market equity in the previous month	Lewellen (2004)
Accruals	The change in non-cash current assets less the change in current liabilities excluding the change in short-term debt and the change in taxes payable,minus depreciation and amortization expense	Hirshleifer, Hou and Teoh (2009)
Equity Share in New Issues	The ratio of equity issuing activity as a fraction of total issuing activity	Baker and Wurgler (2000)
Net Equity Expansion	The ratio of 12-month moving sums of net issues by NYSE listed stocks divided by the total end-of-year market capitalization of NYSE stocks	Welch and Goyal (2007)

Table 2.3: The Fundamental Higher-Order Moments at the Macro Level: Existence

Measure	Fundamental Variable	Literature
	Panel A: Time-Varying Fundamental Volatility	
Volatility	Consumption Growth	Bansal and Yaron (2004), Lettau and Wachter (2007), Longstaff and Piazzessi (2004)
Volatility	Durable Consumption Growth	Yang (2011)
Volatility	Earnings	Longstaff and Piazzessi (2004), Jia and Yan (2016b)
Volatility	Industrial Production	Segal, Shaliastovich, and Yaron (2015), Jia and Li (2016)
	Panel B: Non-Gaussian Shocks to Fundamentals	
Non-Gaussian Shocks	Consumption	Drechsler and Yaron (2011), Gourio (2012), Gourio (2015), Tsai and Wachter (2016), Bansal and Shaliastovich (2011)
Non-Gaussian Shocks	Production	Segal, Shaliastovich, and Yaron (2015), Jia and Li (2016), Jia and Yan (2016b)
	Panel C: Fundamental Skewness	
Skewness	Consumption Growth	Drechsler and Yaron (2011)
Skewness	Profitability and Earnings	Basu (1997), Givoly and Hayn (2000), Segal, Shaliastovich, and Yaron (2015), Jia and Li (2016), Jia and Yan (2016b)
	Panel D: Lumpiness of Fundamentals	
Lumpy	Investment and R & Ds	Caballero, Engel, and Haltiwanger (1995), Caballero and Engel (1999), Cooper, Hailtwanger and Power (1999), Doms and Dunne (1998)

Table 2.4: The Fundamental Higher-Order Moments at the Micro Level: Existence

Measure	Fundamental Variable	Literature
Volatility	Operating Cash Flows	Allayannis, Rountree, and Weston (2008), Han and Qiu (2007), Huang (2009), Jayaraman (2008), Minton and Schrand (1999)
Volatility	Earnings	Dichev and Tang (2009)
Skewness	Gross Profitability	Jia and Yan (2016a)
Skewness	Earnings	Gu and Wu (2003), Jia and Yan (2016a)
Trajectory	Gross Profitability	Akbus, Jiang, and Koch (2015)

Table 2.5: The Theoretical Foundation for the Formation of Fundamental Higher-Order Moments

Rare Disaster	Rietz (1988), Barro (2006), Bansal, Kiku, Shaliastovich, and Yaron (2014), Gourio (2012), Gourio (2015), Kaltenbrunner and Lochstoer (2010), Fernandez-Villaverde, Guerron-Quintana, Rubio-Ramirez, and Uribe (2011)
Rare Booms and Disasters	Segal, Shaliastovich, and Yaron (2015), Tsai and Wachter (2015)
The Granular Origin	Axtell (2001), Horvath (1998), Horvath (2000), Gabaix (2011)
The Network Origin	Acemoglu, Carvalho, Ozdaglar, and Tahbas-Salehi (2012), Bak, Chen, Scheinkman and Woodford (1993), Durlauf (1993), Durlauf (1994), Jovanovic (1987)

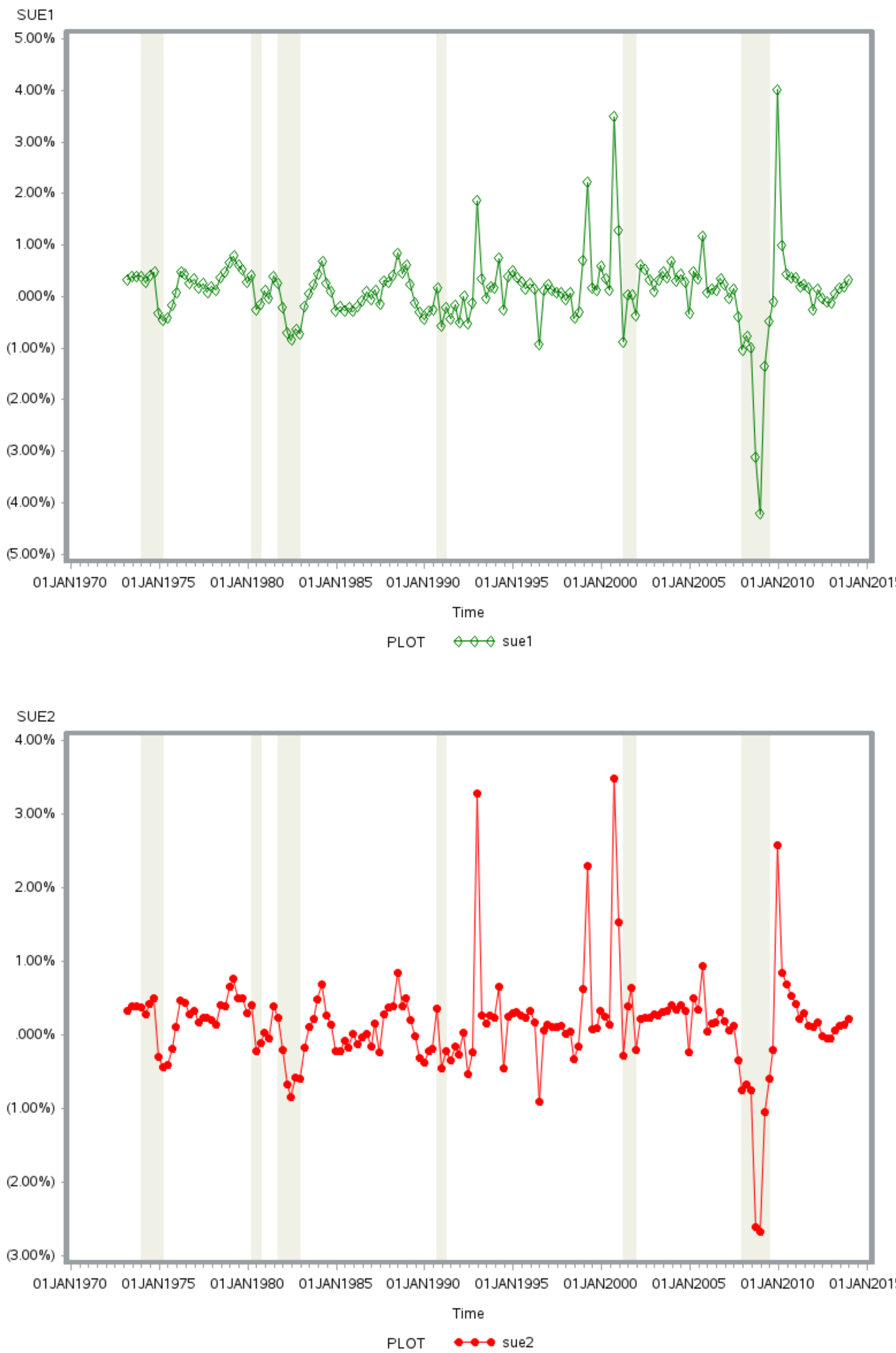
Table 2.6: Skewness of the Firm Fundamentals

Panel A: SK_{GP}										
	Mean	Med	STD	P10	P25	P75	P90	AR(1)	AR(2)	AR(3)
Full Sample	-0.05	0.02	1.02	-1.40	-0.62	0.60	1.19	0.14	0.08	0.05
1974-1975	-0.48	-0.41	1.39	-2.23	-1.97	0.58	1.66			
1976-1977	-0.24	-0.06	1.20	-2.34	-0.84	0.55	1.17			
1978-1979	-0.04	0.06	0.99	-1.28	-0.57	0.61	1.14			
1980-1981	-0.02	0.07	1.01	-1.34	-0.56	0.64	1.17			
1982-1983	0.01	0.09	0.98	-1.27	-0.55	0.64	1.19			
1984-1985	-0.08	-0.01	1.02	-1.47	-0.62	0.59	1.15			
1986-1987	-0.12	-0.01	1.11	-1.71	-0.77	0.61	1.21			
1988-1989	-0.11	-0.02	1.06	-1.62	-0.71	0.57	1.13			
1990-1991	-0.06	0.04	1.00	-1.36	-0.59	0.59	1.12			
1992-1993	-0.06	0.01	1.02	-1.41	-0.63	0.59	1.19			
1994-1995	-0.11	-0.03	1.02	-1.49	-0.71	0.55	1.14			
1996-1997	-0.03	0.03	1.04	-1.42	-0.61	0.64	1.25			
1998-1999	-0.03	0.03	1.02	-1.40	-0.62	0.63	1.22			
2000-2001	-0.06	-0.05	1.00	-1.36	-0.66	0.55	1.20			
2002-2003	-0.03	0.03	1.00	-1.33	-0.60	0.59	1.19			
2004-2005	0.02	0.05	0.99	-1.26	-0.55	0.66	1.24			
2006-2007	0.03	0.05	0.96	-1.20	-0.53	0.64	1.24			
2008-2009	0.01	0.06	0.94	-1.21	-0.53	0.59	1.16			
2010-2011	-0.01	0.03	0.93	-1.15	-0.56	0.58	1.12			
2012-2013	0.02	0.06	0.94	-1.18	-0.58	0.62	1.19			

Table 2.7: Skewness of the Firm Fundamentals

Panel B: SK_{EPS}										
	Mean	Med	STD	P10	P25	P75	P90	AR(1)	AR(2)	AR(3)
Full Sample	-0.13	-0.05	1.22	-1.89	-0.89	0.67	1.38	0.13	0.07	0.05
1974-1975	0.22	0.20	0.85	-0.80	-0.29	0.78	1.32			
1976-1977	0.21	0.23	0.90	-0.90	-0.33	0.80	1.31			
1978-1979	0.15	0.16	0.90	-0.98	-0.39	0.72	1.28			
1980-1981	0.17	0.18	0.96	-1.01	-0.40	0.79	1.37			
1982-1983	0.08	0.13	1.06	-1.36	-0.54	0.76	1.36			
1984-1985	-0.04	0.04	1.17	-1.67	-0.74	0.71	1.38			
1986-1987	-0.12	-0.01	1.25	-1.95	-0.94	0.74	1.44			
1988-1989	-0.13	-0.03	1.20	-1.83	-0.89	0.67	1.33			
1990-1991	-0.22	-0.10	1.23	-2.08	-0.99	0.61	1.31			
1992-1993	-0.24	-0.15	1.26	-2.13	-1.11	0.62	1.36			
1994-1995	-0.22	-0.11	1.25	-2.07	-1.03	0.61	1.35			
1996-1997	-0.31	-0.20	1.33	-2.28	-1.26	0.59	1.40			
1998-1999	-0.17	-0.10	1.30	-2.07	-1.08	0.71	1.50			
2000-2001	-0.28	-0.24	1.25	-2.05	-1.15	0.55	1.35			
2002-2003	-0.21	-0.15	1.21	-1.89	-1.00	0.58	1.28			
2004-2005	-0.07	0.00	1.22	-1.81	-0.81	0.70	1.43			
2006-2007	-0.12	-0.07	1.25	-1.89	-0.93	0.70	1.49			
2008-2009	-0.38	-0.27	1.26	-2.25	-1.25	0.47	1.20			
2010-2011	-0.09	-0.06	1.21	-1.77	-0.81	0.67	1.44			
2012-2013	-0.09	-0.07	1.24	-1.77	-0.88	0.68	1.51			

Figure 2.1: Time Series of SUE Measures



CHAPTER 3

What Does Skewness of Firm Fundamentals Tell Us About Firm Growth, Profitability, and Stock Returns

3.1 Introduction

There is overwhelming evidence in the finance literature that measures of firm fundamentals such as ROE, profitability, investment, and asset growth predict cross-sectional stock returns.[1], Fama and French (2006a, 2008), Aharoni, Grundy, and Zeng (2013), Novy-Marx (2013), and Hou, Xue, and Zhang (2014). 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., Diether, Malloy, and Scherbina (2002), Johnson (2004), Dichev and Tang (2009), and Gow and Taylor (2009). However, little is known whether the higher moments of firm fundamentals are related to stock returns. In this paper, I shed light on this research question by providing two distinct theoretical models, both of which imply a positive relation between the skewness of firm fundamentals and stock returns. I 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.

The 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 bernardo2007growth). In this framework, a firm has growth opportunities as part

[1] A partial list of recent studies include Cohen, Gompers, and Vuolteenaho (2002), Fairfield, Whisenant, Yohn (2003), Titman, Wei, and Xie (2004)

of the firm value, which are then valued as real options. Previous studies assume (log) normal distribution for the firm assets-in-place. I 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 findings in the option pricing theory, I am 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 firm assets-in-place. Second, the asymmetry in option payoffs implies that a higher skewness of the underlying process increases the expected payoff of a call option.

The 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 (2006a, 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, I provide a novel interpretation of the conditional sample skewness of firm cash flows. The key ingredient of my argument is a link between the skewness and the sampling properties of the growth rate process. I 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.

It is important to point out that the positive relation between the skewness of firm fundamentals and stock returns differentiates this paper from the previous research on the return predictability of stock return skewness.[2] In this literature, the return skewness is generally found to be negatively related to stock returns. To explain the negative relation, researchers assume that investors prefer positively skewed stocks. In contrast, my models are preference-free.

To empirically test the model implications, I use two skewness measures: SK_{GP}, skewness of gross profitability (GP) of Novy-Marx (2013), and SK_{EPS}, skewness of earnings per share.[3] Strongly supporting the main implication of the two models, both skewness measures are positively significant 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, I further test whether the skewness measures positively predict some widely accepted proxies of firm growth option or firm profitability. In particular, I 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

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

[3]I have also considered alternative 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.

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 predictability is also significant 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 not surprising given the strong predictive power of GP relative to other earnings-related measures of firm profitability. To address the concern whether my findings are consequences of the existing evidence that return skewness predicts stock returns, I conduct robustness checks by incorporating some widely used measures of return skewness (e.g., Harvey and Siddique (2000), Boyer, Mitton and Vorkink (2011), and Bali, Cakici, and Whitelaw (2011)). I do not find any changes in my results after controlling for the skewness of stock returns.

In spite of a large body of research on higher moments of stock returns, to the best of my knowledge, this paper is the first to examine the information content of higher moments of firm fundamentals. A paper related to this paper is Scherbina (2008) which 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 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 my 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 return. In a separate study, I consider the skewness of aggregate stock market and find that it predicts stock market return.

The rest of the paper is organized as following. In Section 2, I present the theoret-

[4]I find, unreported in the paper, that the skewness of analyst's forecasts is uncorrelated with the skewness measures in this paper. In a separate study, I use the standard skewness measure of analysts' forecasts and find that it positively predicts stock returns.

ical models and their implications. I describe the data and econometric methodology in Section 3. Section 4 discusses the empirical evidence. Section 5 concludes.

3.2 Theoretical Models

I present two distinct models, both of which imply a positive relation between the skewness of firm fundamentals and expected stock return. 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, I present a novel econometric approach of inferring the 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.

3.2.1 Model 1: Growth Option

I 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 this setting because the distribution of the assets-in-place is log normal.

I 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,

[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 my empirical analysis.

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, I 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 my focus is skewness, I assume zero excess kurtosis to simplify my 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]

$$G_t \approx A_t \Phi(d) - Ie^{-rT}\Phi(d - \sigma\sqrt{T}) + \frac{1}{6} A_t \phi(d) \sigma\sqrt{T}(2\sigma\sqrt{T} - d)\gamma, \tag{3.1}$$

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:

$$d = \frac{\log(A_t/I) + (r + \sigma^2/2)T}{\sigma\sqrt{T}}. \tag{3.2}$$

When the skewness is zero, equation (3.1) becomes the Black-Scholes formula. With non-zero skewness, the sign of the last term of equation (3.1) 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. That is, I assume $A_t < I$. Then it can be shown that $2\sigma\sqrt{T} - d > 0$ if in addition 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, I obtain the

[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.

following proposition.

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

The above result is very intuitive because a higher positive skewness increases the chance of an out-of-the-money call option to be in-the-money in the future. Backus-ForesiWu2004 also provide the formula for the call option delta:

$$\Delta_t = \Phi(d) + \frac{1}{6}\phi(d)(d^2 - 3d\sigma\sqrt{T} + 2\sigma^2 T - 1)\gamma. \tag{3.3}$$

For zero skewness, equation (3.3) becomes $\Phi(d)$ which is the delta formula in the Black-Scholes model. For non-zero skewness, the second term in equation (3.3) 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 second term is positive. In other words, the option delta is positively related to the skewness. Again, this makes sense as the option writer needs to hedge more since the option is more likely to be in-the-money in the future.

I next follow the argument of Bernardo, Chowdhry and Goyal (2007) to link the fundamental skewness to expected stock returns. I 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

$$\begin{aligned} \beta_t^G &= \frac{dG_t/dA_t}{G_t/A_t}\beta_t^A \\ &= \frac{\Delta_t}{G_t/A_t}\beta_t^A. \end{aligned} \tag{3.4}$$

One can plug in the formulae of G and Δ into equation (3.4) 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. I can write the beta of the firm value as:

$$\begin{aligned} \beta_t &= \frac{A_t}{A_t + G_t}\beta_t^A + \frac{G_t}{A_t + G_t}\beta_t^G \\ &= \frac{1+\Delta}{1+G_t/A_t}\beta_t^A. \end{aligned} \tag{3.5}$$

To understand the relation between β_t and the skewness, γ, I consider the dependence of $\frac{1+\Delta}{1+G_t/A_t}$ 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 my 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. I 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 I 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 my 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 stocks.

3.2.2 Model 2: Conditional Skewness of Small Samples

In contrast to the real option approach in the first model, my second model follows 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, $\{x_{t-n+1}, ..., x_t\}$, I estimate the conditional skewness, $\hat{b}$, with the standard formula:

$$\hat{b} = \frac{m_3}{s^3} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_{t-n+i} - \bar{x})^3}{\left[\frac{1}{n-1}\sum_{i=1}^{n}(x_{t-n+i} - \bar{x})^2\right]^{3/2}}, \tag{3.6}$$

where $\bar{x}$ is the sample mean, s is the sample standard deviation, and m_3 is the sample third central moment. I 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 $x_t = \sum_{i=1}^{n} \Delta x_{t-n+i}$, I can express the first three sample moments as:

$$\begin{aligned}
\bar{x} &= \frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{i}\Delta x_{t-n+j} \\
&= \frac{1}{n}\sum_{i=1}^{n}(n-i+1)\Delta x_{t-n+i}, && (3.7)\\
s^2 &= \frac{1}{n-1}\sum_{i=1}^{n}\left(\sum_{j=1}^{i}\Delta x_{t-n+j} - \bar{x}\right)^2 \\
&= \frac{1}{n-1}\sum_{i=1}^{n}\left(\sum_{j=1}^{i}\frac{j-1}{n}\Delta x_{t-n+j} - \sum_{j=i+1}^{n}\left(1-\frac{j-1}{n}\right)\Delta x_{t-n+j}\right)^2, && (3.8)\\
m_3 &= \frac{1}{n}\sum_{i=1}^{n}\left(\sum_{j=1}^{i}\Delta x_{t-n+j} - \bar{x}\right)^3 \\
&= \frac{1}{n}\sum_{i=1}^{n}\left(\sum_{j=1}^{i}\frac{j-1}{n}\Delta x_{t-n+j} - \sum_{j=i+1}^{n}\left(1-\frac{j-1}{n}\right)\Delta x_{t-n+j}\right)^3. && (3.9)
\end{aligned}$$

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, I 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 $n = 4$, I 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, I consider the class of AR(1) processes:

$$x_t = \rho x_{t-1} + u_t, \tag{3.10}$$

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, I conduct the following numerical exercise.

To be consistent with my later empirical work, I consider n = 8, 12, 16, and 20 and ρ = 0.9, 0.95, and 1.[7] To take into account of sampling errors, I 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 (3.10). 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 3.1 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, $c(t)$ 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 I have checked various heteroscedastic specifications for

[7]The small sample sizes are appropriate when I 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.

u_t. I have also considered numerous alternative ARMA(p,q) specifications for x_t and find qualitatively similar results. The following proposition summarize the 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 prediction 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:

$$\Delta x_t = u_t + \varepsilon_t \tag{3.11}$$

$$u_t = \mu + \theta u_{t-1} + e_t \tag{3.12}$$

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 this type of models require long time-series data, which are not available. Second, the models are not stable over time. This can happen, for example, when there are structural breaks in the underlying data-generating process. Third, the models are likely 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. I summarize my 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 (2006a)), when everything else is fixed, a higher expected growth rate of firm cash flows implies higher stock returns. Combining this argument with Proposition 4, I 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 my empirical analysis next, after I first test the positive return predictability, I will investigate the validity of both models.

3.3 Data and Methodology

In this section, I first show the definitions of skewness measures of firm fundamentals. I then describe the data. Finally, I discuss the econometric methods.

3.3.1 Definition of Skewness Measures

I consider two measures of firm fundamentals: gross profitability GP and earnings per share EPS. There is significant evidence that GP positively predicts return (e.g., Novy-Marx (2013)). Earnings has been widely accepted as a measure of firm cash flows. At the end of quarter t, I follow Gu and Wu (2003) to define skewness of GP and EPS as the standard skewness coefficient of lagged observations during the rolling window of quarters $t-n$ to $t-1$:

$$SK_{GP,t} = \frac{n}{(n-1)(n-2)} \sum_{\tau=t-n}^{t-1} \left(\frac{GP_\tau - \mu_{GP}}{s_{GP}} \right)^3, \tag{3.13}$$

$$SK_{EPS,t} = \frac{n}{(n-1)(n-2)} \sum_{\tau=t-n}^{t-1} \left(\frac{EPS_\tau - \mu_{EPS}}{s_{EPS}} \right)^3, \tag{3.14}$$

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, I 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 my econometric analysis because the skewness of either variable is unit free due to the definition of skewness.

Note that I 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. I in fact have conducted (unreported) my analysis without skipping quarter t and have found even stronger (but biased) results.[8]

[8] In a related paper, I consider the skewness of analysts' earnings forecasts and show that it positively predicts stock returns. Despite the similarities in return predictability, the information content of the skewness of analysts' forecasts is very different from that in the fundamental skewness.

3.3.2 Data Descriptions

Stock return and accounting data are obtained from the CRSP and COMPUSTAT. I 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. I 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 empirical analysis starts in 1973. For each quarter, the accounting variables are defined as follows.

- GP: Following Novy-Marx (2013), gross profitability is quarterly revenues 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 (2014) (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 (2014)). 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 $t-1$. I follow the convention in the literature by skipping month t when MOM is used to predict returns in month $t+1$. I 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. I use daily returns in the quarter to estimate the regression.

- $Prskew$: It is predicted idiosyncratic skewness defined in Boyer, Mitton, and Vorkink (2010). I 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 I use quarterly frequency instead of monthly frequency.

I 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 skewness of firm fundamentals. I have also considered total return skewness of daily stock returns in the quarter and obtained similar results. I 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 3.1 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 my estimation method of using non-overlapping samples. That is, I 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.

3.3.3 Econometric Methods

I rely mostly on the portfolio sorts and cross-sectional regressions of Fama and MacBeth (1973) for the empirical investigation. For single portfolio sorts, I 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, I expect an increasing pattern of portfolio returns from decile 1 to decile 10. For double portfolio sorts, I 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, I 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, I use the Newey-West adjusted standard errors because of the persistence in the portfolio compositions.

For the Fama-MacBeth regressions, I expect the estimated average coefficient of the 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, I 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.

I also use the Fama-MacBeth regression approach to compare the explanatory power of different skewness measures. To do so, I 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 all the explanatory power of the first measure.

3.4 Empirical Evidence

I show the results of portfolio sorts first and then the estimates of Fama-MacBeth regressions. I next further examine the validity of the theoretical models. I conduct robustness checks at the end of the section.

3.4.1 Single Portfolio Sorts

Table 3.2 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 risks, I 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).[9] The risk-adjusted H-L spreads are even higher at 1.69% and 1.61%. The value-weighted returns are very similar to but slightly smaller than the equal-weighted returns, indicating that the results are not dominated by small stocks.

Next, I 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. One reason of these patterns in control variables is that 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, I will reexamine the predictability by 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

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

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, I find a positive relation between the skewness of firm fundamentals and future stock returns, consistent with the predictions of both theoretical models. The results are robust regardless whether the returns are equal-weighted or value-weighted, and unadjusted or risk-adjusted. I will present further evidence on which model is more appropriate in explaining the return predictability.

3.4.2 Double Portfolio Sorts

I now investigate whether the predictability of the skewness measures are caused by firm characteristics. I use the double portfolio sort approach by first sorting stocks on firm characteristics and then sorting on the skewness measures. Table 3.3 reports the average equal-weighted returns of double-sorted portfolios for the six characteristics reported in Table 3.2. The results for value-weighted returns are very similar but unreported for brevity. I have also examined a number of other control variables and those results are available upon requests.

I 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} can not 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. I will get a clearer picture when I estimate Fama-MacBeth regressions where multiple control variables are jointly considered.

3.4.3 Fama-MacBeth Regressions

I 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 3.4. I 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, I reestimate these models for each skewness measure. Model (8) includes the skewness measure and all six control variables.

First, I 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 (2014) 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.

3.4.4 Skewness and Firm Growth Option

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

Table 3.5 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 my 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 3.6, I present the estimates of Fama-MacBeth regressions where the dependent variable is the next-quarter $MABA$ or Tobin's q. The results for future values of $MABA$ and Tobin's q are very similar and not reported. 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, I consider the estimation results with all the control variables. Because both $MABA$ and Tobin's q are persistent, I include their lagged values as additional control variables in 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 my model implication that firms with higher fundamental skewness have higher growth options.

3.4.5 Skewness and Firm Profitability

I then 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 cash flows. I gauge the firm profitability by two widely used measures in the literature: ROE and GP.

Table 3.7 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 3.8 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 for SK_{EPS} when all controls are included but it is still positive.

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

3.4.6 Comparison of Alternative Skewness Measures

It is interesting to compare the return predictive power of the two skewness measures. To do this, I 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 3.9.

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. My findings support the argument of Novy-Marx (2013) that GP is one of the best accounting measures of firm performance.

3.4.7 Robustness Checks

Long Horizons

I have shown earlier that the fundamental skewness predicts long-run firm growth option and profitability. I now investigate if the return predictability holds for long horizons. I estimate Fama-MacBeth regressions for returns in quarters $t+2$, ..., $t+5$ and report the results in Table 3.10. I 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 $t+5$. Even in the presence of the control variables in model (2), it is significant up to $t+3$. The coefficient on SK_{EPS} is always positive but becomes insignificant beyond $t+2$. As a whole, the return predictability holds at least up to the third quarter. Note that if I 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 $t+5$, consistent with the findings of Novy-Marx (2013).

Controlling for Return Skewness

One concern about my 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. I 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 3.11 reports the estimation results.

In models (1)–(3), I only use one of the three return skewness measures. MAX and $Prskew$ are significant but $Idskew$ is insignificant in predicting returns. However, the sign of average coefficient for MAX changes signs for different samples. 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}. For my samples, the return skewness measures do not appear to consistently predict stock returns.

I next combine the skewness of fundamentals with the return skewness measures in models (5) an (6). In model (5), I 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}. I 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 significant at the 1% level. The evidence indicates that my findings cannot be explained by the skewness of stock returns.

Additional Tests

I perform some additional robustness checks and report the results in Table 3.12. For brevity, I 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, I 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 3.4. As expected, the t-statistics are smaller but remain significant at the 1% level for SK_{GP} and 10% level for SK_{EPS}.

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

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

Finally, I 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 3.4 for the benchmark case. Taken together, the results of these additional tests provide further support my main model implication that the skewness of firm fundamentals is positively related to stock returns.

3.5 Conclusions

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

Because the two models are based on the option pricing theory and the basic stock valuation equation, I am, in the spirit of Fama and French (2006a, 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, the results highlight the importance of incorporating the skewness measures of firm fundamentals in asset pricing research.

Figure 3.1: 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.

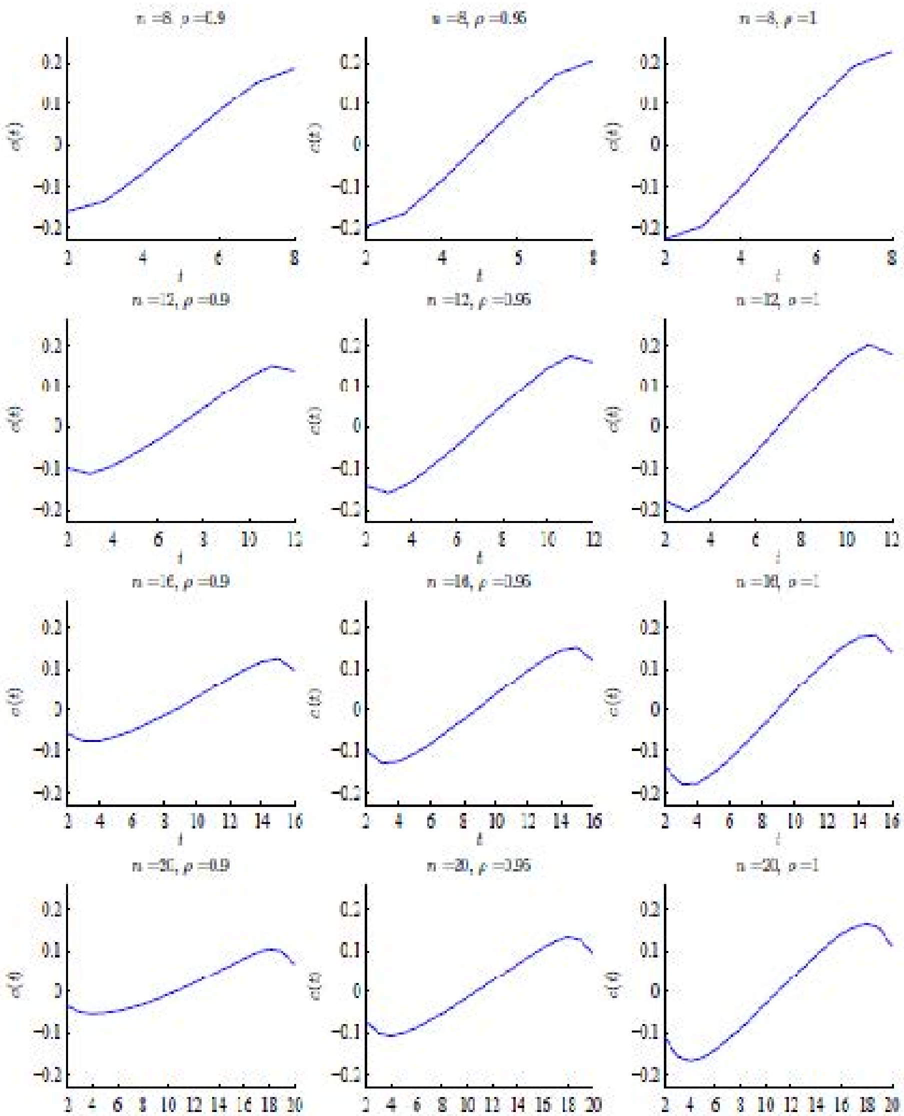


Table 3.1: Data Description

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, I 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, I 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 3.3. 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 3.2: 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. I use two models for risk adjustment: the 3-factor model of FamaFrench1996 and the 5-factor model of FamaFrench2015. 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 3.3: 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, I first sort stocks into quintiles using the characteristic, and then within each quintile, I 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 ?? – 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 3.4: 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 3.5: 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. I 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 3.6: 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 3.7: 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. I 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 3.8: 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 3.9: 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 3.10: 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 3.11: 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 **??**. 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 3.12: 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)

CHAPTER 4

The Skewness of the Firm Fundamentals and Cross-Sectional Stock Returns

4.1 Introduction

It has been well documented that macroeconomic fundamentals such as corporate earnings, industrial production, and durable consumption growth are not normally distributed. In particular, the conditional skewness of these variables are time-varying. Recent studies have proposed models with time-varying volatility and jumps that can capture these empirical regularities (e.g., Longstaff and Piazzessi (2004), Drechsler and Yaron (2011), and Segal, Shaliastovich, and Yaron (2015)). But two important questions remain unanswered. First, is the skewness of macroeconomic fundamentals priced or in other words predictive of the stock market return? Second, what are the "economic channels" linking the skewness with "technological aspects of production, investment and financing opportunities" (Segal, Shaliastovich, and Yaron (2015))?

This paper attempts to shed light on both questions. To answer the first question, I present evidence that the conditional skewness of corporate earnings can strongly predict stock market excess returns for horizons beyond six months and up to eight years, even after controlling for standard predictors such as book-to-market ratio, term spread, default spread, and *cay* (as in Lettau and Wachter (2001)). Regarding the second question, I show that the predictive power of the conditional skewness of corporate earnings can be explained by the interaction of two properties of the underlying process of corporate earnings: (i) Path dependence; and (ii) Non-Gaussian (skewed) shocks. Path dependence of corporate earnings is generated by productivity-enhancing technology spillover, and non-Gaussian shocks refer to non-normally distributed (skewed) innovations of the corporate earnings process. In this setting, non-Gaussian shocks shift the economy across paths of different degrees of technology spillover, leading to different risk profiles of the representative investor's wealth. As a result of path dependence, the corporate earnings skewness reflects the degree of technology spillover and consequently predicts stock returns.

Path dependence means history matters, i.e. the realized history affects the future outcomes. Durlauf (1993, 1994), for example, show that the aggregate output is path dependent. In this article, I use the conditional skewness of the recent past to capture the information contained in the "path" of corporate earnings. As stated in Durlauf (1993), the path dependence also means that "there will be an especially strong relationship between the probability density of shocks and the aggregate dynamics of the model as realizations in the tails of the density determine whether the economy shifts across regimes". When it comes to corporate earnings, this statement indicates the non-Gaussian shocks in the path dependent corporate earnings can capture the information in the tails to determine whether regime-switch appears in the economy.

The conditional earnings skewness measures, simultaneously capturing the non-Gaussian shocks and path dependence in corporate earnings, can identify the appearance and timing of regime-switch in the economy. When the economy encounters a large negative shock which shifts the corporate earnings to a bad path, the conditional earnings skewness, at the occurrence of the jump, decreases sharply due to the large drop in current period earnings. The sharp decrease in earnings skewness indicates an increase in the risk for the market portfolio held by the representative investor. The representative investor needs higher future compensation to bear higher risk. The earnings skewness has a negative relationship with future market returns. Similarly, at the occurrence of a positive jump in earnings, the conditional earnings skewness increases sharply. The sharp increase in earnings skewness implies a decrease in the risk of the market portfolio. The investor requires lower future compensation for the higher earnings skewness.

Besides measuring the risk exposure of the market portfolio at the regime switch, the earnings skewness can also measure the relative risk exposure of the market portfolio regarding the timing of the regime switch. For example, a negative jump in earnings is alleviated as the time goes on before another jump appears. During the alleviation, the earnings skewness increases relative to the skewness at the occurrence of the negative jump. The alleviation of the negative jump indicates a decrease of the relative risk level in the market portfolio compared to that at the occurrence of the jump, thus a negative relationship between skewness and future market returns. In sum, the earnings skewness is a risk-based measure capturing the occurrence and timing of earnings regime switch.

The above economic intuition is translated to my model by extending Lettau and Wachter (2011) from two aspects. First, to capture the non-Gaussian shocks, I specify the earnings growth shocks to follow the skew-normal distribution which has a shape parameter for skewness. Second, the time-varying shape parameter of the skew-normal shocks is path dependent, having two regimes with different autoregressive processes and different conditional innovations. The model yields a negative relationship between earnings skewness and future stock returns.

I then go one step further to provide the microfoundation for earnings skewness. The path dependence feature in corporate earnings can link the earnings skewness to "technological aspects of production". Durlauf (1993, 1994), among others, demonstrate that the path dependence of aggregate output is generated by the interaction of incomplete markets and strong technological complementarities. Following the line of Durlauf's argument, a large negative economy-wide shock (non-Gaussian) leads to a loss of productivity-enhancing technological spillovers among firms, thus an indefinite aggregate output loss. This economy-wide shock indefinitely moves the aggregate output to a riskier "path". The representative investor holding this portfolio of firms (market portfolio) needs larger future compensations for this riskier "path" until a subsequent favorable economy-wide shock. In summary, the earnings skewness predicts market returns by the force of path dependence.

To gauge the conditional skewness of corporate earnings, I consider five time series measures: SK_{SUE1}, SK_{SUE2}, SK_{SUE3}, SK_{SUE4}, and SK_{EPS}. The first four are the conditional skewness of standardized unexpected earnings (SUE) using the historical SUEs of prior 24 quarters. The last one is the skewness of aggregate earnings per share constructed in the same way as the skewness of SUE measures. Specifically, SK_{SUE1} is the skewness of earnings surprises where the surprise for a quarter is the difference between earnings of the current quarter and the same quarter of last year; SK_{SUE2} is similar to SK_{SUE1} but excluding "extraordinary items" in earnings. SK_{SUE3} (SK_{SUE4}) is the skewness of earnings surprises with SUEs defined as the difference between realized earnings of the quarter and the median (mean) for that quarter.

Consistent with the model, all five skewness measures negatively predict stock market returns. For example, univariate regressions of stock market returns on skewness of earnings indicate that a one unit increase in SK_{SUE1} leads to a 1.217% decrease in the future one-year stock market return, 7.722% decrease in future five-year cumulative market returns, and 16.886% decrease in future 10-year cumulative market returns. When I use Nelson and Kim (1993) small sample bias adjustment for regression coefficients and P values, the coefficients for short-horizon prediction increase by three-fold. In general, univariate regressions indicate the skewness of earnings can predict future stock returns from two-quarters to eight-years ahead.

To further test the predicting power of earnings skewness measures, I then run multivariate regressions and control for different groups of return predictors. First, I control for standard market return predictors such as *cay*, book-to-market ratio, term spread and default spread. The earnings skewnss measures can still significantly predict stock market returns at different horizons. In the other group of regressions, I control the historical mean and volatility of corporate earnings. The results indicate that the skewness, but not the mean or volatility of corporate earnings, is the key moment of corporate earnings that can predict stock market returns.

Of the five earnings skewness measures, SK_{SUE3} and SK_{SUE4} dominate the other measures in the short horizons up to three years as other measures lose explanatory power once controlling SK_{SUE3} or SK_{SUE4}. However, SK_{SUE3} and SK_{SUE4} dominate in the long horizons from four years to eight years. These results indicate that firm cash flow risks are driven by multiple factors.

I then empirically inspect how earnings skewness can predict market returns. The earnings skewness can be decomposed into two items: cross-sectional mean of the firm-level earnings skewness (SK_{cs}) and coskewness across firms (SK_{co}). If as I argued, the explanatory power of earnings skewness on returns comes from the path dependence, i.e. the time-varying "productivity-enhancing technology spillovers", the coskewness terms must drive the explanatory power of earnings skewness. The reason is that productivity-enhancing technology spillover is an inter-firm relationship must be captured by coskewness across firms but not mean firm-level earnings skewness. Consequently, if I run predictive regressions of market returns at different horizons on earnings skewness controlling for SK_{cs}, an insignificant coefficient on SK_{cs} but significant coefficients on earnings skewness measures can support the path dependence story. The regressions results confirm that the SK_{cs} is the main component in earnings skewness that can predict market returns. This test supports technology spillover as the economic channels for return predictive power of earnings skewness.

This paper offers at least two solid contributions to the literature. First, in contrast to ex-ante measures or other measures on the higher-order moments of economic quantity variables, the conditional earnings skewness provides a new dimension on scaling information contained in fundamentals. Second, one of the biggest challenges of prior research on the higher-order moments of the fundamentals is to provide clear economic channels for the higher-order moments to determine asset prices. To the best of my knowledge, this paper is the first to clearly state the economic channels for higher-order moments of fundamentals to affect asset prices. The economic channel in this paper is the time-varying productivity-enhancing technological spillover captured by the interaction of path dependence and non-Gaussian shocks of fundamentals.

The rest of the paper is organized as follows. Section 4.2 discusses the related literature. In Section 4.3, I explore the empirical distribution of corporate earnings, emphasizing the properties related to the higher-order moments of corporate earnings. Section 3 also provides an illustrative example to give the economic intuition of the conditional earnings skewness. Section 4.4 presents the model incorporating the empirical facts. I describe the data and econometric methodology in Section 4.5. Section 4.6 reports the empirical results. Section 4.7 concludes.

4.2 Literature Review

This paper bridges two lines of the literature. First, this paper contributes to the literature on the relationship between higher-order moments and asset prices by documenting earnings skewness as a novel stock market return predictor. This paper is also related to the literature on path dependence of aggregate output. The interaction of path dependence and non-Gaussian shocks gives rise to the predictive power of earnings skewness.

4.2.1 Asset Prices and Non-Gaussian Shocks to Fundamentals

The non-Gaussian shocks exist in all kinds of macroeconomic variables. The asset pricing implications of the non-Gaussian shocks to fundamentals are well documented in different strands of recent literature. Yang (2011) documents that the empirical distribution of durable consumption growth is negatively skewed. Thus, non-Gaussian shocks exist in the consumption growth. He shows that the performance of a long run risk model incorporating this empirical feature is significantly improved. Non-Gaussian shocks show up in corporate earnings at the market level. Basu (1997) and Givoly and Hayn (2000) report that the corporate earnings are time varying and negatively skewed. Longstaff and Piazzesi (2004) demonstrate that taking into consideration the jumps risk in corporate earnings helps explain the equity premium puzzle. Segal, Shaliastovich, and Yaron (2015) also add to this line of research by documenting the asset pricing implications of the non-Gaussian shocks of industrial production.

To capture the non-Gaussian shocks in fundamentals, the typical treatment in previous literature is to specify jumps in the processes of consumption growth or dividend. However, only jumps by themselves cannot fully capture the dynamics of higher-order moments in fundamentals because of the potential leverage effects. On the other hand, modeling time-varying volatility in a diffusion process to capture the leverage effect cannot match the empirical distribution of macroeconomic variables with discontinuous and clustered jumps since the diffusion process only allows a continuous path. The time-varying skewness of macroeconomic variables is generated by a combination of jumps and leverage effect.

In this paper, I use the skew-normal shock to capture the mix of leverage effects and jumps in corporate earnings dynamics. Colacito, Ghysels, Meng, and Siwasarit (2015) demonstrate that the skewness pattern generated by skew-normal shocks, comparing with the pattern generated by jump-diffusion process, is closer to that in the real data. In the Section 4.3, I document a strong leverage (or inverse leverage) effect for different corporate earnings measures. The existence of leverage (inverse leverage) effect indicates the importance of using skew-normal shocks to capture the non-Gaussian shocks of corporate earnings.

4.2.2 The Path Dependence in Fundamentals

Path dependence, a term widely used in economics, political science and law, is asserted as "history matters". Specifically, an economy is called path dependent when the effect of a shock on the level of aggregate output (corporate earnings) is permanent in the absence of future offsetting shocks (Durlauf (1993)). Path dependence indicates that multiple equilibrium exists in the economy. An economy-wide large shock can move the economy to a different "path" if no future offsetting shocks occur. The path dependence feature of the aggregate output implies that the statistics on realized values of the output contains information on the future output, thus on asset prices at the aggregate level.

It is well documented in the economics literature, especially growth theory, that strong intertemporal complementarities between agents can imply that history has long lasting effects (Arthur (1989), David (1986, 1988), Krugman (1991a, b)). Durlauf (1993, 1994), among others, illustrate that the productivity-enhancing technology spillover across firms can lead to path dependence in aggregate output.

Finance literature, in contrast to economics literature, concentrates on the econometric expression, but not on the theory of path dependence features in finance data. Cai (1994), Hamilton and Susmel (1994) and Gray (1996), among others, describe the interest rate process as a path-dependent GARCH model. Specifically, there are two regimes for the interest rate in their path-dependent GARCH model. Under each regime, the interest rate conditional variances have different data generating processes. For example, in regime 1 and period 1, the data generating process for interest rate conditional variance is $h_{11} = \omega_1 + a_1\epsilon_0^2 + b_1 h_0$. And $h_{12} = \omega_2 + a_2\epsilon_0^2 + b_2 h_0$ for regime 2. h_{11} (h_{12}) stands for the conditional variance in period 1 under regime 1 (2). Moreover, the shocks also depend on previous states. For example, in period 2, there are two possible unexpected changes: $\epsilon_{1|2}$, representing the unexpected change in the short rate at period 1 given that the process was then in regime 2, and similarly the $\epsilon_{1|1}$. Consequently, there are four possible expressions for interest rate conditional variance h_2 at period 2: $\omega_1 + a_1\epsilon_{1|1}^2 + b_1 h_{1|1}$, $\omega_2 + a_2\epsilon_{1|1}^2 + b_2 h_{1|1}$, $\omega_1 + a_1\epsilon_{1|2}^2 + b_1 h_{1|2}$ and $\omega_2 + a_2\epsilon_{1|2}^2 + b_2 h_{1|2}$. The conditional variance never converges to a single expression. In this specification, the conditional variance of interest rate specified in the path dependent GARCH model depends not only on the current regime but also on the entire history of the process since the unexpected changes of interest rates also depends on regimes.

Gray (1996) finds this generalized path-dependent GARCH model has the best performance among interest rate models. In my model, the treatment on the path dependence of corporate earnings is in spirit similar to that in Gray (1996). The time-varying skewness parameter in my model follows different processes under different regimes. The skewness parameter depends on both "current regime and past history of process".

The possible asset pricing implications of path dependence features embedded in macroeconomic variables are surprisingly not addressed in previous economics or finance literature. This paper is the first to demonstrate that the path dependence feature of corporate earnings, combined with non-Gaussian shocks, provides the explanatory power of historical earnings skewness on market returns. Moreover, the path dependence itself has economic intuition, which is the time-varying technology spillover documented by Durlauf (1994). The path dependence, as an intermediary in this paper, links "technological aspects of production" to earnings skewness, and then to stock market returns.

4.3 Stylized Facts and The Illustrative Example

In this section, first I document two stylized facts about the market-level corporate earnings: the existence of non-Gaussian shocks and path dependence. I use five quarterly measures for corporate earnings: four earnings surprises measures ($SUE1$,

$SUE2$, $SUE3$, $SUE4$) and one earnings per share measure (EPS). The details on data and measures are described in Section 4.5. All five measures are value-weighted averages of the correspondent measures of individual firms. Second, I use an illustrate example to demonstrate that the return predictive power of earnings skewness comes from the interaction of path dependence and non-Gaussian shocks in corporate earnings.

4.3.1 Stylized Facts

I use both figures and summary statistics to illustrate the existence of non-Gaussian shocks in earnings. Figure 4.1 plots the time series of the quarterly corporate earnings measures. Two salient stylized facts emerge. First, corporate earnings measures as indicated in figure 4.1 are highly correlated with NBER business cycles. Corporate earnings are high in booms and low in recessions. Second, corporate earnings are highly volatile, with large movements clustered. These facts confirm the importance of adding jumps in earnings as Longstaff and Piazzesi (2004) did.

Figure 4.2 plots the time series mean and volatility of corporate earnings. The striking pattern is the high correlation between the first and second moments of corporate earnings. The first plot in figure 4.2 indicates that $SUE1$ has an inverse leverage effect, a positive relationship between its mean and variance. In contrast, the second plot shows a strong negative relationship between mean and variance of $SUE3$. The figure also reveals the limitation of previous studies only incorporating the volatility of macroeconomic quantity variables. During certain periods such as the financial crisis between 2007 and 2009, the volatility of corporate earnings jumps. Simultaneously, the level of earnings also jumps. The second moment of fundamentals cannot capture the co-jumps in the mean and volatility of fundamentals. To capture the interaction of mean and variance of corporate earnings, we need to explore the skewness.

Table 4.2 is consistent with the figures, showing that all five corporate earnings measures are all skewed. Specifically, EPS, $SUE1$, and $SUE2$ are positively skewed. But $SUE3$ and $SUE4$ are negatively skewed. I then calculate the correlations of non-overlapping mean and variance for corporate earnings measures and report as "Lev" in table 4.2. The signs of the correlations are consistent with the sign of earnings skewness. Specifically, the mean-variance correlations of $SUE1$, $SUE2$ and EPS are 0.27, 0.51 and 0.85, respectively. The correlations of $SUE3$ and $SUE4$ are -0.62 and -0.60. The consistent signs of skewness and mean-variance correlation measures indicates the leverage effect (inverse leverage effect) is an important component of corporate earnings skewness. One needs to consider earnings skewness, not just the jumps in earnings to capture the non-Gaussian shocks in fundamentals.

The path dependence of aggregate output is widely discussed in previous economics literature. There is no unified test for the path dependence. In this paper, I use three tests to illustrate the different aspects of the path dependence. First, I estimate the serial correlations for each corporate earnings measure. The unreported results indicate that all earnings measures are very persistent. Specifically, the current earnings measures have significant impact on earnings even more than five years ahead. The strong autocorrelations imply earnings history matters for future earnings. I then test whether there are different "paths" in corporate earnings. To do this, I use the Bai-Perron test for structural breaks in the mean of earnings and the Stock-Watson test for breaks in earnings variance. The Bai-Perron test rejects the null hypothesis of no structural break in the mean. Simultaneously, Stock-Watson test implies the existence of structural breaks in the earnings variance. The existence of different regimes in earnings indicates there are different "paths" in earnings. Furthermore, I also find that the band threshold autoregressions (TAR) with different thresholds can fit the earnings data very well. The TAR implies there exists multiple autoregressions for the earnings process.

In summary, this section documents two stylized facts in corporate earnings: (i) Time-varying skewness exists in corporate earnings; and (ii) Path dependence. In section 4.4, I incorporate the two stylized facts in the framework of Lettau and Wachter to help understand the predictive power of earnings skewness on stock market returns.

4.3.2 The Illustrative Example

In this section, I illustrate how earnings skewness, capturing both path dependence and non-Gaussian shocks, can predict future returns. As reported in Table 4.1, suppose there exists an economy with 18 quarters (periods from 1 to 18) of history including both booms and recessions. The level and eight-quarter rolling skewness of earnings are reported for each quarter. In this economy, path dependence and non-Gaussian shocks of earnings are captured by persistence (periods 1 through 8, 9 through 15), and jumps (periods 9 and 16) in earnings, respectively. Following Lettau, Ludvigson, and Wachter (2007), I assume the representative agent cannot observe the true state of the economy but infers it from the historical earnings data. A negative jump (period 9) in the path-dependent earnings, by the knowledge of the agent, indicates the occurrence of a bad state. Earnings skewness sharply decreases at the occurrence of bad state from 0.16 in period 8 to -2.673 in period 9. The representative agent incorporates into his information set this decrease in historical earnings skewness, interpreting the decrease in earnings skewness as an increasing risk level of the market portfolio. Around the occurrence of the bad state, the skewness is negatively related to future returns since the representative investor needs future compensation to hold the market portfolio with increasing risk indicated by decreasing skewness. Similarly, the agent interprets the positive jump in period 16 as a decrease in the risk of holding market portfolio. The positive jump corresponds to a sharp increase in earnings skewness (2.356 in period 16). Thus, during the appearance of the good state, the earnings skewness still has the negative relationship with future market portfolio returns.

Besides identifying the occurrence of a regime switch, the earnings skewness also provides an estimate of how long changes in a regime are expected to last. As shown in the illustrative example, the earnings skewness, after the negative jump in period 9, monotonically increases from period 10 to period 15 right before the positive jump in period 16. From the series of earnings skewness between period 10 and 15 after the negative jump, the representative agent infers that the influence of the negative jump in period 9 is gradually alleviated. The gradual alleviation (between period 10 and 15) of the negative impact indicates fallen risk in holding the market portfolio compared with the risk at the occurrence of the bad state in period 9. The agent thus requires less compensation in future market portfolio returns in periods 10 to 15 than that in period 9. By the same token, the monotonic decrease of skewness after the initial positive jump in period 16 indicates a dilution of the positive news, thus relatively increasing risk in holding the market portfolio compared with the risk at the beginning of the good state in period 16. The investor requires higher future compensation for the decreasing skewness. In sum, the time-varying earnings skewness can predict future market returns because it contains information on the representative agent's future compensation on holding the market portfolio.

4.4 Model

In this section, I introduce a dynamic model taking into consideration both the path dependence and non-Gaussian shocks in corporate earnings. In general, there are two ways to model higher-order moments of corporate earnings and asset prices. One way is to propose a general equilibrium model with a preference of producers, an endowment, and the distribution of cash flows. The second approach is to directly specify the stochastic discount factor and the distribution of corporate earnings, solving the price function (statistical model). If the statistical model for corporate earnings and asset prices coincides with the equilibrium production process, either of the two approaches can give correct implications on the relationship between the skewness of corporate earnings and asset returns.

I employ the second approach by extending the framework of Lettau and Wachter (2011) from two aspects: (i). the shocks to fundamentals in my model are skew-normal shocks taking into consideration the non-Gaussian shocks in earnings; (ii). to capture the path dependence feature, I specify the skewness parameter of skew-normal shocks to have two regimes with different data generating processes. In the baseline model, I assume there exists one representative investor and one representative firm. I first present the general model with an arbitrary number of skewness shocks and then show a specific case with only two shocks, one to corporate earnings, the other to the interest rate.

4.4.1 General Model

Let H_t be a $m \times 1$ vector of state variables at time t and ϵ_{t+1} be a $m \times 1$ vector of shocks. I assume that the state variables evolve according to the vector autoregression

$$H_{t+1} = \Theta_0 + \Theta H_t + \sigma_H \epsilon_{t+1}, \tag{4.1}$$

where Θ_0 is $m \times 1$, Θ is $m \times m$, and σ_H is $m \times (m+1)$. I then assume the shocks ϵ_{t+1} to be identically and independently distributed as skew-normal distribution $SKN(0, 1, \nu_t)$. ν_t is the shape parameter. Specifically, the probability density function (PDF) of ϵ_{t+1} is

$$p(x) = \frac{1}{\sigma\pi} \exp(-\frac{(x-\mu)^2}{2\sigma^2}) \int_{-\infty}^{\frac{\nu(x-\mu)}{\sigma}} exp(-\frac{t^2}{2})dt \tag{4.2}$$

The PDF of skew-normal distribution is the PDF of the standard normal distribution weighted by its cumulative distribution function. The weight depends on the shape parameter ν. When $\nu = 0$, the skew-normal distribution degenerates to the standard normal distribution. When $\nu > 0$ ($\nu < 0$), the positive (negative) component of the standard normal PDF is over weighted relative to its negative (positive) component. In Appendix A, I introduce the lemmas related to skew-normal distribution which are used in the model. By using the skew-normal distribution, the skew-normal shocks ϵ_{t+1} can capture the time-varying skewness existing in the corporate earnings.

To incorporate the path dependence feature of earnings in my model, I assume that the skewness parameter, ν_{t+1} has two regimes, high (H) with the probability P_H to happen and low (L) with probability P_L $(1 - P_H)$ in each period. In different regimes, the skewness parameter evolves in different AR(1) processes with different autocorrelations ($\rho_{H\nu}$ and $\rho_{L\nu}$). Moreover, the shocks are also regime dependent. There are two shocks correspondent to regimes: $\zeta^{\nu}_{t+1|Ht}$ and $\zeta^{\nu}_{t+1|Lt}$. Specifically, $\zeta^{\nu}_{t+1|Ht}$ ($\zeta^{\nu}_{t+1|Lt}$) is the shock to ν_{t+1} if the shape parameter ν is in the high (low) regime in period t. In sum, the skewness parameter can evolve following either of the AR(1) process

$$\nu_{t+1} = \begin{cases} \alpha_{H\nu} + \rho_{H\nu}\nu_t + \zeta^{\nu}_{t+1|Ht}, \\ \alpha_{H\nu} + \rho_{H\nu}\nu_t + \zeta^{\nu}_{t+1|Lt}, \\ \alpha_{L\nu} + \rho_{L\nu}\nu_t + \zeta^{\nu}_{t+1|Ht}, \\ \alpha_{L\nu} + \rho_{L\nu}\nu_t + \zeta^{\nu}_{t+1|Lt}. \end{cases} \tag{4.3}$$

.

The above expression incorporates the path dependence feature because the shape parameter ν_{t+1} in (4.3) is determined not only by the current period shock ζ^{ν} but also by the past regime-dependent history. The four possible paths in (4.3) cannot converge to one identical path, similar to the setting in Cai (1994) and Gray (1996). This setting of path dependence makes my model parsimonious and tractable. We can see in later section that the path dependence feature does not affect the solution form of the contemporaneous price function but affects the future return dynamics.

I assume the earnings (x_t), the earnings growth (Δx_t) and the risk free rate (r^f_{t+1}) follow the general affine functions of the underlying state vector H_t:

$$\begin{aligned} x_t &= \delta_0 + \delta H_t, && (4.4)\\ \Delta x_t &= \eta_0 + \eta H_t, && (4.5)\\ r^f_{t+1} &= \alpha_0 + \alpha H_t. && (4.6) \end{aligned}$$

Following the previous literature[1] on the production based asset pricing (Belo, Bazdresch, and Lin (2014), Belo, Vitorino, and Lin (2014) and Favilukis and Lin (2013)), I assume the form of stochastic discount factor (SDF)[2] takes the form

$$M_{t+1} = exp(-r^f_{t+1} - \sigma_x \Delta x_{t+1}). \tag{4.7}$$

The stochastic discount factor is a function of the interest rate and the change in earnings. Asset prices are determined by the following Euler equation:

$$P^x_{nt} = E_t[M_{t+1} P^x_{n-1,t+1}]. \tag{4.8}$$

The price of the zero coupon equity can be determined recursively from equation (4.8). In the Appendix B, I verify that (4.8) satisfies:

$$\begin{aligned} P^x_{nt} &= exp(A^x_{nt} + B^x_{nt} H_t), && (4.9)\\ A^x_{nt} &= \mu + log(2) + \frac{1}{2}\kappa_1(\kappa_1 + 2\mu) + log\Phi(\frac{\kappa_1 \nu_t}{\sqrt{1+\nu_t^2}}), && (4.10) \end{aligned}$$

[1]Previous literature specifies the stochastic discount factor as a function of incremental productivity. The incremental earnings can be specified as a function of incremental productivity.

[2]The form of stochastic discount factor is acceptable: There are two assets in this economy: bond and stock but the number of shocks is larger than or equal to 2; the market is incomplete, so there are infinite number of SDFs.

$$B^x_{nt} = -\alpha - \theta B^x_{n-1} - \sigma_x \theta \eta, \tag{4.11}$$

where

$$\mu = -\alpha_0 - \sigma_x \eta_0 + A^x_{n-1} + \theta_0 B^x_{n-1} - \sigma_x \eta \theta_0, \tag{4.12}$$

$$\kappa_1 = B^x_{n-1} - \sigma_x \eta. \tag{4.13}$$

This general solution of the model shows that the skewness parameter ν_t can determine contemporaneous stock price. To detect the return predictability of earnings skewness, we need to look at the expression of future n periods cumulative return: $R_{t+n} = P_{t+n}/P_t$. The future n periods return is a function of its contemporaneous shape parameter ν_{t+n}. The ν_{t+n} is determined jointly by period $t+1$ shock and the whole past history of ν_t. Thus, the historical skewness contains information on future market returns.

4.4.2 Model With Shocks Only to Earnings and the Risk-Free Rate

The model introduced in this section is a special case of the general model introduced in last section since it has only two shocks, a shock to the earnings and a shock to the risk-free rate. Let ϵ_{t+1} denote a 2×1 vector of independent skew-normal shocks. The shape parameter ν_t still follows a path-dependent AR(1) process the same as specified in last section. Let x_t denote the level of the corporate earnings at time t. I assume that the growth rate of earnings is conditionally skew-normal distributed with a time-varying mean x_t that follows a first-order autoregressive process

$$x_{t+1} = (1 - \Phi_x)g + \Phi_x x_t + \sigma_x \epsilon_{t+1}, \tag{4.14}$$

$$\Delta x_{t+1} = x_t + \sigma_x \epsilon_{t+1}, \tag{4.15}$$

where σ_x is a 1×2 vector of loadings on the shocks ϵ and Φ_x is the autocorrelation. I also specify a process for the risk free rate. Let r^f_{t+1} denote the continuously compounded risk-free return between times t and $(t+1)$. I assume that

$$r^f_{t+1} = (1 - \Phi_r)r^f + \Phi_r r^f_t + \sigma_r \epsilon_t, \tag{4.16}$$

where σ_r is a 1×2 vector of loadings on the shocks ϵ, r^f is the unconditional mean of r^f_t, and ϕ_r is the autocorrelation term.

Real Bonds

Let P^r_{nt} denote the price of an n-period real bond at time t. In the other words, P^r_{nt} denotes the time-t price of an asset with a fixed payoff of one at the time $t+n$. The price of this real bond can be determined through recursive substitution using the same method as shown in the appendix B. I still use the following Euler equation for recursive substitution:

$$E_t[M_{t+1}P^r_{n-1,t+1}] = P^r_{nt}. \tag{4.17}$$

The boundary condition is $P^r_{0t} = 1$ since the bond pays a face value of 1 at maturity. I conjecture the solution for the real bond as

$$P^r_{nt} = exp(A^r_n + B^r_{n,r}(r^f_t - r) + B^r_{ne}\Delta x_t). \tag{4.18}$$

Solving (4.17) recursively, I get the following explicit solution for the real bond price:

$$\begin{aligned}
P^r_{nt} &= exp(A^r_n + B^r_{n,r}(r^f_t - r) + B^r_{ne}\Delta x_t), && (4.19)\\
A^r_{nt} &= \gamma + A_{n-1} - (1 - 2\Phi_r)r_f + log(2) + \frac{1}{2}\kappa_1^2 + log\Phi(\frac{\kappa_1 \nu_t}{\sqrt{1+\nu_t^2}}), && (4.20)\\
B^r_{nr} &= -\Phi_r(1 - B^r_{n-1,r}), && (4.21)\\
B^r_{nx} &= -\Phi_x(B^r_{n-1,x} - \sigma_x), && (4.22)
\end{aligned}$$

$$\kappa_1 \quad = \quad -\sigma_r(1 - B^r_{n-1,r}) + \sigma_x(B^r_{n-1,x} - \sigma_x). \tag{4.23}$$

I solve equations (4.21) and (4.22) recursively and find that

$$B^r_{nr} \quad = \quad -\frac{1-\Phi_r^n}{1-\Phi_r} < 0, \tag{4.24}$$

$$B^r_{nx} \quad = \quad \frac{\sigma_x\Phi_x(1-\Phi_x^{2n})}{1+\Phi_x} \geq 0. \tag{4.25}$$

Equations (4.24) and (4.25) show that the price of a real bond is determined by the real rate, the earnings growth rate and the time-varying earnings skewness ν_t. The real bond price decreases in the real interest rate. Similar to Lettau and Wachter (2011), equation (4.24) can also replicate the duration effect, i.e. the magnitude of price response to a change in r^f_{t+1} is increasing in maturity. Equation (4.25) implies that the earnings have a positive relationship with bond price. Consequently, this model also has implications on the relationship between earnings skewness and bond yields. Equation (4.23) indicates that

$$\kappa_1 = -\sigma_r(1 - B^r_{n-1,r}) + \sigma_x(B^r_{n-1,x} - \sigma_x), \tag{4.26}$$

$$= -\frac{\sigma_r(1-\Phi_r^n)}{\Phi_r(1-\Phi_r)} - \frac{\sigma_x^2(1-\Phi_x^{2n})}{1+\Phi_x} < 0. \tag{4.27}$$

Combining equations (4.19), (4.20) and (4.27), I find the bond price increases in the contemporaneous skewness of firm fundamentals. The yield to maturity on a real bond is defined as

$$y^r_{nt} = -\frac{1}{n}logP^r_{nt} = -\frac{1}{n}(A^r_n + B^r_{n,r}(r^f_t - r) + B^r_{nx}\Delta x_t). \tag{4.28}$$

I then substitute equation (4.3) into equation (4.28). Since equation (4.3) indicates that there exists a path-dependent predictive component of the time-varying skewness of corporate earnings, the contemporaneous relationship between bond yield and time-varying skewness of earnings becomes a predictive relationship, i.e. time-varying skewness of earnings at time t, ν_t can predict the bond yield at time $t+1$. So this model indicates a positive relationship between bond yield and earnings skewness. The predictive power of earnings skewness on yields is empirically tested in Section 4.6.3.

Equity

To model the equity, I first model a simpler case, the zero-coupon equity. I first assume there exists an equity that only gets the earnings at time $(t+n)$ but no earnings in previous periods. Following Lettau and Wachter (2011), I refer to this asset as zero-coupon equity. P^e_{nt} denotes the price of the zero-coupon equity at time t which will pay aggregate earnings at period $(t+n)$. I conjecture the solution form for the zero-coupon bond the same as that for real bonds:

$$P^x_{nt} = exp(A^x_n + B^x_{n,r}(r^f_t - r) + B^x_{nx}\Delta x_t). \tag{4.29}$$

The key difference between explicit solutions of the real bond and zero-coupon equity is in the boundary conditions. I assume the boundary condition for zero-coupon equity is $P^x_{0t}/x_t = 1$. Even though the solution forms of the zero-coupon equity and real bonds are the same, the difference in boundary conditions leads to different calibration results. The solution for the zero-coupon equity is as follows:

$$\begin{aligned}
P^x_{nt} &= exp(A^x_n + B^x_{n,r}(r^f_t - r) + B^x_{nx}\Delta x_t), && (4.30)\\
A^x_{nt} &= \gamma + A_{n-1} - (1-2\Phi_r)r_f + log(2) + \frac{1}{2}\kappa_1^2 + log\Phi(\frac{\kappa_1\nu_t}{\sqrt{1+\nu_t^2}}), && (4.31)\\
B^x_{nr} &= -\Phi_r(1 - B^x_{n-1,}), && (4.32)\\
B^x_{nx} &= -\Phi_x(B^x_{n-1,x} - \sigma_x), && (4.33)\\
\kappa_1 &= -\sigma_r(1 - B^x_{n-1,r}) + \sigma_x(B^x_{n-1,x} - \sigma_x). && (4.34)
\end{aligned}$$

The parameters A^x_{nt}, B^x_{nr} and B^x_{ne} have the same forms as those of real bonds. My model implies a contemporaneous negative relationship between the skewness of corporate earnings and the zero-coupon equity price. The market portfolio is the aggregation of all zero coupon equities at different horizons. The solution for price of the market portfolio is

$$P^m_t = \sum_{n=1}^{\infty} exp(A^x_n + B^x_{n,r}(r^f_t - r) + B^x_{nx}\Delta x_t). \tag{4.35}$$

In summary, this set of models indicates that the earnings skewness has a positive relationship with real bond yield and a negative relationship with contemporaneous market portfolio prices. If earnings skewness is persistent, the model indicates earnings skewness has a positive relationship with future bond yields and a negative relationship with future market portfolio (market index) returns.

4.5 Data, Measures and Methodology

4.5.1 Data

The quarterly earnings data is obtained from the COMPUSTAT database. To be included in the sample, the firm must have at least 16 earnings observations in the COMPUSTAT universe. I then take the value-weighted (weighted by the size of previous quarter) average of earnings per share and earnings surprises of individual firms to get the earnings and earnings surprises measures at the market level. Book-to-market ratio (B/M), default spread (DEF), term spread (TMS) and other fundamental variables are obtained from Amit Goyal's website. The S&P 500 quarterly return data is also obtained from Amit Goyal's website[3]. I aggregate the quarterly S&P 500 returns to obtain cumulative market returns for different horizons.

[3] The link for the website of Amit Goyal is http://www.hec.unil.ch/agoyal/.

4.5.2 Skewness Measures

Consistent with the arguments in Cai (1994) and Hamilton and Susmel (1994), the parameters in a path-dependent autoregressive model are essentially intractable and impossible to estimate due to the dependence of the skewness parameter ν_t on the entire past history of the data. I use a non-parametric way to measure the path dependent non-Gaussian shocks on earnings by estimating the coefficients of skewness for earnings and earnings surprises. The five skewness measures (SK_{SUE1}, SK_{SUE2}, SK_{SUE3}, SK_{SUE4} and SK_{EPS}) can be separated into three groups based on different measures of corporate earnings. Specifically, SK_{SUE1} and SK_{SUE2} are time-series skewness of earnings surprises with earnings surprises constructed using a random walk model. SK_{SUE3} and SK_{SUE4} are skewness of earnings surprises with earnings surprises defined using analyst earnings forecasts. SK_{EPS} is the skewness of earnings per share.

Historical SUE Skewness

I first construct four measures for standardized unexpected earnings (SUE): Following the convention in Livnat and Mendenhall (2006), I define $SUE1$ for individual stocks using the seasonal random walk model

$$SUE1_t = \frac{EPS_t - EPS_{t-4}}{P_t}, \tag{4.36}$$

where EPS_t is the earnings per share before extraordinary items of quarter t, and P_t is the stock price at the end of quarter t. I define $SUE2$ the same way as $SUE1$ but excluding "extraordinary items". I define $SUE3$ and $SUE4$ using analyst forecasts (Livnat and Mendenhall (2006)) as

$$SUE3_t = \frac{EPS_t - \widehat{EPS}_t}{P_t}, \tag{4.37}$$

where $\widehat{EPS}_t$ is the median of analyst earnings forecast for quarter t made in the 90 days prior to the earning announcement date. $SUE4$ is defined similar to $SUE3$ except using the mean of analyst earning forecast.

I take the value-weighted averages (using market capitalization in previous quarter($t-1$)) of SUEs for each quarter. I construct skewness of aggregate SUE as the coefficient of skewness of value-weighted SUEs during the rolling window of quarter $t-n$ to $t-1$

$$SK_{SUE} = \frac{n}{(n-1)(n-2)} \sum_{\tau=t-n}^{t-1} \left(\frac{SUE_\tau - \overline{SUE}}{s} \right)^3, \tag{4.38}$$

where SUE_τ is the value-weighted average quarterly standardized unexpected earnings. $\overline{SUE}$ and s are sample averages and standard deviations of $SUEs$ within the rolling windows, respectively. I choose the benchmark case $n = 24$ for the rolling window in this paper since the average length of the NBER business cycle is around 6 years. Using 24 quarters rolling window could largely filter out seasonality issues. As a robustness check, I also used $n = 16$ and 20 and obtained similar results. I do not use earnings or SUE information at quarter t because earnings at time t is not reported until quarter $t+1$.

Historical Total Earnings Skewness

The historical total earnings skewness measure is defined in line with its SUE counterparts. I first construct the value-weighted average (using market capitalization in the last quarter $(t-1)$ of earnings per share. The total earnings skewness is defined as the coefficient of corporate earnings skewness

$$SK_{EPS} = \frac{n}{(n-1)(n-2)} \sum_{\tau=t-n}^{t-1} \left(\frac{TOT_\tau - \overline{TOT}}{s} \right)^3, \tag{4.39}$$

where EPS is the value weighted average quarterly earnings per share. $\overline{EPS}$ and s are the sample average and the standard deviation of EPS within the rolling windows, respectively. The benchmark rolling window is 24 quarters in line with the designs for SUE skewness measures.

4.5.3 Econometric Methods

When I regress returns of various holding periods on variables measured in previous period, the regression coefficient is subject to an upward small-sample bias. This bias is more severe when the sample size is small, the independent variable is highly persistent or when the correlation between the regression errors and the innovations in the independent variable is strong (Campbell, Lo and, Mackinlay (1997), Hirshleifer, Hou, and Teoh (2009)). The t statistics and p value of the regression should also be adjusted for the serial correlation.

I employ two methods to adjust the potential biases in the predictive regression. I first use Newey and West (1987) standard errors with 12 lags for all the OLS regressions to adjust the serial correlation. Since this method is quite stylized, the details are ignored. The second approach is to bootstrap a randomization p-value for regression coefficients on the skewness of corporate earnings following the Nelson and Kim (1993) procedure. Specifically, I simulate artificial series of returns and the independent variable under the null hypothesis that earnings skewness has no predictability by randomly drawing with replacement of the residual pairs from the return predictive regression and a first-order autoregression of the earnings skewness. I then regress the bootstrapped returns on the bootstrapped skewness of corporate earnings at the market level to get the regression coefficient. This procedure is repeated for 10,000 times. The empirical distribution of the regression coefficient is generated under the null hypothesis of no predictability. If there is a huge fraction of simulated regression coefficients are further to zero than the regression coefficient from the true regression, the null hypothesis must be accepted. The randomization p value is then the fraction of the 10,000 simulated regression coefficients further away from zero than the actual coefficient estimate.

To explore the economic significance of the return predictability of earnings skewness, I also calculate the bias-adjusted regression coefficients following Kendall (1954), Stambaugh (2000) and Hirshleifer, Hou, and Teoh (2009) by assuming there exists a general autoregressive framework for return R_t and a return predictor X_t:

$$R_t = \alpha + \beta X_{t-1} + u_t, u \sim i.i.d.N(0, \sigma_u^2), \tag{4.40}$$

$$X_t = \mu + \phi X_{t-1} + \nu_t, \nu \sim i.i.d.N(0, \sigma_\nu^2). \tag{4.41}$$

The bias in the OLS estimate of β in the predictive regression is proportional to the bias in the OLS estimate of ϕ in the first-order autoregression for the earnings skewness. Combining

$$E(\hat{\beta} - \beta) = \frac{\sigma_{uv}}{\sigma_v^2} E(\hat{\phi} - \phi), \tag{4.42}$$

where $\hat{\phi}$ is the OLS estimate of ϕ. Kendall (1954), Stambaugh (2000) prove that the bias in the OLS estimate of ϕ is

$$E(\hat{\phi} - \phi) = -\frac{1 + 3\phi}{n} + O(n^{-2}), \tag{4.43}$$

where σ_{uv}, σ_v, and n are sample covariance, sample standard deviation and sample size respectively. Combining equation (4.42) and equation , we can calculate the bias-adjusted estimate of β in the predictive regression and that of ϕ in the autoregression using the following formula:

$$\beta_{adj} = \hat{\beta} + \frac{\sigma_{uv}}{\sigma_v^2} \frac{1 + 3\phi_{adj}}{n}, \tag{4.44}$$

$$\phi_{adj} = \frac{n\hat{\phi} + 1}{n - 3}, \tag{4.45}$$

where β_{adj} is the bias-adjusted coefficient, ϕ_{adj} is the bias-adjusted estimate for ϕ. I report the bias-adjusted coefficients and randomization P value for univariate regressions.

4.6 Empirical Results

In this section, I empirically analyze the asset pricing implications of corporate earnings skewness. Section 4.6.1 discusses the time series properties of corporate earnings skewness measures. I then explore the market return predictability of this skewness in Section 4.6.2. Section 4.6.2 also explores the coskewness of corporate earnings to confirm the microfoundation of corporate earnings skewness. Finally, in Section 4.6.3, I examine the predictability of earnings skewness on government bond yields. In this section, I also detect the explanatory power of bond yields on returns and show it can be decomposed into a cash flow part which is captured by earnings skewness and a discount rate part.

4.6.1 Descriptive Statistics

Table 4.3 reports the summary statistics for the corporate earnings skewness measures and other control variables. Corporate earnings have significant time-varying skewness. Of the five measures of corporate earnings skewness, SK_{SUE1}, SK_{SUE2}, and SK_{EPS} are on average significantly positive. In contrast, SK_{SUE3} and SK_{SUE4} are on average slightly negatively skewed. The difference in the levels of corporate earnings measures is consistent with the findings in Livnat and Mendenhall (2006) that different types of SUEs capture different information. The corporate earnings skewness measures are quite volatile. For example, SK_{EPS} ranges from -5.56 to 8.52. Figures 4.3 and 4.4 confirm the fluctuation of earnings skewness. Moreover, these figures also indicate the earnings skewness measures are procyclical, high in booms and low in recessions. Moreover, consistent with my model assumption, the skewness measures are highly persistent with first-order autocorrelations ranging from 0.87 to 0.96.

Table 4.4 reports the contemporaneous correlations of quarterly earnings skewness measures and control variables. Of the five measures of earnings skewness, SK_{SUE1} and SK_{SUE2} are almost perfectly correlated. Similarly, SK_{SUE3} and SK_{SUE4} have a large correlation of 0.99. The high correlations across skewness measures indicate that the information contained in the skewness measures does not vary whether or not I exclude special items for earnings or use the mean of analyst earnings forecasts.

The earnings skewness measures seem to be correlated with most control variables as they are positively correlated with LTY, TBL and *cay* but negatively correlated with TMS, BM, and DEF. Among the control variables, the earnings skewness measures have the strongest correlations with government bond yields. Specifically, the correlations between long-term yield and skewness measures are around 0.52 to 0.55. The correlations between short-term yield and skewness measures are between 0.5 to 0.62. The earnings skewness has a positive correlation with long-term/short-term yields even though the two yields have different relationships with business cycles. The implications of earnings skewness on bond yields will be discussed in Section 4.6.3.

4.6.2 Stock Market Predictive Regressions

In this section, I discuss the return predictability of the earnings skewness on stock market excess returns using multiple econometric techniques and controlling for different return predictors. The results indicate that earnings skewness is a robust market return predictor. I also design tests to inspect whether or not the predictive power of earnings skewness comes from earnings coskewness which is an inter-firm relationship. A dominant role of coskewness term in the predictive power of earnings skewness supports my argument that the predictive power of earnings skewness comes from the time-varying degree of technology spillover across firms.

Univariate Tests

Table 4.5 reports the results for the univariate regressions of corporate earnings skewness measures on two-quarters ahead to eight-years ahead stock market returns in excess of short-term risk-free rates. I skip one quarter for earnings skewness measures to make sure accounting information is known to investors. For the OLS regressions, Newey-West standard errors with 12 lags are used to adjust t statistics for each regression. All earnings skewness measures have a negative relation with future stock market excess returns. Earnings skewness can significantly predict future stock market returns from two-quarters ahead to eight-years ahead. For example, a one unit increase in SK_{SUE1} leads to 0.122 (coefficient is -1.217) percent decrease in one-year cumulative stock market excess returns. The predicting power (parameters and t statistics) of earnings skewness increases in horizon. The coefficient of eight-year returns predictive regression (-16.886) is more than 15 times larger than that of the one-year return predictive regression (-1.217). If daily returns are slightly predictable by a slow moving variable, predictability adds up over long horizons. Corporate earnings skewness measures are highly persistent, so the increase in predicting power along horizons reflects a single underlying phenomenon that earnings skewness predicts stock returns. Among fundamental skewness measures, SK_{SUE1}, SK_{SUE3} and SK_{SUE4} have relatively stronger predicting power since they have predicting powers among all prediction horizons. SK_{SUE2} is relatively weaker in short horizon but catches up after the four-year horizon.

To address the potential small-sample bias in the OLS regression, I report bootstrapping randomization p values and bias adjusted coefficients following Nelson and Kim (1993). The randomized p values (bias adjusted coefficients) are reported in the row marked as Rand:P (Adj-β) in each panel of Table 4.5. In general, the results are even stronger than those using OLS regressions. The return predictability patterns differ for different earnings skewness measures. For random walk based SUE skewness

(SK_{SUE1} and SK_{SUE2}), random p values show that they have predicting power starting from short horizon, i.e. two-quarters ahead and four-quarters ahead, respectively. Moreover, the bias-adjusted coefficients for SK_{SUE1} and SK_{SUE2} are larger than OLS regression coefficients, especially in the short horizon regressions. The bootstrapping results indicate that the explanatory power of random walk based SUE skewness on returns seems to be underestimated by OLS regressions. Similarly, adjusting the small sample bias does not affect the explanatory power of analyst forecasts based earnings skewness (SK_{SUE3} and SK_{SUE4}). Under adjustment of small sample bias, SK_{SUE3} and SK_{SUE4} can still significantly predict future market excess returns in all horizons. However, the bootstrapping approach shows the explanatory power of analyst forecast based earnings skewness is slightly overstated in the short run. Specifically, the bias-adjusted coefficient for earnings skewness on the two-quarters ahead cumulative market excess return is -0.434, smaller than the OLS regression coefficient of -0.578. In contrast to the skewness of earnings surprise, the skewness of earnings per share (SK_{EPS}) has inferior explanatory power. The bias-adjusted approach indicates random walk based earnings skewness measures have a stronger explanatory power than measures based on analyst earnings forecasts. In summary, the univariate regressions indicate a strong negative relationship between earnings skewness and future stock market cumulative excess returns at different horizons from two-quarters to eight-year aheads.

Multivariate Tests

To see whether corporate earnings skewness has incremental power to predict stock market returns after controlling for other aggregate return predictors, I employ multivariate regressions in Table 4.6. I control for four popular return predictors whose predicting power are confirmed in previous studies: book-to-market ratio (B/M), default spread (DEF), term spread (TMS) and consumption-wealth ratio (cay). The

Newey-West standard errors with 12 lags are used to adjust t statistics for regressions. In general, consistent with univariate regressions, earnings skewness is a strong negative return predictor. The explanatory power of different skewness measures differs. SK_{SUE1} and SK_{SUE2} are relative long-horizon return predictors, having predictive power from one-year until eight-year horizons. In contrast, SK_{SUE3} and SK_{SUE4} are short-run return predictors. They can predict stock market excess returns from two-quarter to four-year horizons but lose predictive power in the long run after a 5-year horizon. In contrast to earnings surprise skewness, the skewness of earnings per share (SK_{EPS}) loses explanatory power at all horizons when controlling for other return predictors. The SK_{EPS} seems to contain different information than earnings surprise skewness measures.

Table 4.6 also shows that the R^2s in long-horizon predictive regressions for SUE skewness measures are quite high, around 0.86 to 0.90 in eight-year horizons. In unreported tables, I regress stock market excess returns on four control variables but not earnings skewness measures. The R^2s of regressions are at most 0.60, consistently smaller than those including earnings skewness. The differences in R^2s indicate that earnings skewness has strong economic significance in return predictions. Thus, the path dependence feature of earnings skewness contains unique information on future market returns.

To test whether skewness dominates other moments in corporate earnings, I then run multivariate predictive regressions controlling the 24 quarters rolling mean and volatility of corporate earnings measures ($SUE1, SUE2, SUE3, SUE4$, and EPS). Table 4.7 shows that the explanatory power of earnings skewness is not affected even when controlling for the mean and volatility of historical earnings. In contrast to the coefficients on skewness, the coefficients of earnings mean and volatility are insignificant in most regressions at different horizons. On the other hand, the monotonic increasing pattern in horizons for coefficients does not exist for earnings mean and volatility. This also indicates that the earnings mean and volatility measures do not have significant return predictive power.

In summary, this section shows that the earnings skewness measures can predict future market excess returns even when controlling for different variables, prevailing return predictors or other moments of earnings.

Comparative Regressions

In light of previous findings, it is interesting to examine the relative predictive power of different measures of earnings skewness. To do this, I first use principle component analysis (PCA) to investigate whether the five earnings skewness measures have the same information content. The results regarding PCA are shown in Table 4.8. I then estimate predictive regressions with multiple earnings skewness measures as explanatory variables. The estimated results are reported in Table 4.9.

In Table 4.8, I first include only random-walk model based earnings surprise skewness, SK_{SUE1} and SK_{SUE2}. The PCA analysis indicates that the first principle component can explain more than 99 percent of the variation in these two skewness measures. In other words, only one factor drives SK_{SUE1} and SK_{SUE2}. The PCA analysis shows the first principle can explain 94 percent of the variation in all four earnings surprise skewness measures (SK_{SUE1}, SK_{SUE2}, SK_{SUE3} and SK_{SUE4}). But the first two principle components can cover most of the variation. If all five earnings skewness measures are included in PCA, one needs three factors to explain the dynamics of the earnings skewness. The PCA analysis is consistent with the previous findings: earnings skewness measures are driven by multiple factors and have different explanatory power on future market returns.

I then do a return predictability horse race for different earnings skewness measures. Since SK_{SUE1} (SK_{SUE3}) and SK_{SUE2} (SK_{SUE4}) are driven by the same factor, I ignore the comparative regressions among them. I compare the return predictive power of earnings skewness measures on three-year, five-year and eight-year ahead cumulative excess returns. The results are reported in Table 4.9. For each horizon in model (1) through (3), I include two of the three measures (SK_{SUE1}, SK_{SUE2}, and SK_{EPS}) of earnings skewness as explanatory variables. This allows us to directly compare the explanatory power of each pair. In model (4), I use all three measures. In all the models, control variables are included in the regression specifications.

For three-year ahead return predictability, the estimates of model (1) indicate that SK_{SUE3} dominates SK_{SUE1} as its coefficient is significant, however the coefficient for SK_{SUE1} is insignificant. Models (2) and (3) indicate both SK_{SUE1} and SK_{SUE3} dominate SK_{EPS} in the three-year return predictability. Model (4) indicates that SK_{SUE3} dominate SK_{SUE1} and SK_{EPS} in the short run. The pattern for five-year ahead return predictability is different. SK_{SUE1} dominates the other two earnings skewness measures. SK_{EPS} marginally dominates SK_{SUE3}. The results for five-year return predictability are consistent with those in multivariate regressions since the predictive power of SK_{SUE3} also disappears in predictive regressions with horizons longer than four years. The results for eight-year return predictability confirms the superiority of SK_{SUE1} in long run return predictability. In summary, the results in this section indicate that earnings skewness measures have different information content. SK_{SUE1} and SK_{SUE2} are relatively long run return predictors. In contrast, SK_{SUE3} and SK_{SUE4} are short to medium run return predictors.

Economic Channels: Coskewness of Corporate Earnings

I demonstrate in the previous section that the microfoundation of earnings skewness comes from the interaction of path dependence and non-Gaussian shocks, thus from the productivity-enhancing technology spillover across firms. On the other hand, the earnings skewness at the market level can be decomposed into two terms: average firm-level earnings skewness and *coskewness* across firms. The productivity-enhancing technology spillover, as an inter-firm relationship, must be strongly related to the coskewness terms which capture the inter-firm interaction in the earnings skewness measures. If the predictive power of earnings skewness on returns does come from technological spillover across firms as argued in this paper, the “coskewness” of earnings, but not the average firm-level earnings skewness, must dominate the prediction of earnings skewness on returns. In this section, I first illustrate the decomposition of earnings skewness into coskewness terms and average firm-level skewness terms. I then estimate regressions to show coskewness of earnings dominates the return predicting power of earnings skewness.

Suppose there are N firms in one economy. The corporate earnings at the market level are constructed by the cash flows of these N firms. Assuming equal weights for simplicity, let $e_{pt} = N^{-1}\sum_{i=1}^{N} e_{it}$ be the time t aggregate corporate earnings, $\bar{e}_i = T^{-1}\sum_{t=1}^{T} e_{it}$ be the mean sample earnings (earnings surprises) for firm i, and $\bar{e}_p = T^{-1}\sum_{t=1}^{T} e_{pt}$ be the mean sample market return. Then the sample skewness is

$$\begin{aligned} T^{-1}\sum_{t}(e_{pt}-\bar{e}_p)^3 &= \frac{1}{N^3}\sum_{i=1}^{N}\frac{1}{T}\sum_{t}(e_{it}-\bar{e}_i)^3 \\ &+ \frac{3}{TN^3}\sum_{t}\sum_{i=1}^{N}(e_{it}-\bar{e}_i)\sum_{i'\neq i}(e_{i't}-\bar{e}_{i'})^2 \\ &+ \frac{6}{TN^3}\sum_{t}\sum_{i=1}^{N}(e_{it}-\bar{e}_i)\sum_{i'>i}^{N}\sum_{l>i'}^{N}(e_{i't}-\bar{e}_{i'})(e_{lt}-\bar{e}_l). \end{aligned}$$

The first term in the above equation is the mean of individual firm earnings skewness. The second and third terms are *coskewness* terms capturing the average comovement in one firm's earnings with the earnings variance of the portfolio that comprises the remaining firms. The coskewness of corporate earnings, depending on the cross-sectional heterogeneity of firms' earnings comovement, is a measure of the time-varying technological spillover across firms.

The effect of earnings coskewness increases in the number of firms. If there are N firms in the economy, there will be $N(N-1)+N!/[3!(N-3)!]$ coskewness terms. Since the number of firms in the economy is large, the amount of coskewness terms is far larger than that of firm-level earnings skewness terms. This does not immediately imply that coskewness terms dominate the magnitude of earnings skewness. But when we compare the magnitude of corporate earnings skewness and mean firm-level earnings skewness, we can find that coskewness terms dominate. In unreported results, for example, the skewness of $SUE1$ ($SUE2$) in the full sample is 2.34 (4.03). But the mean firm-level $SUE1$ skewness is -0.78 (-0.52). The difference between aggregate earnings skewness and mean firm-level earnings skewness is the coskewness of corporate earnings. The magnitude of coskewness is much larger than that of mean firm-level skewness.

Even though the magnitude of coskewness dominates that of earnings skewness, we cannot directly argue the return predicting power of earnings skewness comes from earnings coskewness. To test whether earnings coskewness is the driving force of the return predictability of earnings skewness, I estimate predictive regressions with both earnings skewness and mean firm-level earnings skewness as explanatory variables. If the earnings skewness measures outperform mean firm-level earnings skewness, the earnings coskewness (productivity-enhancing technology spillover) is the main component contributing to the return predictability of earnings skewness.

The regression results reported in Table 4.10 confirm my argument. In general, adding in mean firm-level earnings skewness does not affect the return predictive power of earnings skewness. Specifically, SK_{SUE1} and SK_{SUE2} can still significantly predict future market returns even when controlling for mean firm-level skewness. Comparing the predictive regression coefficients for SK_{SUE1} and SK_{SUE2} in Table 4 and 9, we can find that the coefficients of SK_{SUE1} and SK_{SUE2} controlling for mean firm-level earning skewness are almost identical to those without controlling for mean firm-level skewness. SK_{SUE3} (SK_{SUE4}) outperforms mean firm-level earnings skewness in return predictability with horizons shorter than or equal to 5 years. The mean firm-level earnings skewness dominates SK_{SUE3} (SK_{SUE4}) in long horizon regressions. However, since SK_{SUE3} and SK_{SUE4} only have return predicting power in short to medium run (2 quarters to 5 years), the significance of mean-firm level SUE skewness can be absorbed by other return predictors. The results for SK_{SUE3} and SK_{SUE4} are still consistent with my argument.

In sum, the results in Table 4.10 indicate that the predictive power of earnings skewness comes from that of earnings coskewness. The coskewness, capturing the firm cash flow comovement, is a proxy for productivity-enhancing technology spillover across firms. Thus, the confirmation of the return predicting power of earnings coskewness provides the causality relationships from technology spillover to the return predictability of earnings coskewness, and finally to the return predictability of earnings skewness.

4.6.3 Discussion: Government Bond Yield and Earnings Skewness

This section reports the explanatory power of earnings skewness on government bond yields. On one hand, the earnings skewness can predict future bond yields. On the other hand, adding earnings skewness in the return predictive regressions with the long-term yield as explanatory variable can filter out the cash flow component of long-term yield.

Bond Yield Predictive Regressions

Table 4.11 reports the regressions of one-quarter or one-year ahead long-term/short-term government bond yields and term spreads on aggregate SUE skewness measures. Newey-West standard error with 12 lags is used for all regressions. Consistent with my model prediction, aggregate fundamental skewness measures negatively predict long-term and short-term bond yields. In the unreported results, I find that aggregate fundamental skewness measures have predicting power on bond yield for more than five years. In comparison to the predicting power on bond yields, aggregate earnings skewness has a relatively modest predicting power on term spreads. Since government bond cash flow is pre-determined, the cash flow shocks to long-term/short-term bonds are relatively flat. The modest predicting power of aggregate earnings skewness on term spreads confirms the fundamental skewness measures are measures of cash flow term structures.

Yield Decomposition

In this section, I explore the interaction of aggregate fundamental skewness and long-term yield on stock market return predictability. Table 4.12 reports univariate regression and multivariate return predictive regression results for long-term yields. Panel A of Table 4.12 reports the univariate return predictive regression results for long-term government bond yields with different horizons. Long-term yield is a positive long-term market return predictor since it starts to significantly positively predict returns in the four-year horizon (RET_{t+16}). However, if I include aggregate fundamental skewness measures in panels B through E, the coefficient on the long-term yield (LTM) changes to negative. Moreover, the long-term yield becomes a significant negative return predictor throughout all forecasting horizons if I include aggregated earnings skewness measures.

These results have important implications: aggregate earnings skewness measures have a negative relationship with stock market excess returns; and the long-term yield has a slow-growing positive effect on stock market returns. The long term yield has a cash flow component and a discount rate component and these two components have opposite effects on return predictability. The offsetting effects reduce the ability of the long-term yield to forecast stock market returns.

4.7 Conclusions

Motivated by the empirical evidence that the distributions of macroeconomic fundamentals are skewed, this paper documents that the conditional skewness of aggregate corporate earnings negatively predicts the stock market returns for horizons beyond six months and up to eight years. The evidence is robust to controlling for standard predictors such as the book-to-market ratio, interest rates, *cay*, and the first two moments of earnings. The results are also robust to alternative econometric estimation methods.

I present a theoretical model that provides the microfoundation for the predictive evidence. The model has two key ingredients: path dependence and non-Gaussian innovations in the aggregate corporate earnings process, which are motivated by the recent research on productivity-enhancing technology spillover. The interaction of the two factors implies that the skewness of macroeconomic fundamentals not only is time-varying but also negatively predicts the stock market returns.

4.8 The skew-normal distribution

I introduce in this section the skew-normal distribution and three related lemmas used in the derivation of the model.

Skew-normal distribution (Azzalini (1985)). A skew-normal distribution $SKN(\mu, \sigma, \nu)$ with a local parameter μ, scale parameter σ, and shape parameter ν, has a probability density function

$$p(x) = \frac{1}{\sigma\pi} \exp(-\frac{(x-\mu)^2}{2\sigma^2}) \int_{-\infty}^{\frac{\nu(x-\mu)}{\sigma}} exp(-\frac{t^2}{2})dt. \tag{4.46}$$

Lemma 1 (Azzalini (1985)): The closed form of a skew-normal distribution $SKN(\mu, \sigma, \nu)$ has the following closed form first three moments as follows:

$$\begin{aligned} mean &= \mu + \sigma\Phi\sqrt{\frac{2}{\pi}}, & (4.47) \\ variance &= \sigma^2(1 - \frac{2\Phi^2}{\pi}), & (4.48) \\ skewness &= \frac{4-\pi}{2}\frac{(\Phi\sqrt{2/\pi})^3}{(1-2\Phi^2/\pi)^{3/2}}. & (4.49) \end{aligned}$$

Lemma 2 (Linear Transformation):If a random variable x follows skew-normal distribution $SKN(0, 1, \nu)$, the random variable $Y = a+bx$ follows skew-normal distribution $SKN(a, b^2, \nu)$

Lemma 3 (Colacito, Ghysels and Meng (2013)):If z follows $SKN(\mu, \sigma, \nu)$, then

$$logE_t exp(\kappa_1 z) = log(2) + \frac{\kappa_1(\kappa_1 + 2\mu)}{2} + log\Phi(\frac{\nu\kappa_1}{\sqrt{1+\nu^2}}) \tag{4.50}$$

4.9 Solution to the model in Section 4.2

In this appendix, I describe the solution method for zero coupon bond. We conjecture that the solution takes the form

$$P^e_{nt} = exp(A^e_n + B^e_n H_t) \tag{A1}$$

where P^e_{nt} stands for the price of a time t equity with payoff only at period $(t+n)$. By the same token, $P^e_{n-1,t+1}$ stands for the price of a time $(t+1)$ equity with payoff only at period $(t+n-1)$. A^e_n is a scalar and B^e_n is $1 \times m$ vector. Substituting (A1) and (10) into (11) and expanding out the expectation following Lemma 3 implies

$$\begin{aligned} exp(A^e_n + B^e_n H_t) = E_t[&exp(-\alpha_0 - \alpha H_t - \sigma_e \eta_0 + A^e_{n-1} + B^e_{n-1}\theta_0 - \sigma_e \theta_0 \eta \\ &+ B^e_{n-1}\theta H_t - \sigma_e \eta \theta H_t + (B^e_{n-1} - \sigma_e \eta \sigma_H)\epsilon_{t+1}] \end{aligned} \tag{A2}$$

Matching coefficients lead to equations for A^e_{nt} and B^e_{nt} in (13) and (14) respectively.

Table 4.1: The Illustrative Example

This table corresponds to an example to illustrate the economic intuition of earnings skewness. Suppose there exists an economy with 18 quarters of history. The level of aggregate earnings for each period is reported in the table. The skewness of earnings at each period t is constructed as the coefficient of skewness of earnings during the rolling window of period $t-7$ to t.

Periods	1	2	3	4	5	6	7	8	9
Earnings	1.8	1.9	1.85	1.8	1.9	2	1.95	1.9	0.9
Skew	.	.	.	.	.	.	.	0.160	-2.673
Periods	10	11	12	13	14	15	16	17	18
Earnings	0.95	1.05	1.11	1.15	1.2	1.1	2	1.95	1.85
Skew	-1.370	-0.621	-0.042	0.550	1.198	1.250	2.356	1.308	0.640

Table 4.2: Summary Statistics for Corporate Earnings

This table reports the summary statistics for measures of the firm fundamentals including standardized unexpected earnings (SUE) and earnings per share (EPS). $SUE1$ and $SUE2$ are unexpected earnings based on the seasonal random walk model. $SUE3$ and $SUE4$ rely on mean and median of analyst earnings forecasts. Mean, STD, Skew and Kurt stands for the mean, standard deviation, skewness and kurtosis of each measure, respectively. "Lev" stands for the leverage effect for each measures, which is defined as the correlation between the two-year non-overlapping mean and volatility of firm fundamentals. The sample period for $SUE1$, $SUE2$ and EPS is $Q1, 1973 - Q4, 2013$. The sample period for $SUE3$ and $SUE4$ is from $Q1, 1983 - Q4, 2013$.

	Mean	STD	Skew	Kurt	MIN	25th	MED	75th	MAX	Lev
SUE1	0.13%	1.37%	2.34	20.14	-6.91%	-0.24%	0.11%	0.36%	8.30%	0.27
SUE2	0.18%	1.09%	4.03	31.05	-3.46%	-0.11%	0.12%	0.34%	8.36%	0.51
SUE3	-0.05%	0.18%	-2.65	13.70	-1.16%	-0.13%	-0.01%	0.05%	0.42%	-0.62
SUE4	-0.05%	0.19%	-2.49	12.43	-1.13%	-0.12%	-0.01%	0.04%	0.42%	-0.60
EPS	2.60	3.91	2.59	6.75	-3.69	0.91	1.09	2.15	19.86	0.85

Table 4.3: Summary Statistics for Measures of the Skewness of Firm Fundamentals

This table reports the summary statistics for the 'fundamental' skewness measures and control variables. SK_{SUE} stands for the skewness of each correspondent standardized unexpected earnings measures. LTY is the long-term yield. TMS is the term spread. TBL is the short-term yield. BM is the book-to-market ratio. DEF is the default spread and CAY is the consumption-wealth ratio from Lettau and Wachter (2001). The sample period for SK_{SUE1}, SK_{SUE2} and SK_{EPS} is $Q1, 1977 - Q4, 2013$. The sample period for SK_{SUE3} and SK_{SUE4} is $Q1, 1987 - Q4, 2013$.

	Mean	STD	MIN	25th	Median	75th	MAX	AR(1)	AR(2)	AR(3)
SK$_{SUE1}$	2.340	1.610	-0.440	1.520	2.170	4.160	4.630	0.87	0.78	0.75
SK$_{SUE2}$	2.740	1.790	-0.790	2.310	2.770	4.550	4.710	0.85	0.77	0.73
SK$_{SUE3}$	-0.090	0.780	-1.450	-0.350	0.150	0.290	1.430	0.92	0.83	0.75
SK$_{SUE4}$	-0.070	0.790	-1.440	-0.310	0.170	0.330	1.470	0.92	0.84	0.75
SK$_{EPS}$	1.588	4.102	-5.558	-0.477	1.088	5.124	8.521	0.96	0.95	0.91
LTY	0.072	0.027	0.022	0.051	0.072	0.086	0.148	0.98	0.96	0.95
TMS	0.021	0.015	-0.035	0.010	0.024	0.033	0.045	0.81	0.66	0.60
TBL	0.052	0.034	0	0.029	0.051	0.071	0.154	0.95	0.92	0.91
BM	0.502	0.295	0.125	0.284	0.393	0.735	1.201	0.98	0.96	0.94
DEF	0.011	0.005	0.006	0.008	0.01	0.013	0.034	0.84	0.68	0.56
CAY	0.005	0.020	-0.050	-0.010	0.000	0.023	0.039	0.94	0.90	0.86

Table 4.4: Correlation Matrix

This table reports the pairwise correlations between each variables used in the analysis. The sample period for each correlation is determined by the relative shorter sample between each two variables. For instance, since the sample period for SK_{SUE3} is shorter than that for SK_{SUE1}, the correlation between SK_{SUE1} and SK_{SUE3} is determined by the sample of SK_{SUE3}.

	SK_{SUE1}	SK_{SUE2}	SK_{SUE3}	SK_{SUE4}	SK_{EPS}	LTY	TMS	TBL	BM	DEF	CAY
SK_{SUE1}	1										
SK_{SUE2}	0.99	1									
SK_{SUE3}	0.9	0.88	1								
SK_{SUE4}	0.89	0.88	0.99	1							
SK_{EPS}	0.09	0.13	0.20	0.21	1						
LTY	0.52	0.48	0.56	0.55	-0.65	1					
TMS	-0.26	-0.25	-0.36	-0.36	-0.24	-0.23	1				
TBL	0.54	0.5	0.62	0.62	-0.45	0.9	-0.64	1			
BM	-0.43	-0.49	-0.41	-0.42	-0.77	0.7	-0.27	0.68	1		
DEF	-0.40	-0.42	-0.46	-0.45	-0.51	0.34	0.08	0.23	0.48	1	
CAY	0.32	0.33	0.37	0.36	-0.31	0.37	0.27	0.17	-0.15	-0.05	1

Table 4.5: Univariate Regressions

The table reports the time series univariate regressions of two-quarter to eight-year ahead cumulative aggregate market returns on measures of skewness of the firm fundamentals. R_{t+i}, $i = 2...32$ is the cumulative stock market return until i quarters ahead. I skip one quarter for fundamental skewness measures and stock market returns in order to make sure the information of fundamentals is known to the investors. Newey and West (1987) standard errors with 12 lags are used to adjust the t statistics. Rand. P stands for the randomization P-values which are calculated following Nelson and Kim (1993). $Adj - \beta$s are the bias-adjusted betas calculated following Stambaugh (2000) and Kendall (1954).

		R_{t+2}	R_{t+4}	R_{t+6}	R_{t+8}	R_{t+12}	R_{t+16}	R_{t+18}	R_{t+20}	R_{t+24}	R_{t+28}	R_{t+30}	R_{t+32}
							Panel A: SK_{SUE1}						
SK_{SUE1}	β	-0.606	-1.217	-1.679	-1.908	-2.656	-4.512	-6.292	-7.722	-10.244	-14.126	-15.968	-16.886
	t stats	(-1.63)	(-1.79)	(-1.71)	(-1.51)	(-1.66)	(-2.66)	(-2.82)	(-2.54)	(-2.82)	(-3.77)	(-4.28)	(-4.43)
	Adj-β	-1.395	-3.163	-4.357	-4.875	-5.420	-7.894	-9.628	-11.680	-14.007	-16.507	-17.452	-17.490
	Rand. P	0.037	0.001	0.0002	0.0007	0.0068	0.002	0.0002	$\leq$0.0001	$\leq$0.0001	$\leq$0.0001	$\leq$0.0001	$\leq$0.0001
							Panel B: SK_{SUE2}						
SK_{SUE2}	β	-0.463	-0.887	-1.154	-1.216	-1.72	-3.462	-4.958	-6.15	-8.849	-13.298	-15.505	-16.638
	t stats	(-1.20)	(-1.26)	(-1.14)	(-0.93)	(-1.00)	(-1.84)	(-2.07)	(-2.25)	(-2.88)	(-4.45)	(-5.43)	(-5.86)
	Adj-β	-0.744	-1.655	-2.094	-2.176	-2.487	-5.352	-7.242	-9.377	-12.138	-15.426	-16.796	-17.034
	Rand. P	0.149	0.0476	0.0408	0.0689	0.0805	0.0125	0.0024	0.0002	$\leq$0.0001	$\leq$0.0001	$\leq$0.0001	$\leq$0.0001

Table 4.5 – Continued

		R_{t+2}	R_{t+4}	R_{t+6}	R_{t+8}	R_{t+12}	R_{t+16}	R_{t+18}	R_{t+20}	R_{t+24}	R_{t+28}	R_{t+30}	R_{t+32}
Panel C: SK_{SUE3}													
SK_{SUE3}	β	-0.578	-1.263	-2.016	-2.521	-3.796	-6.139	-8.891	-11.148	-16.750	-23.273	-28.510	-35.162
	t stats	(-1.73)	(-2.06)	(-2.14)	(-2.10)	(-2.37)	(-2.66)	(-2.82)	(-2.37)	(-2.82)	(-4.00)	(-5.18)	(-6.19)
	Adj-β	-0.434	-0.977	-3.709	-6.528	-7.206	-10.550	-12.382	-14.352	-19.217	-24.911	-29.966	-37.080
	Rand. P	0.0259	0.0119	0.0045	0.0021	0.0014	0.0004	$\leq$0.0001	$\leq$0.0001	$\leq$0.0001	$\leq$0.0001	$\leq$0.0001	$\leq$0.0001
Panel D: SK_{SUE4}													
SK_{SUE4}	β	-0.614	-1.336	-2.123	-2.66	-4.03	-6.619	-9.703	-12.45	-17.753	-23.952	-28.877	-35.199
	t stats	(-1.80)	(-2.09)	(-2.17)	(-2.15)	(-2.47)	(-2.81)	(-3.08)	(-2.72)	(-3.17)	(-4.31)	(-5.45)	(-6.36)
	Adj-β	-0.391	-0.948	-3.667	-6.484	-7.508	-11.421	-13.429	-15.477	-20.228	-25.525	-30.399	-37.112
	Rand. P	0.0169	0.0076	0.003	0.0012	0.0007	0.0003	$\leq$0.0001	$\leq$0.0001	$\leq$0.0001	$\leq$0.0001	$\leq$0.0001	$\leq$0.0001
Panel E: SK_{EPS}													
SK_{EPS}	β	-0.019	-0.029	-0.05	-0.082	-0.135	-0.171	-0.184	-0.2	-0.203	-0.212	-0.22	-0.239
	t stats	(-0.63)	(-0.76)	(-0.98)	(-1.37)	(-1.93)	(-2.43)	(-2.80)	(-3.35)	(-3.61)	(-3.30)	(-3.37)	(-3.21)
	Adj-β	-0.002	-0.003	-0.018	-0.048	-0.116	-0.176	-0.198	-0.212	-0.208	-0.219	-0.231	-0.249
	Rand. P	0.4821	0.3975	0.1182	0.0272	0.0026	$\leq$0.0001	$\leq$0.0001	$\leq$0.0001	$\leq$0.0001	$\leq$0.0001	$\leq$0.0001	$\leq$0.0001

Table 4.6: Multivariate Regressions

The table reports the time series multivariate regressions of two-quarter to eight-year ahead cumulative aggregate market returns on measures of skewness of the firm fundamentals and other return predictors. R_{t+i}, $i = 2...32$ is the cumulative stock market return until i quarters ahead. I skip one quarter for fundamental skewness measures and stock market returns in order to make sure the information of fundamentals is known to the investors. CAY is the consumption-wealth ratio in Lettau and Wachter (2001). B/M is the book-to-market ratio at the aggregate level. DEF is is the difference between Moodys Baa yield and Aaa yield. TMS is the difference between ten- and one-year treasury constant maturity rates. Newey and West (1987) standard errors with 12 lags are used to adjust the t statistics.

	R_{t+2}	R_{t+4}	R_{t+6}	R_{t+8}	R_{t+12}	R_{t+16}	R_{t+20}	R_{t+24}	R_{t+28}	R_{t+32}
Panel A: 24 QTRs SK_{SUE1}										
SK_{SUE1}	-0.008	-0.016	-0.019	-0.024	-0.029	-0.039	-0.070	-0.068	-0.061	-0.059
	(-1.48)	(-1.90)	(-1.92)	(-2.00)	(-2.40)	(-3.05)	(-3.37)	(-3.04)	(-2.97)	(-3.55)
CAY	1.707	4.239	6.130	8.504	11.151	12.792	9.863	5.377	3.509	3.135
	(1.91)	(2.53)	(2.89)	(3.62)	(4.61)	(4.60)	(3.71)	(1.95)	(1.68)	(2.85)
B/M	0.025	-0.118	-0.204	-0.442	-0.559	-0.514	0.005	1.034	1.991	2.404
	(0.14)	(-0.39)	(-0.54)	(-1.09)	(-1.24)	(-1.05)	(0.01)	(1.79)	(5.77)	(9.05)
DEF	1.910	4.253	6.024	7.391	9.695	15.978	10.772	-31.176	-30.178	-5.904
	(0.44)	(0.94)	(1.09)	(1.02)	(1.62)	(3.08)	(0.67)	(-1.89)	(-2.14)	(-0.70)
TMS	-0.103	1.455	3.952	5.939	7.924	7.857	8.709	8.247	5.687	3.818
	(-0.11)	(0.98)	(2.13)	(3.05)	(4.28)	(3.72)	(2.87)	(2.63)	(1.92)	(2.13)
ADJ R square	0.06	0.23	0.37	0.50	0.58	0.65	0.59	0.64	0.79	0.89
Panel B: 24 QTRs SK_{SUE2}										
SK_{SUE2}	-0.006	-0.012	-0.014	-0.018	-0.022	-0.035	-0.063	-0.066	-0.062	-0.057
	(-1.05)	(-1.44)	(-1.38)	(-1.46)	(-1.73)	(-2.74)	(-3.43)	(-3.82)	(-3.91)	(-3.94)
CAY	1.606	4.137	5.957	8.371	11.211	13.297	10.717	6.268	4.407	4.175
	(1.75)	(2.40)	(2.70)	(3.37)	(4.26)	(4.53)	(3.80)	(2.23)	(2.15)	(4.05)
B/M	0.043	-0.100	-0.165	-0.411	-0.556	-0.615	-0.163	0.843	1.778	2.212
	(0.22)	(-0.30)	(-0.40)	(-0.92)	(-1.12)	(-1.22)	(-0.33)	(1.43)	(4.90)	(7.80)
DEF	2.162	4.840	6.769	8.186	11.034	17.308	8.483	-35.638	-33.805	-9.567
	(0.49)	(1.06)	(1.20)	(1.09)	(1.80)	(3.42)	(0.50)	(-1.94)	(-2.32)	(-1.14)
TMS	-0.018	1.604	4.178	6.204	8.086	7.865	8.726	8.383	5.928	4.110
	(-0.02)	(1.10)	(2.33)	(3.27)	(4.62)	(3.71)	(2.86)	(2.85)	(2.16)	(2.34)
ADJ R square	0.05	0.20	0.34	0.47	0.56	0.64	0.58	0.64	0.79	0.90

Table 4.6 – Continued

	R_{t+2}	R_{t+4}	R_{t+6}	R_{t+8}	R_{t+12}	R_{t+16}	R_{t+20}	R_{t+24}	R_{t+28}	R_{t+32}
Panel C: 24 QTRs SK_{SUE3}										
SK_{SUE3}	-0.008	-0.018	-0.025	-0.033	-0.040	-0.035	-0.028	0.040	0.114	-0.028
	(-1.70)	(-2.07)	(-2.13)	(-2.33)	(-3.25)	(-2.59)	(-0.61)	(0.46)	(1.82)	(-0.46)
CAY	1.772	4.369	6.419	8.926	11.366	12.514	9.343	5.449	5.113	5.026
	(1.94)	(2.41)	(2.88)	(3.89)	(4.58)	(3.79)	(2.68)	(1.58)	(1.92)	(3.67)
B/M	0.034	-0.104	-0.216	-0.474	-0.563	-0.355	0.462	1.887	3.016	2.662
	(0.18)	(-0.29)	(-0.49)	(-1.03)	(-1.23)	(-0.72)	(0.89)	(2.27)	(6.13)	(6.47)
DEF	1.559	3.345	4.597	5.430	6.393	15.301	7.305	-39.453	-27.630	-18.545
	(0.33)	(0.72)	(0.85)	(0.73)	(0.87)	(2.33)	(0.36)	(-1.85)	(-1.68)	(-2.50)
TMS	-0.324	0.979	3.202	4.893	6.889	7.042	7.103	5.941	3.240	3.984
	(-0.31)	(0.64)	(1.75)	(2.60)	(4.25)	(2.75)	(1.60)	(1.54)	(1.14)	(2.02)
ADJ R square	0.06	0.22	0.38	0.51	0.59	0.61	0.49	0.56	0.75	0.86
Panel D: 24 QTRs SK_{SUE4}										
SK_{SUE4}	-0.009	-0.018	-0.025	-0.033	-0.040	-0.033	-0.021	0.032	0.108	-0.029
	(-1.71)	(-2.02)	(-2.08)	(-2.27)	(-3.14)	(-2.31)	(-0.45)	(0.37)	(1.77)	(-0.49)
CAY	1.753	4.308	6.321	8.787	11.202	12.398	9.336	5.480	5.360	4.952
	(1.91)	(2.38)	(2.86)	(3.85)	(4.52)	(3.76)	(2.68)	(1.58)	(1.94)	(3.50)
B/M	0.033	-0.102	-0.212	-0.466	-0.552	-0.343	0.483	1.849	2.973	2.661
	(0.17)	(-0.29)	(-0.47)	(-1.00)	(-1.18)	(-0.69)	(0.93)	(2.26)	(6.22)	(6.76)
DEF	1.593	3.442	4.764	5.678	6.818	16.047	9.076	-40.308	-28.241	-18.682
	(0.34)	(0.74)	(0.88)	(0.77)	(0.93)	(2.50)	(0.46)	(-1.89)	(-1.71)	(-2.53)
TMS	-0.326	0.989	3.226	4.938	6.945	7.064	7.039	6.028	3.303	4.004
	(-0.31)	(0.64)	(1.76)	(2.61)	(4.29)	(2.76)	(1.59)	(1.55)	(1.14)	(2.02)
ADJ R square	0.06	0.22	0.38	0.51	0.58	0.61	0.49	0.56	0.75	0.86
Panel E: 24 QTRs SK_{EPS}										
SK_{EPS}	0.0003	0.0005	0.0006	0.0003	0.0001	-0.0001	-0.0005	-0.0010	-0.0010	-0.0009
	(1.25)	(1.32)	(1.37)	(0.71)	(0.10)	(-0.10)	(-0.74)	(-1.41)	(-1.58)	(-1.68)
CAY	1.748	3.567	4.935	5.185	6.429	8.131	8.234	8.921	9.979	11.798
	(2.76)	(3.36)	(3.44)	(3.11)	(2.92)	(3.63)	(3.99)	(4.65)	(5.56)	(5.99)
B/M	0.056	0.124	0.180	0.191	0.173	0.147	0.223	0.344	0.475	0.619
	(1.08)	(1.47)	(1.69)	(1.57)	(1.55)	(1.23)	(1.59)	(2.61)	(3.54)	(4.97)
DEF	2.559	1.862	1.061	-1.213	2.886	10.777	4.148	-8.972	-11.050	-11.752
	(0.96)	(0.45)	(0.18)	(-0.16)	(0.38)	(1.20)	(0.35)	(-0.76)	(-1.05)	(-1.57)
TMS	1.347	2.545	3.779	4.537	4.789	3.471	1.638	-1.274	-1.044	0.273
	(1.67)	(2.29)	(2.80)	(2.55)	(2.83)	(1.85)	(0.61)	(-0.46)	(-0.42)	(0.11)
ADJ R square	0.08	0.18	0.26	0.30	0.37	0.44	0.39	0.44	0.50	0.60

Table 4.7: Predictive Regressions Controlling Other Moments

This table reports the predictive regressions of future stock market returns on the skewness of the firm fundamentals controlling the mean and volatility of the measures of the firm fundamentals. M_{SUEi} $(i = 1, 2, 3)$is the 24-quarter rolling mean of the SUEs. VOL_{SUE1} $(i = 1, 2, 3)$ is the 24-quarter rolling volatility of the SUEs.

	R_{t+12}	R_{t+16}	R_{t+20}	R_{t+24}	R_{t+28}	R_{t+32}
Panel A: SK_{SUE1}						
SK_{SUE1}	-2.254	-4.835	-8.198	-9.892	-14.07	-17.527
	(-1.25)	(-2.22)	(-2.47)	(-2.36)	(-3.30)	(-4.61)
M_{SUE1}	-0.654	0.958	1.324	0.406	0.471	0.848
	(-0.36)	(0.54)	(0.70)	(0.28)	(0.30)	(0.56)
VOL_{SUE1}	-0.624	-0.410	-0.381	-0.678	-0.543	-0.408
	(-1.14)	(-0.74)	(-0.68)	(-1.49)	(-1.20)	(-0.80)
Panel B: SK_{SUE2}						
SK_{SUE2}	-1.245	-3.561	-6.233	-8.385	-13.052	-16.971
	(-0.63)	(-1.48)	(-2.11)	(-2.54)	(-4.09)	(-6.77)
M_{SUE2}	-0.981	0.567	0.900	0.115	0.283	0.802
	(-0.55)	(0.32)	(0.50)	(0.09)	(0.19)	(0.55)
VOL_{SUE2}	-0.670	-0.496	-0.522	-0.804	-0.680	-0.540
	(-1.22)	(-0.87)	(-0.95)	(-1.94)	(-1.77)	(-1.22)
Panel C: SK_{SUE3}						
SK_{SUE3}	-4.726	-4.492	-6.668	-4.612	-8.374	-24.984
	(-1.69)	(-1.83)	(-1.30)	(-0.50)	(-0.78)	(-1.95)
M_{SUE3}	-10.121	-10.064	-15.501	-6.226	9.667	15.405
	(-0.79)	(-0.60)	(-0.64)	(-0.22)	(0.39)	(0.91)
VOL_{SUE3}	-6.687	2.323	3.120	18.912	35.523	32.098
	(-0.44)	(0.13)	(0.15)	(0.85)	(1.80)	(1.33)

Table 4.8: Principle Component Analysis

This table reports the principle component analysis (PCA) for the skewness of the firm fundamentals. The PCA extracts the common components of the five fundamental skewness measures. The element in the table is the cumulative percentage of the sample variance that the principle component can explain.

	Proportion of Cumulative Eigenvalues				
Elements	1	2	3	4	5
SK_{SUE1} & SK_{SUE2}	0.994	1			
$SK_{SUE1,2,3}$	0.949	0.996	1		
$SK_{SUE1,2,3,4}$	0.943	0.997	1.000	1	
$SK_{SUE1,2,3,4}$ & SK_{EPS}	0.784	0.959	0.998	1	1

Table 4.9: Comparative Regressions

This table reports the results of comparative regressions. I compare the predicting power of different skewness of the firm fundamentals measures including SK_{SUE1}, SK_{SUE2} and SK_{EPS} at different horizons. R_{t+12} is the future three-year cumulative market return. R_{t+20} is the future five-year cumulative market returns. And R_{t+32} is the future eight-year cumulative market returns. Newey and West (1987) standard errors with 12 lags are used for t statistics.

	R_{t+12}				R_{t+20}				R_{t+32}			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
SK_{SUE1}	-0.178	-4.539		-0.62	-5.386	-9.768		-9.835	-6.042		-6.058	-6.224
	(-0.07)	(-2.64)		(-0.24)	(-2.72)	(-4.32)		(-4.71)	(-3.46)		(-3.63)	(-3.64)
SK_{SUE3}	-5.919		-6.124	-5.59			-4.588	0.4269	-1.983	1.6184		-1.849
	(-3.14)		(-7.22)	(-2.9)			(-0.66)	(0.09)	(-0.36)	(0.20)		(-0.34)
SK_EPS		-2.032	-0.496	-0.734	-1.437	-7.09	-3.257	-7.112		0.7841	-0.392	-0.352
		(-1.15)	(-0.29)	(-0.43)	(-0.26)	(-3.67)	(-1.65)	(-3.75)		(0.73)	(-0.39)	(-0.33)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 4.10: Predictive Regressions Controlling Firm-Level SUE Skewness

This table reports the predictive regressions of future cumulative market returns at different horizons on skewness of the firm fundamentals measures controlling the mean of firm-level skewness of the firm fundamentals. iSKEW1 (2 and 3) is the cross-sectional mean of the firm-level SUE1 (SUE2 and SUE3). Newey and West (1987) standard errors with 12 lags are used for calculating t statistics.

	R_{t+16}	R_{t+20}	R_{t+22}	R_{t+24}	R_{t+26}	R_{t+28}	R_{t+32}
Panel A: Controlling Firm-Level SUE1 Skewness							
SK_{SUE1}	-4.269	-7.601	-8.849	-10.33	-12.634	-14.582	-18.221
	(-2.01)	(-2.66)	(-2.76)	(-2.91)	(-3.52)	(-3.85)	(-4.54)
iSKEW1	-0.063	-0.149	-0.122	-0.067	-0.002	0.020	0.172
	(-0.33)	(-0.80)	(-0.72)	(-0.41)	(-0.01)	0.12	0.94
Panel B: Controlling Firm-Level SUE2 Skewness							
SK_{SUE2}	-3.18	-5.995	-7.262	-8.88	-11.34	-13.649	-17.711
	(-1.40)	(-2.30)	(-2.60)	(-2.93)	(-3.72)	(-4.30)	(-5.58)
iSKEW2	-0.070	-0.129	-0.102	-0.050	0.019	0.044	0.187
	(-0.38)	(-0.70)	(-0.63)	(-0.34)	(0.13)	(0.31)	(1.30)
Panel C: Controlling Firm-Level SUE3 Skewness							
SK_{SUE3}	-6.994	-10.593	-11.005	-13.206	-15.941	-19.73	-32.662
	(-3.26)	(-1.97)	(-2.36)	(-1.66)	(-2.42)	(-2.76)	(-5.35)
iSKEW3	-0.361	-0.629	-0.774	-0.826	-0.867	-0.917	-0.766
	(-1.28)	(-1.95)	(-2.19)	(-2.21)	(-2.35)	(-2.46)	(-2.12)

Table 4.11: Bond Yield Predictability

This table reports the time series regressions of the future bond yields on the skewness of the firm fundamentals. LTY is the long-term yield. TBL is the short-term yield and TMS is the term spread. Newey and West (1987) standard errors with 12 lags are used for calculating t statistics.

		LTY_{t+1}	TBL_{t+1}	TMS_{t+1}	LTY_{t+4}	TBL_{t+4}	TMS_{t+4}
SUE1 Skew	Coefficient	0.297	0.399	-0.102	0.272	0.394	-0.122
	t stats	(3.24)	(3.04)	(-1.49)	(2.78)	(2.89)	(-1.77)
	ADJ R	0.27	0.28	0.06	0.22	0.25	0.08
SUE2 Skew	Coefficient	0.271	0.368	-0.097	0.253	0.379	-0.126
	t stats	(2.97)	(2.83)	(-1.42)	(2.64)	(2.93)	(-1.87)
	ADJ R	0.23	0.25	0.05	0.20	0.25	0.08
SUE3 Skew	Coefficient	0.331	0.480	-0.162	0.311	0.445	-0.134
	t stats	(5.30)	(7.79)	(-2.73)	(4.82)	(6.79)	(-2.33)
	ADJ R	0.31	0.38	0.14	0.26	0.29	0.08
SUE4 Skew	Coefficient	0.331	0.485	-0.149	0.309	0.446	-0.136
	t stats	(5.01)	(7.39)	(-2.56)	(4.42)	(6.31)	(-2.32)
	ADJ R	0.29	0.37	0.12	0.25	0.27	0.08

Table 4.12: Predictive Regressions with Long-Term Yield

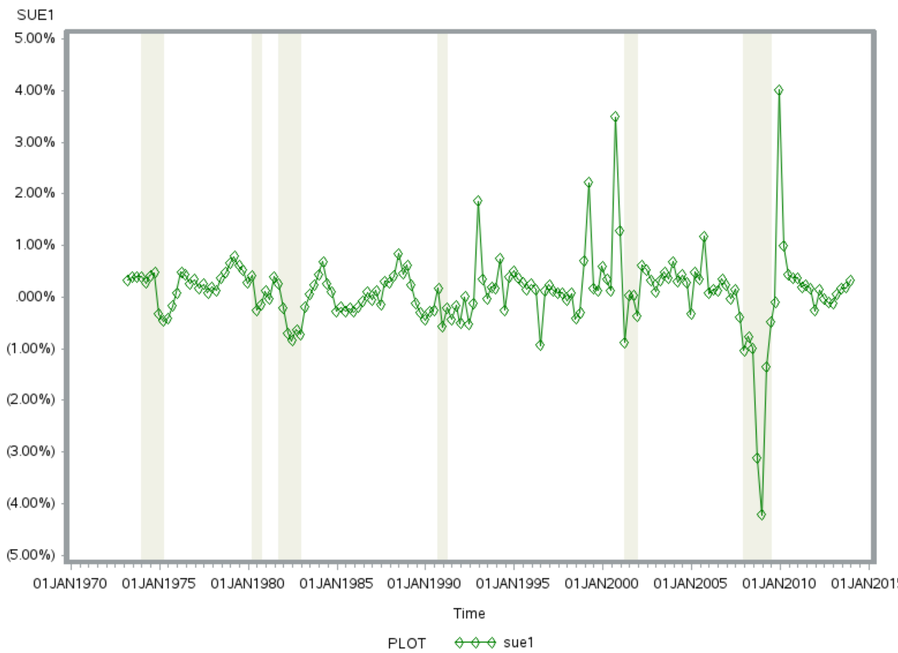
This table reports the predictive regressions of future stock market returns on skewness of the firm fundamentals controlling for the long-term yield. R_{t+i}, $i = 2...32$ is the cumulative stock market returns of future i quarters. Panel A reports the univariate regression of stock market returns on the long-term yield. Panel B through E report the predictive regressions of stock market returns on long-term yield, skewness of the firm fundamentals and other control variables. Newey and West (1987) standard errors with 12 lags are used for t statistics.

	R_{t+2}	R_{t+4}	R_{t+6}	R_{t+8}	R_{t+12}	R_{t+16}	R_{t+20}	R_{t+22}	R_{t+24}	R_{t+26}	R_{t+28}	R_{t+32}
Panel A: Long-Term Yield and Return Predictability												
LTY	0.087	0.139	0.362	1.052	1.922	3.158	5.217	5.713	6.289	6.513	6.863	7.146
	(0.27)	(0.33)	(0.45)	(0.84)	(1.26)	(1.81)	(3.97)	(5.25)	(5.54)	(5.72)	(6.35)	(7.32)
Panel B: SUE1 Skewness and Return Predictability												
SK_{SUE1}	0.188	-0.005	0.062	-0.128	-0.424	-1.758	-4.799	-5.541	-5.076	-5.075	-5.005	-5.196
	(0.37)	(-0.01)	(0.07)	(-0.12)	(-0.37)	(-1.04)	(-2.22)	(-2.47)	(-2.44)	(-2.87)	(-2.42)	(-2.65)
CAY	3.313	7.254	10.733	14.596	18.257	18.207	14.909	10.632	7.622	6.349	5.216	5.307
	(3.44)	(4.23)	(5.18)	(7.36)	(9.53)	(6.54)	(4.67)	(3.07)	(2.10)	(1.75)	(1.53)	(3.41)
B/M	0.277	0.350	0.490	0.457	0.434	0.224	0.420	0.691	1.141	1.690	2.121	2.701
	(1.28)	(1.03)	(1.30)	(1.18)	(0.86)	(0.38)	(0.67)	(0.95)	(1.54)	(2.96)	(5.77)	(12.04)
DEF	-0.599	0.552	1.939	2.653	6.377	16.655	26.260	4.300	-18.778	-26.898	-21.510	0.339
	(-0.14)	(0.14)	(0.49)	(0.49)	(1.10)	(2.22)	(1.49)	(0.19)	(-1.01)	(-1.91)	(-1.75)	(-0.04)
LTY	-3.462	-6.256	-9.318	-12.220	-13.527	-9.595	-6.633	-2.877	-0.752	-1.341	-1.351	-4.141
	(-2.91)	(-3.22)	(-3.98)	(-4.54)	(-4.59)	(-3.01)	(-2.14)	(-0.83)	(-0.20)	(-0.37)	(-0.38)	(-3.23)
ADJ R	13%	33%	47%	58%	61%	62%	53%	50%	55%	66%	75%	89%
Panel C: SUE2 Skewness and Return Predictability												
SK_{SUE2}	0.4043	0.3962	0.6732	0.4769	0.144	-1.53	-4.312	-5.049	-4.863	-5.061	-5.101	-5.249
	(0.85)	(0.54)	(0.86)	(0.50)	(0.13)	(-1.02)	(-2.37)	(-2.66)	(-2.66)	(-3.1)	(-2.75)	(-3.20)
CAY	3.272	7.258	10.722	14.618	18.376	18.627	15.889	11.685	8.627	7.393	6.303	6.481
	(3.54)	(4.40)	(5.33)	(7.41)	(9.29)	(6.55)	(4.71)	(3.26)	(2.29)	(1.95)	(1.83)	(4.63)
B/M	0.329	0.439	0.627	0.586	0.534	0.214	0.359	0.617	1.040	1.563	1.977	2.552
	(1.49)	(1.26)	(1.69)	(1.54)	(1.04)	(0.37)	(0.61)	(0.87)	(1.40)	(2.63)	(5.24)	(10.58)
DEF	-0.598	0.536	1.920	2.643	6.590	16.795	24.584	1.192	-21.588	-29.376	-23.674	-1.870
	(-0.14)	0.14	(0.50)	(0.49)	(1.13)	(2.28)	(1.37)	(0.05)	(-1.09)	(-1.94)	(-1.90)	(-0.23)
LTY	-3.686	-6.738	-10.035	-12.931	-14.172	-10.070	-7.507	-3.738	-1.460	-2.025	-2.020	-4.835
	(-3.34)	(-3.83)	(-4.85)	(-5.19)	(-4.87)	(-3.29)	(-2.35)	(-1.03)	(-0.38)	(-0.54)	(-0.57)	(-3.68)
ADJ R	14%	33%	48%	58%	61%	62%	52%	50%	56%	67%	76%	89%

Table 4.12 – Continued

	R_{t+2}	R_{t+4}	R_{t+6}	R_{t+8}	R_{t+12}	R_{t+16}	R_{t+20}	R_{t+22}	R_{t+24}	R_{t+26}	R_{t+28}	R_{t+32}
Panel D: SUE3 Skewness and Return Predictability												
SK_{SUE3}	0.2575	-0.145	-0.780	-1.694	-2.521	-2.045	3.569	2.6775	9.8553	9.9432	14.4116	-3.538
	(0.47)	(-0.15)	(-0.69)	(-1.37)	(-2.21)	(-1.18)	(0.07)	(0.35)	(0.91)	(1.06)	(1.74)	(-0.45)
CAY	3.301	7.234	10.624	14.482	18.044	18.439	15.514	10.789	7.479	6.569	6.009	7.597
	(3.45)	(4.38)	(5.48)	(7.79)	(9.28)	(6.20)	(4.34)	(2.85)	(1.87)	(1.75)	(1.87)	(4.60)
B/M	0.286	0.326	0.345	0.204	0.190	0.318	0.940	1.412	2.091	2.629	3.161	2.941
	(1.32)	(0.88)	(0.82)	(0.48)	(0.38)	(0.64)	(1.56)	(1.79)	(2.00)	(3.01)	(4.95)	(5.76)
DEF	-0.440	0.457	1.420	1.392	2.959	13.739	26.120	-0.704	-21.447	-28.962	-17.863	-11.018
	(-0.11)	(0.12)	(0.36)	(0.26)	(0.61)	(1.64)	(1.56)	(-0.04)	(-1.34)	(-1.98)	(-1.51)	(-2.01)
LTY	-3.515	-6.091	-8.356	-10.666	-12.128	-10.544	-9.040	-4.578	-0.418	-1.061	-0.298	-5.812
	(-2.80)	(-3.01)	(-3.59)	(-3.76)	(-4.16)	(-3.94)	(-2.32)	(-1.00)	(-0.10)	(-0.29)	(-0.09)	(-2.35)
ADJ R	14%	33%	48%	60%	62%	61%	48%	44%	52%	64%	74%	86%
Panel E: SUE4 Skewness and Return Predictability												
SK_{SUE4}	0.231	-0.163	-0.784	-1.686	-2.486	-1.957	0.704	2.966	9.299	9.368	14.119	-4.252
	(0.42)	(-0.16)	(-0.69)	(-1.36)	(-2.12)	(-1.10)	(0.13)	(0.39)	(0.85)	(1.01)	(1.71)	(-0.54)
CAY	3.301	7.229	10.610	14.454	18.008	18.415	15.542	10.838	7.654	6.731	6.226	7.543
	(3.45)	(4.39)	(5.49)	(7.74)	(9.23)	(6.19)	(4.32)	(2.83)	(1.90)	(1.78)	(1.91)	(4.66)
B/M	0.280	0.323	0.347	0.211	0.203	0.329	0.950	1.414	2.045	2.582	3.113	2.928
	(1.30)	(0.87)	(0.83)	(0.50)	(0.40)	(0.66)	(1.58)	(1.80)	(2.00)	(3.03)	(4.98)	(5.92)
DEF	-0.463	0.452	1.448	1.462	3.116	14.023	26.813	-0.451	-21.922	-29.493	-18.155	-11.708
	(-0.11)	0.12	0.37	0.28	0.65	1.67	1.62	(-0.02)	(-1.37)	(-2.01)	(-1.52)	(-2.14)
LTY	-3.474	-6.076	-8.382	-10.739	-12.249	-10.636	-9.007	-4.456	-0.287	-0.930	-0.002	-6.057
	(-2.81)	(-3.03)	(-3.63)	(-3.81)	(-4.20)	(-3.98)	(-2.31)	(-0.98)	(-0.07)	(-0.25)	(0.16)	(-2.34)
ADJ R	14%	33%	36%	60%	62%	61%	48%	44%	52%	63%	74%	86%

Figure 4.1: Time Series of SUE Measures



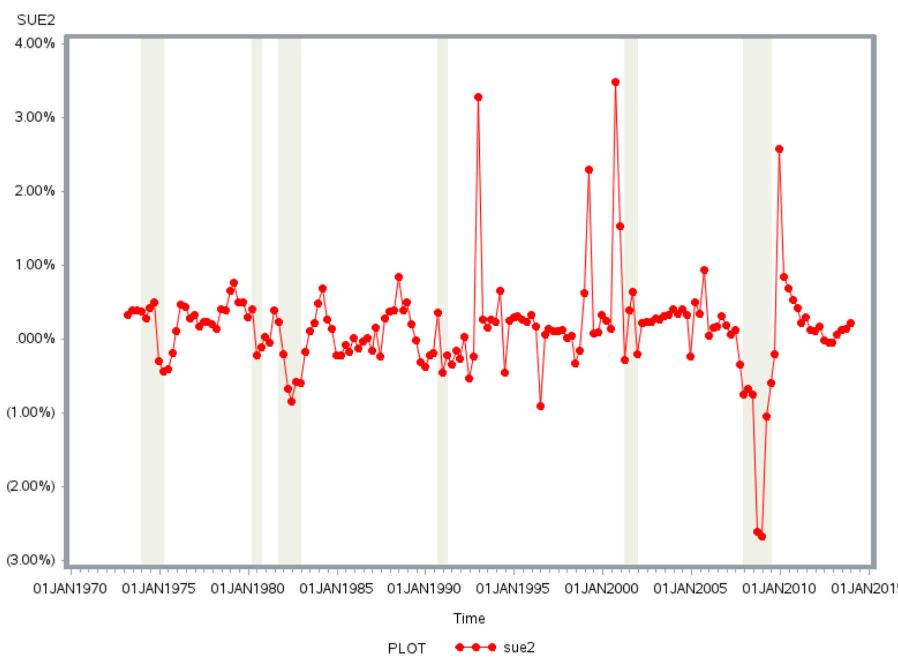
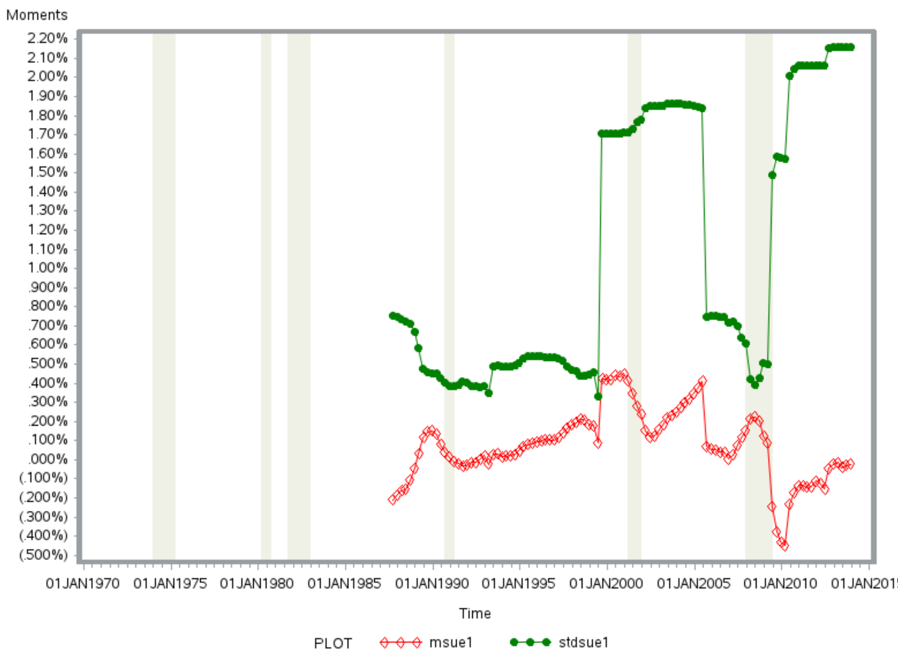


Figure 4.2: Time Series Average and Volatility of SUEs



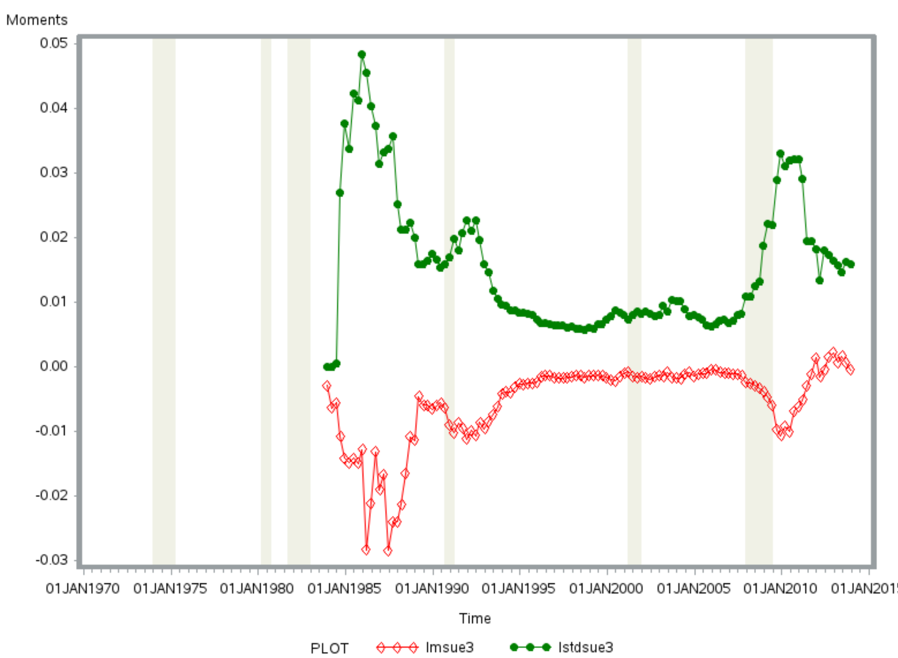
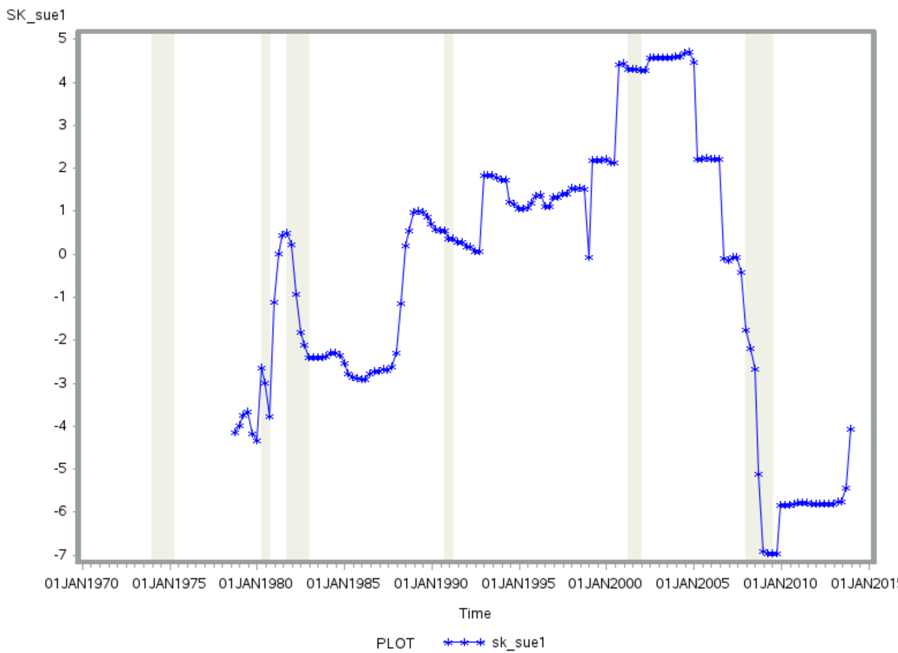


Figure 4.3: SK_{SUE1} and SK_{SUE2}



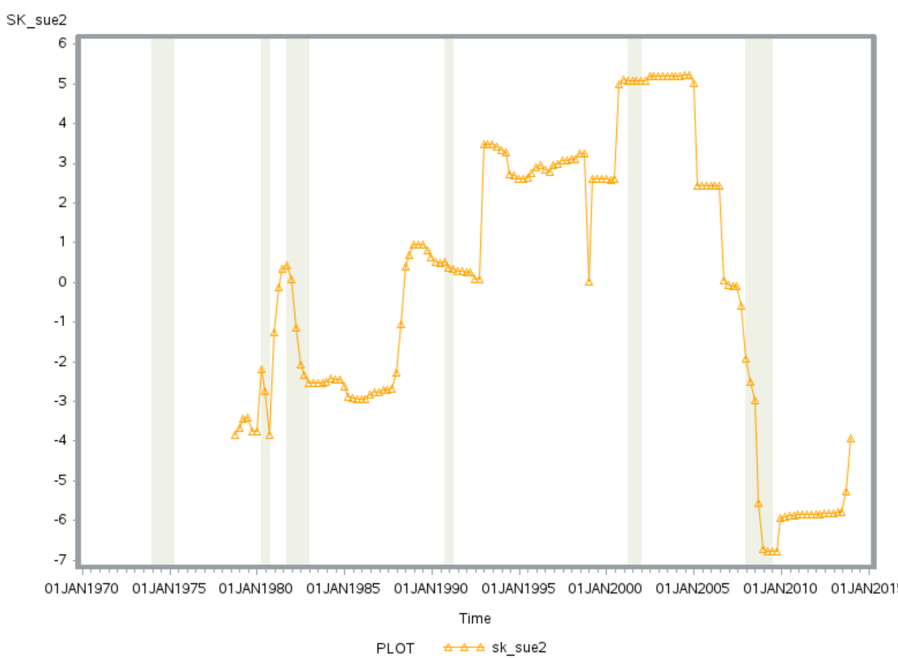
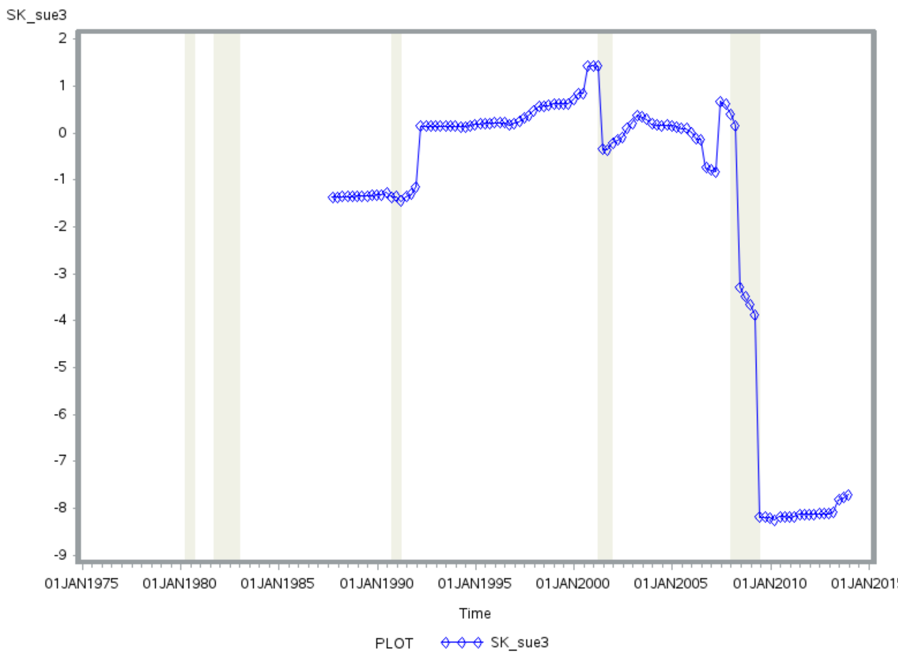


Figure 4.4: SK_{SUE3} and SK_{SUE4}



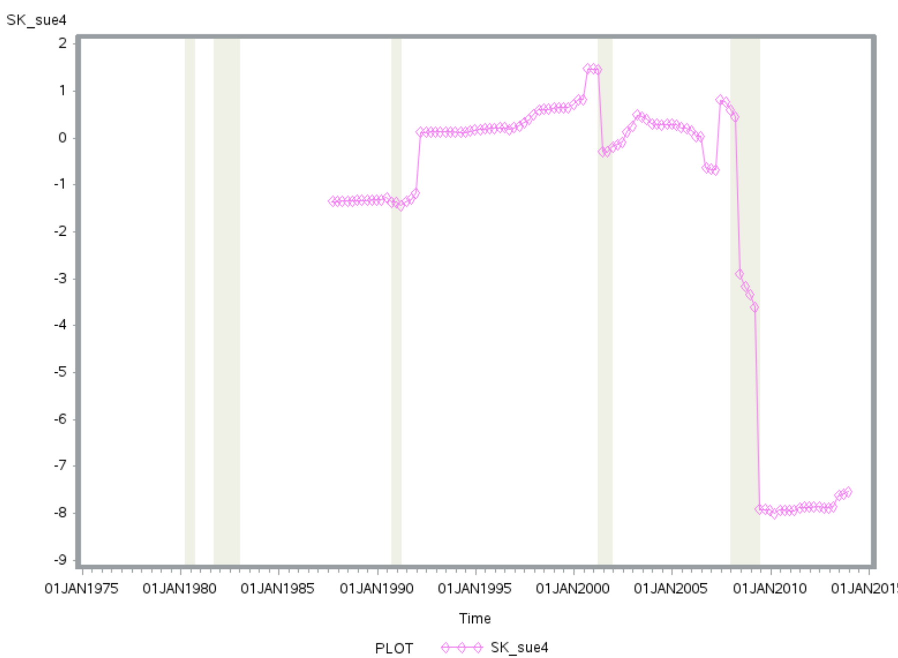
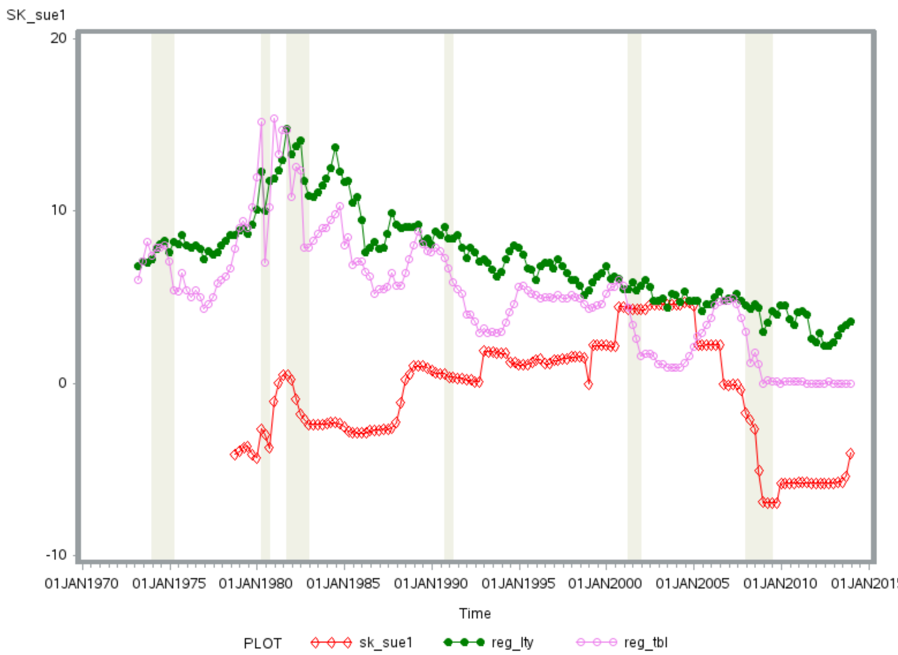


Figure 4.5: SK_{SUE1}, SK_{SUE2} and Bond Yields



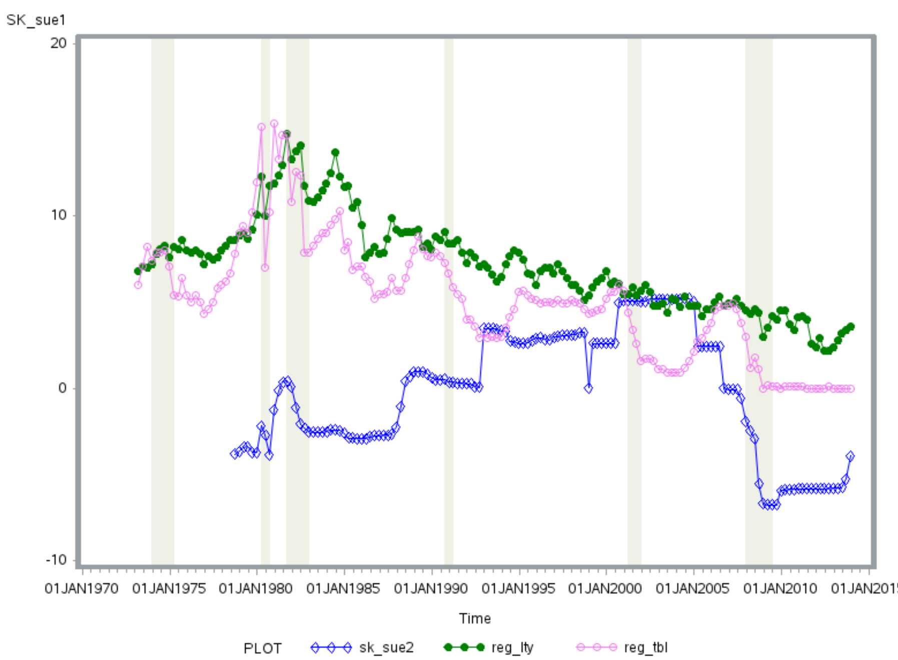
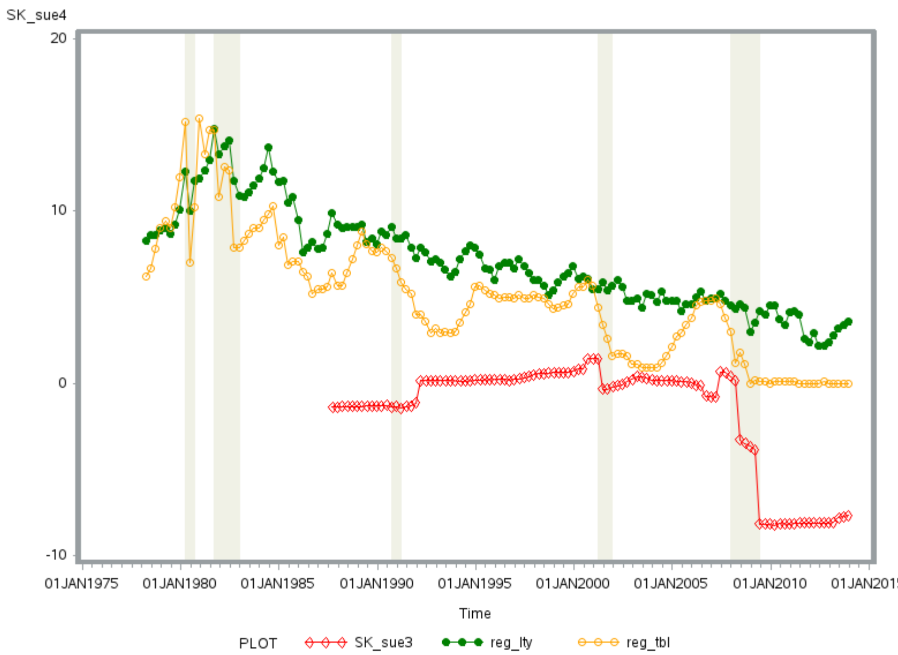
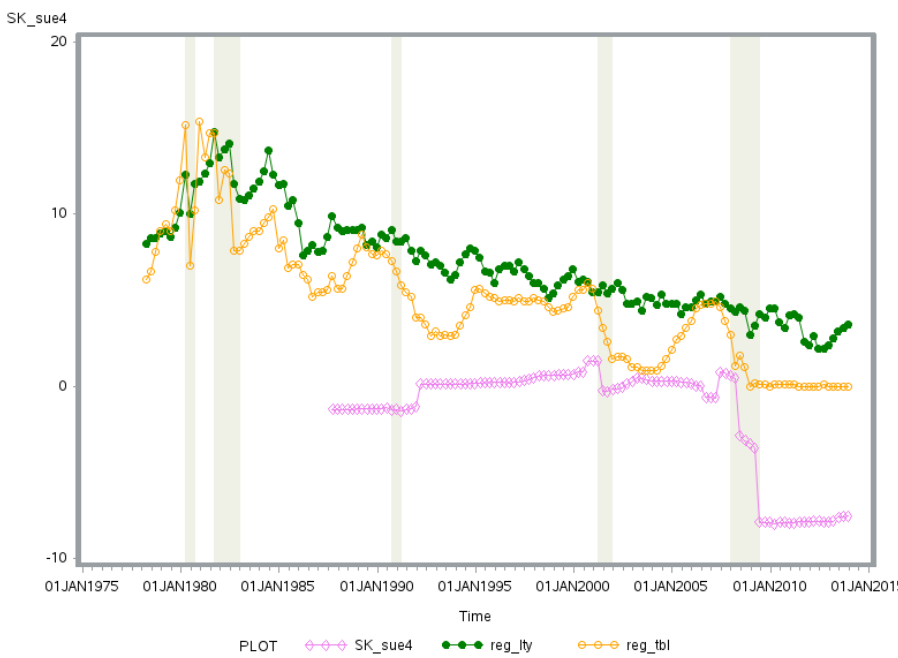


Figure 4.6: SK_{SUE3}, SK_{SUE4} and Bond Yields





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