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# The Higher Moments of Future Earnings

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**ABSTRACT:** We evaluate whether reported accounting numbers are informative about earnings uncertainty and whether earnings uncertainty is priced. We use quantile regressions to forecast the standard deviation, skewness, and kurtosis of future earnings. These three moments are important measures of earnings uncertainty because they reflect the size of the average deviation from expected earnings and the amount of extreme upside potential, extreme downside risk, or both. We develop a novel approach for evaluating the reliability of our forecasts and we show that they are reliable. We also document that: (1) equity prices are increasing (decreasing) in the standard deviation and skewness (kurtosis) of lead return on equity and (2) credit spreads are increasing (decreasing) in the standard deviation and kurtosis (skewness) of lead return on assets. Our results indicate that historical financial statements are informative about earnings uncertainty and that earnings uncertainty is priced.

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**Keywords:** earnings uncertainty; higher moments; forecasting; equity prices; credit spreads.

## I. INTRODUCTION

We investigate two questions: Are historical financial statements informative about earnings uncertainty? If so, do investors use this information when pricing equity and debt securities? We focus on earnings because they are a key, if not *the* key, summary accounting measure of performance. We focus on uncertainty because it plays a central role in business. Assessing it is at the core of security analysis. It is a key determinant of firms' investment and financing policies. And it affects firms' abilities to write contracts and the terms of the contracts they write. Consequently, investors and

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Supplemental materials can be accessed by clicking the links in Appendix A.

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other stakeholders demand information that helps them assess uncertainty and a primary objective of financial reporting is to supply this information.[1]

Despite the above, there is little evidence about whether financial statements convey information about earnings uncertainty, and if they do, how this information affects stakeholders' decisions. A small set of studies focus on earnings volatility (e.g., Beaver, Kettler, and Scholes 1970; Baginski and Wahlen 2003; Pástor and Veronesi 2003; Donelson and Resutek 2015). But volatility is not the only type of uncertainty. Stakeholders also care about extreme downside risk (i.e., negative skewness), extreme upside potential (i.e., positive skewness) or both (i.e., kurtosis). At present, Konstantinidi and Pope (2016; hereafter, KP) is the only other study of these phenomena. KP develop forecasts of the standard deviation, skewness, and kurtosis of return on equity, *ROE*, and they show that their forecasts are associated with various risk proxies.[2] However, KP do not evaluate the reliability of their forecasts or the relation between their forecasts and equity prices.

We begin by making improvements to the forecasting approach described in KP. KP base their forecasts on out-of-sample predictions obtained from quantile regressions of lead *ROE* on historical accounting numbers.[3] Their forecasts are based on *ad hoc* formulas that are a function of only seven quantiles of *ROE* that lie between 0.125 and 0.875. Consequently, KP's forecasts are inconsistent (i.e., they exhibit large-sample bias) and do not reflect the tails of the distribution. Like KP, we also use quantile regressions. However, our forecasts are based on general formulas that are a function of 150 quantiles that are evenly spread between 0 and 1. Hence, our forecasts are consistent and they reflect the tails of the distribution. The latter fact is important because skewness and kurtosis are driven by tail events.

After developing our forecasts of the standard deviation, skewness and kurtosis of *ROE*, we take a step back and ask a fundamental question: Are they reliable? Reliability is important for three reasons. First, our forecasts are a function of historical accounting numbers. Hence, if they are reliable, we have *prima facie* evidence that financial reports are informative about earnings uncertainty. Second, evidence about reliability helps us interpret the results of the tests of the relation between our forecasts and security prices. If we want to use these tests to draw conclusions about the pricing of the standard deviation, skewness and kurtosis of *ROE*, we need evidence that our forecasts actually capture these phenomena. Finally, by evaluating reliability, we can compare our forecasts to forecasts generated by alternative approaches.

Evaluating reliability requires subtlety. The reason for this is that the realized moments of *ROE* are not observable at the firm-year level. We devise two novel approaches for circumventing this problem. First, we graph the relation between our out-of-sample forecasts of the moments of *ROE* and the location, dispersion and tails of the distribution of lead *ROE*. These graphs show that our forecasts of the mean and standard deviation are reliable indicators of location and dispersion, respectively. They also show that our forecasts of skewness and kurtosis capture downside risk but are less reliable indicators of upside potential.

Although the graphs described above are intuitive, they can only be evaluated via visual inspection, and thus we cannot use them to compare our forecasts to other forecasts. To deal with this issue, in our second approach, we conduct industry-level tests in which we use the law of total moments described in Brillinger (1969) to convert forecasts of firm-year moments into forecasts of industry-year moments. The advantage of this approach is that we can objectively compare industry-year forecasts based on our forecasting approach to industry-year forecasts based on alternative approaches.

The industry-level tests reveal that each of our forecasts of industry-level moments has a positive association with its realized industry-level counterpart and explains a significant portion of the cross-sectional variation in this counterpart. Moreover, and perhaps more important, we find that our industry-year forecasts always contain incremental explanatory power and are typically more (and never less) reliable than industry-year forecasts based on: (1) KP's approach; (2) the firm's historical *ROE*; and (3) an extension of the matched-sample approach that Donelson and Resutek (2015) use to forecast earnings volatility.

The results of the two sets of tests described above imply that historical accounting numbers *do* provide stakeholders with information that they can use to assess earnings uncertainty. However, whether stakeholders use this information remains an open empirical question. Given it is beyond the scope of one study to evaluate all stakeholders' decisions, we focus on investors and we evaluate the relations between our forecasts of higher moments of future earnings and equity prices and credit spreads. We focus on investors and security prices for two reasons. First, investors are important users of financial statements. Second, securities play a key role in allocating capital and facilitating risk sharing and consumption smoothing (Arrow 1964);

[1] See, for example, Statement of Financial Accounting Concepts No. 1 issued by FASB (2008) and *The Conceptual Framework for Financial Reporting* issued by IASB (2010).

[2] KP evaluate seven risk proxies: (1) lead stock return volatility; (2) analysts' equity risk ratings; (3) the absolute value of analysts' earnings exclusions; (4) the absolute value of analysts' forecast errors; (5) bond yields; (6) bond ratings; and (7) an indicator variable that equals 1 (0) when a firm's bond rating is speculative (investment) grade.

[3] Quantiles and percentiles are basically the same. The only difference between them relates to labeling: Quantile $q$ equals the $(100 \times q)$th percentile *not* the $q$th percentile. For instance, quantile 0.25 is the 25th percentile of the distribution. Quantile regressions generate predictions of the conditional quantiles of the dependent variable.

and security prices are information signals that economic agents can use when making real decisions (e.g., Bond, Edmans, and Goldstein 2012).

We find that equity prices are increasing in our forecasts of the standard deviation of lead *ROE*. This result implies that the model developed by Pástor and Veronesi (2003; hereafter, PV), who predict a positive relation between equity prices and the volatility of *ROE*, describe the pricing of earnings volatility better than the model developed by Merton (1987), who predicts a negative relation between equity prices and stock return volatility. We find that equity prices are increasing (decreasing) in our forecasts of the skewness (kurtosis) of lead *ROE*. These results are consistent with results in Brunnermeier, Gollier, and Parker (2007), Barberis and Huang (2008), Mitton and Vorkink (2007) and Conrad, Dittmar, and Ghysels (2013), who focus on the skewness and kurtosis of stock returns. Hence, our evidence suggests that the skewness and kurtosis of both future *ROE* and future stock returns are priced similarly. Finally, we find that our results remain after controlling for the moments of historical, firm-level *ROE*; the moments of historical, firm-level stock returns; and other firm-year characteristics. This is important because it implies that our forecasts of earnings uncertainty contain information beyond the information embedded in the historical distribution of either the firm's earnings or its stock returns.

Regarding credit spreads, we show that they have a positive association with our forecasts of the standard deviation and kurtosis of lead return on assets, *ROA*, and a negative association with our forecast of the skewness of lead *ROA*.[4] This leads to the intuitive conclusion that creditors dislike exposure to volatility, downside risk, and the risk of extreme outcomes. These results are fairly robust. In particular, the relations between either credit default swap (i.e., CDS) spreads or bond ratings and skewness and kurtosis are insensitive to including a set of controls in the regression that consists of the moments of historical, firm-level *ROA*; the moments of historical, firm-level stock returns; and other firm-year characteristics.

We make four contributions. First, we show that historical financial statements are informative about earnings uncertainty, that this information is priced, and that it is incrementally value relevant *vis-à-vis* information embedded in either historical earnings or historical stock returns. This contribution is fundamental because it shows that financial reporting achieves one of its key objectives: Providing information that can be used to assess uncertainty. This contribution also adds to the vast body of literature relating to financial statement analysis and the valuation role of accounting numbers. Virtually all the studies in this literature focus on either realized or expected earnings. We show that this focus is too narrow. The higher moments of future earnings are also important.

Second, we develop a general approach for forecasting the higher moments of future earnings. Our approach captures the likelihood of extreme outcomes, generates consistent forecasts and is more reliable than alternative approaches. Third, we develop an empirical approach for validating forecasts of higher moments. These second two contributions are important because they lay a path for future research. Specifically, because it is reliable, researchers can use our forecasting approach to further study the higher moments of future earnings. Similarly, researchers can use our validation approach to evaluate the usefulness of new methodologies that they propose for forecasting the higher moments of earnings or *any* other variable.

Finally, we add to the evidence provided by KP regarding the relation between earnings skewness and credit spreads. Similar to KP, we find only weak evidence of a relation between bond yields and earnings skewness. However, unlike KP, we also evaluate CDS spreads, which are a better indicator of priced credit risk than bond yields. We find that there is a robust, negative relation between CDS spreads and the skewness of *ROA*. Hence, we provide support for an intuitive argument made by practitioners (e.g., Dynkin, Gould, Hyman, Konstantinovsky, and Phelps 2007): Credit investors demand compensation for bearing downside risk.

## II. RESEARCH QUESTIONS AND RELATED LITERATURE

A firm's stakeholders have either a direct or indirect interest in its ability to generate future cash flows. *Ceteris paribus*, firms that generate more cash flows hire more employees, purchase more from suppliers, pay larger dividends, are more likely to meet their contractual obligations, etc. Moreover, because future cash flows are unknown, stakeholders are exposed to uncertainty. Consequently, a fundamental objective of financial reporting is to "provide information to help investors, creditors, and others assess the amounts, timing, and *uncertainty* of prospective net cash inflows to the related enterprise" (FASB 2008; emphasis added).

Although cash flows are the ultimate determinant of a firm's performance, historical and near-term future cash flows are often a poor indicator of a firm's cash flow generating ability. For this reason, firms are required to use accrual accounting. Under accrual accounting, revenues are recognized in the period when they are earned, and then related expenses are deducted from these revenues. Hence, *a priori*, accounting earnings are a better indicator of a firm's periodic performance than

[4] Bondholders have a claim on the assets, which implies that, from their perspective, *ROA* is the relevant performance metric. Hence, we relate credit spreads to the moments of *ROA* not the moments of *ROE*.

contemporaneous cash flows. Empirical evidence supports this conjecture (e.g., Dechow 1994; Penman and Sougiannis 1998; Nichols and Wahlen 2004).

The above discussion leads to a fundamental question: Are financial reports informative about earnings uncertainty? The answer to this question is not obvious for two reasons. First, higher moments, and especially skewness and kurtosis, which are driven by rare tail events, are inherently difficult to forecast. Second, financial statements are published infrequently, are primarily based on historical costs, and reflect aggregated data. Hence, whether historical financial reports are informative about earnings uncertainty is an empirical question and there is scant empirical evidence. Donelson and Resutek (2015) evaluate the reliability of their matched-sample-based forecasts of earnings volatility. However, they do not evaluate earnings skewness and kurtosis, they do not compare their forecasts to forecasts obtained from quantile regressions and their approach for evaluating reliability can only be used to evaluate forecasts of volatility—i.e., it cannot be used to evaluate forecasts of skewness and kurtosis.

Assuming financial statements are informative about earnings uncertainty, whether and how stakeholders use this information are also empirical questions. We focus on investors and we study equity prices and credit spreads. The analytical and empirical evidence regarding the relation between security prices and earnings uncertainty is limited. Regarding equity prices, PV develop a model in which current equity market value is an increasing, *convex* function of future growth in equity book value. Thus, given growth in equity book value is increasing in *ROE*, equity market value is increasing in the volatility of future *ROE*. PV provide empirical evidence that is consistent with their analytical results.

PV make an important contribution. However, their study only relates to earnings volatility. Equity investors are also exposed to extreme downside risk, extreme upside potential, or both. Although analytical and empirical results in Brunnermeier et al. (2007), Barberis and Huang (2008), Mitton and Vorkink (2007), and Conrad et al. (2013) imply that equity prices are increasing (decreasing) in skewness (kurtosis), these studies evaluate the skewness and kurtosis of stock returns. *A priori*, it is unclear whether earnings skewness (kurtosis) is priced the same way as stock return skewness (kurtosis). If analytical results regarding the pricing of volatility are any guide, they are not. Specifically, Merton (1987) shows that when market segmentation leaves investors exposed to idiosyncratic risk, equity market value is a *decreasing* function of stock return volatility. This is the exact opposite of the analytical result in PV, who, as discussed above, study earnings volatility.

In addition to the studies mentioned above, there is a small set of studies in the accounting literature that focus on the relation between measures of earnings uncertainty and measures of equity risk.[5] Most of these studies focus on earnings volatility and ignore higher moments of the earnings distribution (e.g., Beaver et al. 1970; Baginski and Wahlen 2003).[6] The key exception is the study by KP. KP use quantile regressions to forecast the standard deviation, skewness, and kurtosis of lead *ROE*, and then they evaluate the association between their forecasts and various risk proxies. However, KP do not evaluate the association between equity prices and either their forecasts of earnings moments or the risk proxies they study. Moreover, KP do not evaluate the reliability of their forecasts.

Regarding credit spreads, well-known analytical results in Black and Scholes (1973) and Merton (1974) show that they are increasing in the volatility of stock returns. Moreover, KP provide empirical evidence that credit spreads are increasing in earnings volatility and kurtosis. However, they do not find any evidence of a relation between credit spreads and earnings skewness. This is counterintuitive given that creditors are more exposed to downside risk than to upside potential. Hence, additional analysis of the relation between earnings skewness and credit spreads is warranted.

Finally, we are unaware of any extant study that provides evidence about whether measures of earnings uncertainty are related to either equity prices or credit spreads after controlling for the moments of stock returns. Hence, the relative importance of earnings uncertainty *vis-à-vis* stock return uncertainty is unclear. Moreover, whether information about earnings uncertainty gleaned from financial reports is subsumed by information in historical stock returns is an open, empirical question.

## III. FORECASTING HIGHER MOMENTS

We use quantile regressions to develop out-of-sample forecasts of the quantiles of lead *ROE*, and then we convert the forecasted quantiles into out-of-sample forecasts of higher moments. We use the formulas shown below to calculate our year $t$ forecasts of the mean, standard deviation, skewness, and kurtosis of firm $i$'s *ROE* in year $t+1$.[7]

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[5] Ryan (1997) reviews prior research that relates accounting numbers to market-based measures of risk and discusses the disclosure-policy implications of this research.

[6] There is also a set of studies in the accounting literature that focuses on the relation between the moments of future stock returns and either accounting information or accounting/disclosure quality. For example, Sridharan (2015) shows that earnings-to-price and book-to-price ratios can be used to forecast option straddle returns and stock return volatility. Another set of studies evaluate whether "crash" risk—i.e., the risk of extreme negative stock returns—is affected by accounting quality and/or the disclosure environment (e.g., Bleck and Liu 2007; Hutton, Marcus, and Tehranian 2009; Bradshaw, Hutton, Marcus, and Tehranian 2010; Kim and Zhang 2014, 2016; DeFond, Hung, S. Li, and Y. Li 2015; Kim, Li, Lu and Yu 2016).

[7] We use the formulas for standardized skewness and *excess* standardized kurtosis. Excess standardized kurtosis reflects the difference between: (1) standardized kurtosis and (2) the standardized kurtosis of a normally distributed variable, which is equal to three.

$$q\_mean_{i,t+1} = \frac{1}{Q}\sum\nolimits_{q \in Z}\left(quant_q^*\left(ROE_{i,t+1}|\cdot\right)\right) \tag{1}$$

$$q\_std_{i,t+1} = \sqrt{\frac{1}{Q}\sum\nolimits_{q \in Z}\left(quant_q^*\left(ROE_{i,t+1}|\cdot\right) - q\_mean_{i,t+1}\right)^2} \tag{2}$$

$$q\_skew_{i,t+1} = \frac{1}{Q}\sum\nolimits_{q \in Z}\left(\frac{\left(quant_q^*\left(ROE_{i,t+1}|\cdot\right) - q\_mean_{i,t+1}\right)}{q\_std_{i,t+1}}\right)^3 \tag{3}$$

$$q\_kurt_{i,t+1} = \frac{1}{Q}\sum\nolimits_{q \in Z}\left(\frac{\left(quant_q^*\left(ROE_{i,t+1}|\cdot\right) - q\_mean_{i,t+1}\right)}{q\_std_{i,t+1}}\right)^4 - 3 \tag{4}$$

In the above equations, $quant_q^*\left(ROE_{i,t+1}|\cdot\right)$ is our year $t$ out-of-sample forecast of quantile $q$ of firm $i$'s *ROE* in year $t$+1, $ROE_{i,t+1}$.[8] We use the superscript $*$ to denote the fact that $quant_q^*\left(ROE_{i,t+1}|\cdot\right)$ is obtained from the *rearranged* quantile function. We explain why we use the rearranged quantile function below. The variable $q$ is an element of the set $Z = \{a \ldots q \ldots z\} \subset (0, 1)$, which is an ordered sequence of $Q = 150$ numbers that are spread evenly between 0 and 1.[9]

Equations (1) through (4) are very similar to the formulas for calculating the sample mean, standard deviation, skewness, and kurtosis. However, instead of using realizations drawn from the distribution of historical *ROE*, the equations use forecasts of the quantiles of the distribution of lead *ROE*. Whether these equations yield accurate forecasts depends on the accuracy of the forecasted quantiles and on the number of quantiles forecasted. The reason for this is that extreme deviations relate to rare tail events. Hence, to determine the potential for extreme deviations, which is the main determinant of skewness and kurtosis, forecasts of a large number of quantiles that encompass the distribution of *ROE* are needed.

**Forecasting a Single Quantile**

Our *initial* year $t$ forecast of conditional quantile $q$ of $ROE_{i,t+1}$ is:

$$quant_q\left(ROE_{i,t+1}|\cdot\right) = \sum\nolimits_{j=0}^{7} b_{j,EY}^q x_{i,t,j} \tag{5}$$

In Equation (5), $b_{0,EY}^q \cdots b_{7,EY}^q$ are coefficients that are estimated using data that were observable on or before the end of year *EY*, which we refer to as the estimation year. The variable $x_{i,t,0}$ equals 1 and the variables $x_{i,t,1} \cdots x_{i,t,7}$ are firm-specific realizations for year $t$ of seven predictor variables, which we describe in a subsequent subsection. Note that $quant_q\left(ROE_{i,t+1}|\cdot\right)$ is our initial forecast of quantile $q$. It is *not* obtained from the rearranged quantile function. Hence, we omit the $*$ superscript and we refer to values of $quant_q\left(ROE_{i,t+1}|\cdot\right)$ as "non-rearranged" quantiles.

The forecast generated by Equation (5) is similar to the forecast generated by an ordinary least squares (i.e., OLS) regression. That is, it is a linear combination of the estimated coefficients $b_{0,EY}^q \cdots b_{7,EY}^q$ and the predictor variables $x_{i,t,0} \cdots x_{i,t,7}$. However, unlike the predicted value from an OLS regression, which is a forecast of the conditional mean of $ROE_{i,t+1}$, Equation (5) generates a forecast of conditional quantile $q$ of $ROE_{i,t+1}$. The reason for this is that the estimated coefficients are quantile specific—i.e., they vary with $q$. Specifically, if we let $\varepsilon_{i,t+1}^q = ROE_{i,t+1} - \sum_{j=0}^{7} b_{j,EY}^q x_{i,t,j}$, the estimated coefficients $b_{0,EY}^q \cdots b_{7,EY}^q$ solve the minimization problem shown below:

$$\underset{b_{0,EY}^q \cdots b_{7,EY}^q}{\arg\min} \frac{1}{N}\left\{\sum\nolimits_{i:\varepsilon_{i,t+1}^q \geq 0}\left(q \times \left|\varepsilon_{i,t+1}^q\right|\right) + \sum\nolimits_{i:\varepsilon_{i,t+1}^q < 0}\left((1-q) \times \left|\varepsilon_{i,t+1}^q\right|\right)\right\} \tag{6}$$

In the above equation, $N$ is the sample size. The intuition underlying Equation (6) is straightforward. For a given value of $q$, the weight put on positive forecast errors (i.e., values of $\varepsilon_{i,t+1}^q \geq 0$) is $q$ whereas the weight put on negative forecast errors (i.e., values of $\varepsilon_{i,t+1}^q < 0$) is $(1-q)$. Hence, the relative penalty applied to positive forecast errors *vis-à-vis* negative forecast errors is $\frac{q}{1-q}$.

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8 We use lower-case letters to refer to forecasts and upper-case letters to refer to either population values or realized amounts. Hence, $quant_q^*\left(ROE_{i,t+1}|\cdot\right)$ is a forecast of $quant_q\left(ROE_{i,t+1}|\cdot\right)$, $q\_std_{i,t+1}$ is a forecast of the population standard deviation of $ROE_{i,t+1}$, etc.

9 The smallest and largest numbers in the set $Z$ are $\frac{1}{151}$ and $\frac{150}{151}$, and each number in $Z$ equals the sum of the previous number and $\frac{1}{151}$. That is, $Z = \left\{\frac{k}{151}\right\}_{k=1}^{150}$. The number 150 is based on the results of Monte Carlo simulations. Specifically, we find that for simulated samples of firms, 150 quantiles guarantees that the correlation between the true population moments and the estimated moments is at least 0.80.

For example, when $q = 0.90$, the penalty applied to positive forecast errors is nine times (i.e., $9 = \frac{0.90}{(1-0.90)}$) larger than the penalty applied to negative forecast errors. This implies that, per the objective function underlying Equation (6), negative forecast errors cost less; so there are more of them. In fact, when $q = 0.90$, 90 percent of the forecast errors are negative. Consequently, the predicted value from Equation (5) is approximately equal to quantile 0.90 of the population distribution. More generally, as shown in Koenker and Bassett (1978), for any arbitrary quantile $q$, the percentage of negative forecast errors converges to $100 \times q$ percent as the sample size approaches infinity. That is, Equation (5) generates consistent forecasts of quantile $q$.

Although Equation (5) generates consistent forecasts, the rate at which the non-rearranged quantiles obtained from Equation (5) converge to their true population values varies with $q$. Moreover, forecasts of extreme non-rearranged quantiles will tend to converge at a slower rate than forecasts of interior non-rearranged quantiles. To understand why this is true, consider estimates of two non-rearranged quantiles: (1) $quant_{0.50}\left(ROE_{i,t+1}|\cdot\right)$, which is a forecast of the median, and (2) $quant_{0.95}\left(ROE_{i,t+1}|\cdot\right)$, which is a forecast of the 95th percentile. For the typical distribution and most samples of data, realized values cluster around the center of the *population* distribution. Consequently, except for a small number of forecast errors (i.e., values of $\varepsilon_{i,t+1}^{0.50}$) that are very near the center of the *empirical* distribution of $\varepsilon_{i,t+1}^{0.50}$, the sign of $\varepsilon_{i,t+1}^{0.50}$ is accurate. This implies that the forecast of the median is relatively accurate. However, the forecast of the 95th percentile will, by definition, depend on a relatively small number of forecast errors (i.e., values of $\varepsilon_{i,t+1}^{0.95}$). Although the forecasts related to these errors will be extreme relative to the *empirical* distribution, how extreme they are relative to the *population* distribution is unclear. They may truly be extreme, or it may be the case that there are too little data to reveal the tails of the population distribution. Consequently, the forecast of the 95th percentile is less accurate than the forecast of the median.

### Estimating the Quantile Function

Equations (5) and (6) relate to a single quantile. However, the moments of $ROE_{i,t+1}$ are a function of *all* the quantiles. Hence, we need to forecast the quantile function of $ROE_{i,t+1}$, which is the set of *all* the true quantiles of $ROE_{i,t+1}$. Because the quantile function consists of an infinite number of quantiles, we can never develop a complete forecast of it. However, we can (and do) forecast a large number of quantiles. In particular, we estimate 150 quantiles. Hence, the set $Z = \{a \ldots q \ldots z\}$ consists of an ordered sequence of 150 numbers that are spread evenly between 0 and 1. Consequently, our estimate of the quantile function virtually encompasses the distribution of $ROE_{i,t+1}$.

A benefit of the above is that our forecasts of the moments are based on forecasted quantiles that relate to the tails of the distribution. However, as discussed in the previous subsection, for any sample of data, forecasts of extreme quantiles generated by Equation (5) are typically less accurate than forecasts of interior quantiles. In fact, as discussed in Bassett and Koenker (1982), it is possible that the non-rearranged quantiles obtained from Equation (5) are not monotonically increasing in $q$. That is, *forecasts* of lower quantiles obtained from Equation (5) may exceed *forecasts* of higher quantiles. This is referred to as quantile crossing. Quantile crossing is more likely to occur for forecasts of extreme quantiles and the likelihood of crossing is higher for values of forecasted quantiles that relate to members of the set $Z$ that are close together. Nonetheless, even forecasted quantiles that relate to members of the set $Z$ that are far apart can cross.

Quantile crossing is *prima facie* evidence that the forecast of the quantile function is inaccurate. Moreover, because different non-rearranged quantiles converge to their true population values at different rates, quantile crossing can occur in large samples. Hence, when the forecasted quantile function is based on non-rearranged quantiles, it and the forecasts of the moments derived from it can exhibit both small- and large-sample bias.

To circumvent the quantile crossing problem described above we use the method of rearranged quantiles described in Chernozhukov, Fernandez-Val, and Galichon (2010). Specifically, we first solve the minimization problem shown in Equation (6) for a sequence of $Q = 150$ quantiles. Next, we rearrange these forecasted quantiles in the manner described in Chernozhukov et al. (2010). (We elaborate on the rearrangement in the Online Appendix [see the link in Appendix A to download the document].) As shown in Chernozhukov et al. (2010), this rearranged quantile function: (1) is monotonically increasing in $q$; (2) exhibits less small-sample bias than the non-rearranged quantile function; and (3) converges to the true population quantile function.

### Implementation of the Empirical Model

For each estimation year $EY$ and each of the 150 values of $q \in Z$, we use Equation (6) to solve for the coefficients in the quantile regression shown below.[10]

[10] Our model is similar to the OLS model that Hou, van Dijk, and Zhang (2012) use to forecast the mean of earnings.

$$quant_q\left(ROE_{i,t+1}|\cdot\right) = b^q_{0,EY} + b^q_{1,EY}ROE_{i,t} + b^q_{2,EY}LOSS_{i,t} + b^q_{3,EY}\left(ROE_{i,t} \times LOSS_{i,t}\right) + b^q_{4,EY}ACC_{i,t} + b^q_{5,EY}LEV_{i,t} + b^q_{6,EY}PAYER_{i,t} + b^q_{7,EY}PAYOUT_{i,t} + \varepsilon^q_{i,t+1} \quad (7)$$

The variables in Equation (7) are described in Panel B of Table 1. The motivation for the variables is straightforward. First, Freeman, Ohlson, and Penman (1982) show that *ROE* is persistent. Hence, we include $ROE_{i,t}$ in our model. Second, Brooks and Buckmaster (1976) show that losses follow a different time-series process than profits. Thus, we allow the coefficient on $ROE_{i,t}$ to vary with the sign of $ROE_{i,t}$. Third, evidence provided by Sloan (1996) implies that accruals are less persistent than cash flows. Consequently, we control for the portion of year *t ROE* that is attributable to year *t* accruals, $ACC_{i,t}$. Finally, well-known results in finance (e.g., Lintner 1956; Modigliani and Miller 1958; Miller and Rock 1985) show that firms' capital structure and payout policies are associated with the level, dispersion, and persistence of *ROE*. Hence, we include $LEV_{i,t}$, $PAYER_{i,t}$ and $PAYOUT_{i,t}$ in our model.

We use panel data to estimate the coefficients in Equation (7). We never use more than ten years of data to construct a panel; and we include a firm in the panel if it has at least one valid observation during the relevant time span. For example, suppose we want to develop out-of-sample forecasts for the year 1991. We set the estimation year to 1990 (i.e., $EY = 1990$), which implies that we use values of the dependent variable (independent variables) realized in the years 1981 through 1990 (1980 through 1989).

After estimating the coefficients, we develop our out-of-sample forecasts. To develop a forecast for year $t+1$, we first obtain the *lagged* (i.e., $EY = t$) set of estimated coefficients for each of the 150 values of $q$. We then compute our 150 forecasts of the conditional quantiles of $ROE_{\ i,t+1}$. In particular, for each value of $q \in Z$, we calculate $quant_q\left(ROE_{i,t+1}|\cdot\right)$ by inputting the relevant estimated coefficients and the year $t$ values of the predictor variables for firm $i$ into Equation (5). Next, as discussed above, we rearrange the forecasted quantiles. Finally, we use the rearranged quantiles and the formulas for the sample moments to arrive at our out-of-sample forecasts. For example, we use Equation (2) to compute our forecast of the standard deviation. As discussed in the Online Appendix, our forecasts of the moments are consistent.

### Comparison to KP

We make three improvements to KP's forecasting approach. First, we use the rearranged quantile function. This implies that our predicted quantiles do not cross whereas KP's might and sometimes do.[11] Consequently, our forecasts of the quantile function: (1) are consistent whereas KP's are not and (2) exhibit less small-sample bias than the forecasts developed by KP. Second, we use the formulas for the sample moments to calculate our forecasts. This is important because when the rearranged quantiles are plugged into these formulas, the formulas generate consistent forecasts. KP, on the other hand, use *ad hoc* formulas that do not generate consistent forecasts even when the rearranged quantiles are used.[12] Finally, our forecasts of the moments are based on 150 predicted quantiles that are spread evenly between 0 and 1. Hence, they reflect the tails of the distribution, which are the key determinants of skewness and kurtosis. KP, on the other hand, use only seven quantiles to calculate their forecasts of the moments and they ignore the tails of the distribution: Quantiles 0.875 and 0.125 are the most extreme quantiles that they consider.

## IV. SAMPLE CONSTRUCTION AND DESCRIPTIVE STATISTICS

### Sample Construction

We form two samples: (1) an estimation sample and (2) a prediction sample. The estimation sample contains observations that are used to estimate the coefficients shown in Equation (7).[13] The prediction sample contains observations for which we develop out-of-sample, firm-level forecasts of the moments of lead *ROE*. We describe all our variables in Table 1.

Our primary data source is the Compustat North America Annual file. To form the estimation sample, we first delete observations that have either missing values of the variables shown in Equation (7) or negative equity book value in year *t*. Next, we delete outliers, which we define as observations for which: $\left|ROE_{i,t+1}\right| > 2$, $\left|ROE_{i,t}\right| > 2$, $\left|ACC_{i,t}\right| > 2$, $\left|LEV_{i,t}\right| \notin [1, 20]$; or, $PAYOUT_{i,t} \notin [0, 1]$. The estimation sample contains 174,215 firm-years with independent (dependent) variables drawn from the time-period spanning 1963 to 2010 (1964 to 2011).[14]

[11] When we implement KP's approach we find that for 1,183 firm years the predicted quantiles are not monotonically increasing in $q$. This is nontrivial given that KP estimate a small number of quantiles that are relatively far apart. Moreover, for 237 of these firm years the estimate of quantile 0.250 exceeds the estimate of quantile 0.750—i.e., the estimate of the interquartile range, which KP use as their forecast of the standard deviation, is negative.

[12] KP's forecasts of the standard deviation is the inter-quartile range, *IQR*, which equals $(quant_{0.75} - quant_{0.25})$. Their forecast of skewness is $\{(quant_{0.75} - quant_{0.50}) - (quant_{0.50} - quant_{0.25})\}/IQR$. And their forecast of kurtosis is $\{(quant_{0.875} - quant_{0.625}) + (quant_{0.375} - quant_{0.125})\}/IQR$.

[13] We discuss the empirical estimates of the quantile regression slope coefficients in the Online Appendix.

[14] The results shown in the figures and tables are not attributable to any specific time-period. In particular, we replicate our tests for separate ten-year time-periods—i.e., 1973–1982, etc. The untabulated results of these replications are similar to the results shown in the paper.


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**TABLE 1**

**Variable Definitions**

**Panel A: Variables from Compustat North America Annual File and the Center for Research in Security Prices (i.e., CRSP) Monthly Stock File**

| Variable Name | Description per Compustat or CRSP |
|---|---|
| Compustat Variables | |
| $ACT_{i,t}$ | Current assets − Total at the end of year $t$ for firm $i$. |
| $AT_{i,t}$ | Assets − Total at the end of year $t$ for firm $i$. |
| $CEQ_{i,t}$ | Common/Ordinary equity − Total at the end of year $t$ for firm $i$. |
| $CHE_{i,t}$ | Cash and short-term investments at the end of year $t$ for firm $i$. |
| $CSHO_{i,t}$ | Common shares outstanding at the end of year $t$ for firm $i$. |
| $DLC_{i,t}$ | Debt in current liabilities − Total at the end of year $t$ for firm $i$. |
| $DP_{i,t}$ | Depreciation and amortization for year $t$ and firm $i$. |
| $DVPSX\_F_{i,t}$ | Dividends per share − Ex-date − Fiscal at the end of year $t$ for firm $i$. |
| $EBITDA_{i,t}$ | Earnings before interest, taxes, depreciation, and amortization for year $t$ and firm $i$. |
| $IB_{i,t}$ | Income before extraordinary items for year $t$ and firm $i$. |
| $LCT_{i,t}$ | Current liabilities − Total at the end of year $t$ for firm $i$. |
| $LT_{i,t}$ | Liabilities − Total at the end of year $t$ for firm $i$. |
| $PRCC\_F_{i,t}$ | Price close − Annual − Fiscal at the end of year $t$ for firm $i$. |
| $TXP_{i,t}$ | Income taxes payable at the end of year $t$ for firm $i$. |
| CRSP Variables | |
| $Ret_{i,m,t}$ | Market return on firm $i$'s common equity from the end of the previous month to the end of month $m$ of year $t$, with ordinary dividends reinvested at the month-end. |
| $Vwretd_{i,m,t}$ | Return (including all distributions) in month $m$ of year $t$ on the CRSP value-weighted index. |

**Panel B: Variables Shown in Equation (7)**

| Variable Name | Description |
|---|---|
| $quant_q\left(ROE_{i,t+1}\vert\cdot\right)$ | Forecast of conditional quantile $q$ of $ROE_{i,t+1}$. |
| $ROE_{i,t+1}$ | Firm $i$'s return on equity in year $t$+1. $ROE_{i,t+1} = \frac{IB_{i,t+1}}{CEQ_{i,t}}$. |
| $ROE_{i,t}$ | Firm $i$'s return on equity in year $t$. $ROE_{i,t} = \frac{IB_{i,t}}{CEQ_{i,t}}$. |
| $LOSS_{i,t}$ | An indicator variable that equals 1 (0) if $ROE_{i,t} < 0$ $\left(ROE_{i,t} \geq 0\right)$. |
| $ACC_{i,t}$ | The ratio of firm $i$'s accruals for year $t$ to its year $t$ equity book value. $ACC_{i,t} = \frac{\left(\Delta ACT_{i,t} - \Delta CHE_{i,t}\right) - \left(\Delta LCT_{i,t} - \Delta DLC_{i,t} - \Delta TXP_{i,t}\right) - DP_{i,t}}{CEQ_{i,t}}$. |
| $LEV_{i,t}$ | Firm $i$'s year $t$ leverage ratio. $LEV_{i,t} = \frac{AT_{i,t}}{CEQ_{i,t}}$. |
| $PAYER_{i,t}$ | An indicator variable that equals 1 (0) if $PAYOUT_{i,t} > 0$ ($PAYOUT_{i,t} = 0$). |
| $PAYOUT_{i,t}$ | Firm $i$'s dividend-payout ratio in year $t$. $PAYOUT_{i,t} = \frac{DVPSX\_F_{i,t} \times CSHO_{i,t}}{CEQ_{i,t}}$. |

**Panel C: Forecasts and Realizations of Firm- and Industry-Level Moments**

| Variable Name | Description |
|---|---|
| Forecasts of Firm-Level Moments | |
| $q\_mean_{i,t+1}$ | Year $t$ quantile-based forecast of the mean of firm $i$'s *ROE* (or, in Table 8, *ROA*) in year $t$+1. Calculated using Equation (1). |
| $q\_std_{i,t+1}$ | Year $t$ quantile-based forecast of the standard deviation of firm $i$'s *ROE* in year $t$+1. Calculated using Equation (2). |
| $q\_skew_{i,t+1}$ | Year $t$ quantile-based forecast of the skewness of firm $i$'s *ROE* (or, in Table 8, *ROA*) in year $t$+1. Calculated using Equation (3). |
| $q\_kurt_{i,t+1}$ | Year $t$ quantile-based forecast of the kurtosis of firm $i$'s *ROE* (or, in Table 8, *ROA*) in year $t$+1. Calculated using Equation (4). |
| $q\_cv_{i,t+1}$ | Year $t$ quantile-based forecast of the coefficient of variation of firm $i$'s *ROE* in year $t$+1. $q\_cv_{i,t+1} = \frac{q\_std_{i,t+1}}{\lvert q\_mean_{i,t+1}\rvert}$. |
| Forecasts of Industry-Level Moments | |
| $q\_std_{IND,t+1}$ | Year $t$ quantile-based forecast of the standard deviation of industry *IND*'s *ROE* in year $t$+1. Calculated using Equation (2) and the law of total moments per Equation [IA.3] in the Online Appendix. |

*(continued on next page)*

**TABLE 1 (continued)**

| Variable Name | Description |
|---|---|
| $q\_skew_{IND,t+1}$ | Year $t$ quantile-based forecast of the skewness of industry *IND*'s *ROE* in year $t+1$. Calculated using Equation (3) and the law of total moments per Equation [IA.4] in the Online Appendix. |
| $q\_kurt_{IND,t+1}$ | Year $t$ quantile-based forecast of the kurtosis of industry *IND*'s *ROE* in year $t+1$. Calculated using Equation (4) and the law of total moments per Equation [IA.5] in the Online Appendix. |
| $kp\_std_{IND,t+1}$ | Year $t$ quantile-based forecast of the standard deviation of industry *IND*'s *ROE* in year $t+1$. Calculated using the approach described in KP and the law of total moments per Equation [IA.3] in the Online Appendix. |
| $kp\_skew_{IND,t+1}$ | Year $t$ quantile-based forecast of the skewness of industry *IND*'s *ROE* in year $t+1$. Calculated using the approach described in KP and the law of total moments per Equation [IA.4] in the Online Appendix. |
| $kp\_kurt_{IND,t+1}$ | Year $t$ quantile-based forecast of the kurtosis of industry *IND*'s *ROE* in year $t+1$. Calculated using the approach described in KP and the law of total moments per Equation [IA.5] in the Online Appendix. |
| $hms\_std_{IND,t+1}$ | Year $t$ forecast of the standard deviation of industry *IND*'s *ROE* in year $t+1$. Calculated using the historical, matched-sample approach and the law of total moments per Equation [IA.3] in the Online Appendix. |
| $hms\_skew_{IND,t+1}$ | Year $t$ forecast of the skewness of industry *IND*'s *ROE* in year $t+1$. Calculated using the historical, matched-sample approach and the law of total moments per Equation [IA.4] in the Online Appendix. |
| $hms\_kurt_{IND,t+1}$ | Year $t$ forecast of the kurtosis of industry *IND*'s *ROE* in year $t+1$. Calculated using the historical, matched sample-approach and the law of total moments per Equation [IA.5] in the Online Appendix. |
| $hfl\_std_{IND,t+1}$ | Year $t$ forecast of the standard deviation of industry *IND*'s *ROE* in year $t+1$. Calculated using the historical, firm-level approach and the law of total moments per Equation [IA.3] in the Online Appendix. |
| $hfl\_skew_{IND,t+1}$ | Year $t$ forecast of the skewness of industry *IND's ROE* in year $t + 1$. Calculated using the historical, firm-level approach and the law of total moments per Equation [IA.4] in the Online Appendix. |
| $hfl\_kurt_{IND,t+1}$ | Year $t$ forecast of the kurtosis of industry *IND*'s *ROE* in year $t+1$. Calculated using the historical, firm-level approach and the law of total moments per Equation [IA.5] in the Online Appendix. |
| $hil\_std_{IND,t+1}$ | Year $t$ forecast of the standard deviation of industry *IND*'s *ROE* in year $t+1$. It equals the standard deviation of the *ROE*s realized by the members of industry *IND* in year $t$. |
| $hil\_skew_{IND,t+1}$ | Year $t$ forecast of the skewness of industry *IND*'s *ROE* in year $t+1$. It equals the skewness of the *ROE*s realized by the members of industry *IND* in year $t$. |
| $hil\_kurt_{IND,t+1}$ | Year $t$ forecast of the kurtosis of industry *IND*'s *ROE* in year $t+1$. It equals the kurtosis of the *ROE*s realized by the members of industry *IND* in year $t$. |
| Realized Industry-Level Moments | |
| $R\_STD_{IND,t+1}$ | The standard deviation of the *ROE*s realized by the members of industry *IND* in year $t+1$. |
| $R\_SKEW_{IND,t+1}$ | The skewness of the *ROE*s realized by the members of industry *IND* in year $t+1$. |
| $R\_KURT_{IND,t+1}$ | The kurtosis of the *ROE*s realized by the members of industry *IND* in year $t+1$. |

**Panel D: Dependent Variables and Control Variables Shown in Tables 7 and 8**

| Variable Name | Description |
|---|---|
| Dependent Variables | |
| $EP_{i,t}$ | Earnings-to-price ratio for firm $i$ in year $t$. $EP_{i,t} = \frac{IB_{i,t}}{CSHO_{i,t} \times PRCC\_F_{i,t}}$. |
| $BP_{i,t}$ | Book-to-market ratio for firm $i$ in year $t$. $BP_{i,t} = \frac{CEQ_{i,t}}{CSHO_{i,t} \times PRCC\_F_{i,t}}$. |
| $CDS_{i,t}$ | CDS spread for firm $i$ in the fourth month following the end of year $t$. Obtained from the MarkIt Group and equal to the quoted spread on five-year CDS contracts of senior unsecured debts with modified restructuring clauses. Higher values imply higher credit risk. |
| $BY_{i,t}$ | Bond yield for firm $i$ in the fourth month after the end of year $t$. Obtained from either the Trace or Mergent Fixed Income Security database. We use the yield on the largest bond that traded in the fourth month after the end of year $t$. Higher values imply higher credit risk. |
| $BR_{i,t}$ | Credit rating for firm $i$ in year $t$. Ranges between 1 and 24 and are obtained from Standard & Poor's. Higher values imply higher credit risk. |
| Control Variables in Table 7 but not Table 8 | |
| $SIZE_{i,t}$ | Equity market value of firm $i$ in year $t$. $SIZE_{i,t} = CSHO_{i,t} \times PRCC\_F_{i,t}$. |
| $BETA_{i,t}$ | Levered equity beta of firm $i$ in year $t$. Estimated in three steps. (1) For each industry based on the Fama-French 48 classifications, we estimate the slope coefficient obtained from a weighted least squares regression of industry-level monthly returns on the contemporaneous return on the market portfolio. The weights equal the contemporaneous equity market values. We use monthly returns drawn from a 60-month period ending three months after the last month of fiscal-year $t$. (2) We un-lever the estimated levered industry beta using the industry leverage ratio. (3) We estimate the levered firm beta using firm $i$'s leverage ratio to re-lever the unlevered industry beta. |

*(continued on next page)*


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**TABLE 1 (continued)**

| Variable Name | Description |
|---|---|
| Control Variables in Table 7 and Table 8 | |
| $hfl\_mean_{i,t+1}$ | Year $t$ forecast of the mean of firm $i$'s *ROE* (or, in Table 8, *ROA*) in year $t+1$. Calculated using the historical, firm-level approach, which sets the year $t$ forecast equal to the sample mean of firm $i$'s realized *ROE* (or, in Table 8, *ROA*) in years $t-9$ through $t$. |
| $hfl\_std_{i,t+1}$ | Year $t$ forecast of the standard deviation of firm $i$'s *ROE* (or, in Table 8, *ROA*) in year $t+1$. Calculated using the historical, firm-level approach, which sets the year $t$ forecast equal to the sample standard deviation of firm $i$'s realized *ROE* (or, in Table 8, *ROA*) in years $t-9$ through $t$. |
| $hfl\_skew_{i,t+1}$ | Year $t$ forecast of the skewness of firm $i$'s *ROE* (or, in Table 8, *ROA*) in year $t+1$. Calculated using the historical, firm-level approach, which sets the year $t$ forecast equal to the sample skewness of firm $i$'s realized *ROE* (or, in Table 8, *ROA*) in years $t-9$ through $t$. |
| $hfl\_kurt_{i,t+1}$ | Year $t$ forecast of the kurtosis of firm $i$'s *ROE* (or, in Table 8, *ROA*) in year $t+1$. Calculated using the historical, firm-level approach, which sets the year $t$ forecast equal to the sample kurtosis of firm $i$'s realized *ROE* (or, in Table 8, *ROA*) in years $t-9$ through $t$. |
| $ANNRET_{i,t}$ | Firm $i$'s annual stock return for year $t$. Measured over the 12-month period beginning on the fourth month of fiscal-year $t$ and ending on the third month of fiscal-year $t+1$. $ANNRET_{i,t} = \prod_{m=1}^{12}\left(1 + Ret_{i,m+3,t}\right)$. |
| $RET\_STD_{i,t}$ | Year $t$ standard deviation of monthly market-model residuals for firm $i$. Market-model residuals are obtained from regressions of firm-level monthly returns (i.e., $Ret_{i,m,t}$) on the contemporaneous return on the market portfolio (i.e., $Vwretd_{i,m,t}$). We use 12 monthly returns drawn from the 12-month period ending three months after the last month of fiscal-year $t$. |
| $RET\_SKEW_{i,t}$ | Year $t$ skewness of monthly market-model residuals for firm $i$. Market-model residuals are obtained from regressions of firm-level monthly returns (i.e., $Ret_{i,m,t}$) on the contemporaneous return on the market portfolio (i.e., $Vwretd_{i,m,t}$). We use 12 monthly returns drawn from the 12-month period ending three months after the last month of fiscal-year $t$. |
| $RET\_KURT_{i,t}$ | Year $t$ kurtosis of monthly market-model residuals for firm $i$. Market-model residuals are obtained from regressions of firm-level monthly returns (i.e., $Ret_{i,m,t}$) on the contemporaneous return on the market portfolio (i.e., $Vwretd_{i,m,t}$). We use 12 monthly returns drawn from the 12-month period ending three months after the last month of fiscal-year $t$. |
| Control Variables in Table 8 but not Table 7 | |
| $BP_{i,t}$ | Book-to-market ratio for firm $i$ in year $t$. $BP_{i,t} = \frac{CEQ_{i,t}}{CSHO_{i,t} \times PRCC\_F_{i,t}}$. |
| $LN\_SIZE_{i,t}$ | The natural log of the ratio of firm $i$'s year $t$ equity market value to the sum of all firm's contemporaneous equity market values. $LN\_SIZE_{i,t} = \frac{CSHO_{i,t} \times PRCC\_F_{i,t}}{\sum_i CSHO_{i,t} \times PRCC\_F_{i,t}}$. |
| $LIAB\_ASST_{i,t}$ | The ratio of firm $i$'s liabilities in year $t$ to its assets in year $t$. $LIAB\_ASST_{i,t} = \frac{LT_{i,t}}{AT_{i,t}}$. |
| $EBITDA\_LIAB_{i,t}$ | The ratio of firm $i$'s earnings before interest, taxes, depreciation and amortization in year $t$ to its liabilities in year $t$. $\frac{EBITDA_{i,t}}{LT_{i,t}}$. |
| $T2MAT_{i,t}$ | The remaining number of years to the date on which the bond matures. |
| $BOND\_SIZE_{i,t}$ | The natural log of the aggregate par value of the bond on the date it was issued. |

To form our prediction sample we identify all firm-years with positive equity book value in year $t$ and non-missing values of $ROE_{i,t}$, $LOSS_{i,t}$, $ROE_{i,t} \times LOSS_{i,t}$, $ACC_{i,t}$, $LEV_{i,t}$, $PAYER_{i,t}$ and $PAYOUT_{i,t}$.[15] We do not remove outliers or observations that have missing values of lead *ROE*. We limit our prediction sample to firm-years drawn from 1973 to 2011. The prediction sample contains 170,522 firm-years. However, because some of our tests involve comparing *ex ante* forecasts to *ex post* realizations, the number of observations underlying the results shown in Tables 4 through 8 is lower. Finally, sample sizes underlying our tests also vary because some of our tests involve: (1) comparing our quantile-based forecasts to alternative forecasts that cannot be calculated for all the observations in the prediction sample or (2) control variables that are missing for some of the observations in the prediction sample.

[15] If we did not remove observations with negative equity book values, then our estimation (prediction) sample would contain 177,997 (175,506) firm-years, which is a 2.1 (2.8) percent difference. Whether our results generalize to firms with negative equity book values is an empirical question.

**TABLE 2**

**Descriptive Statistics and Correlations for the Estimation Sample**

**Panel A: Descriptive Statistics**

| | Mean | Std. Dev. | Min. | p1 | p10 | p25 | p50 | p75 | p90 | p99 | Max. | n |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $ROE_{i,t+1}$ | 0.03 | 0.33 | −2.00 | −1.31 | −0.33 | −0.01 | 0.10 | 0.18 | 0.27 | 0.70 | 1.99 | 174,215 |
| $ROE_{i,t}$ | 0.02 | 0.30 | −2.00 | −1.31 | −0.26 | 0.01 | 0.10 | 0.16 | 0.22 | 0.51 | 1.98 | 174,215 |
| $LOSS_{i,t}$ | 0.24 | 0.43 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 1.00 | 1.00 | 174,215 |
| $ROE_{i,t} \times LOSS_{i,t}$ | −0.08 | 0.24 | −2.00 | −1.31 | −0.26 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 174,215 |
| $ACC_{i,t}$ | −0.06 | 0.31 | −2.00 | −1.12 | −0.34 | −0.16 | −0.05 | 0.06 | 0.23 | 0.84 | 1.98 | 174,215 |
| $LEV_{i,t}$ | 2.41 | 1.60 | 1.00 | 1.05 | 1.22 | 1.47 | 1.97 | 2.78 | 3.88 | 9.24 | 20.00 | 174,215 |
| $PAYER_{i,t}$ | 0.44 | 0.50 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 1.00 | 1.00 | 1.00 | 174,215 |
| $PAYOUT_{i,t}$ | 0.02 | 0.05 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.04 | 0.07 | 0.19 | 0.99 | 174,215 |

Please refer to Table 1 for variable definitions and descriptions.

**Panel B: Cross-Sectional Correlations**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| (1) $ROE_{i,t+1}$ | | 0.60 | −0.42 | 0.42 | 0.11 | 0.01 | 0.20 | 0.22 |
| | | (30.41) | (−10.00) | (6.70) | (5.83) | (0.43) | (5.92) | (20.48) |
| (2) $ROE_{i,t}$ | 0.70 | | −0.65 | 0.85 | 0.28 | −0.06 | 0.25 | 0.27 |
| | (35.42) | | (−23.04) | (15.60) | (10.55) | (−1.89) | (13.08) | (9.75) |
| (3) $LOSS_{i,t}$ | −0.43 | −0.63 | | −0.61 | −0.20 | 0.08 | −0.30 | −0.19 |
| | (−7.79) | (−7.58) | | (−68.54) | (−10.31) | (2.83) | (−19.52) | (−16.46) |
| (4) $ROE_{i,t} \times LOSS_{i,t}$ | 0.44 | 0.65 | −0.99 | | 0.26 | −0.15 | 0.22 | 0.13 |
| | (7.47) | (7.38) | (−199.46) | | (11.92) | (−5.64) | (14.11) | (13.84) |
| (5) $ACC_{i,t}$ | 0.12 | 0.22 | −0.20 | 0.21 | | −0.16 | −0.03 | −0.06 |
| | (5.25) | (9.93) | (−10.08) | (10.33) | | (−3.59) | (−2.16) | (−4.80) |
| (6) $LEV_{i,t}$ | 0.08 | 0.05 | 0.01 | −0.02 | −0.21 | | −0.01 | 0.08 |
| | (2.65) | (1.81) | (0.34) | (−0.64) | (−8.29) | | (−0.22) | (1.79) |
| (7) $PAYER_{i,t}$ | 0.23 | 0.28 | −0.30 | 0.31 | −0.06 | 0.07 | | 0.58 |
| | (6.52) | (9.29) | (−19.52) | (18.53) | (−3.27) | (1.02) | | (27.91) |
| (8) $PAYOUT_{i,t}$ | 0.31 | 0.36 | −0.29 | 0.29 | −0.09 | 0.11 | 0.88 | |
| | (21.23) | (23.72) | (−13.20) | (12.85) | (−5.41) | (2.00) | (18.21) | |

Please refer to Table 1 for variable definitions and descriptions.
Pearson product moment (Spearman rank order) correlations are shown above (below) the diagonal. Correlations are calculated as the means of the annual correlations. t-statistics are shown in parentheses. A particular t-statistic equals the mean of the annual correlations divided by the standard error of the mean. We use Newey-West adjusted standard errors assuming a lag-length of ten years.

## Descriptive Statistics

In Table 2 we provide descriptive statistics for the estimation sample and we show the correlation structure of the variables shown in Equation (7). These descriptive statistics and correlations are similar to amounts reported in numerous extant studies.

In Table 3 we provide descriptive statistics and correlations for our forecasts of the mean, standard deviation, skewness, and kurtosis of $ROE_{i,t+1}$. Panel A contains descriptive statistics. Several comments are warranted. First, the average (typical) firm has positive $q\_mean_{i,t+1}$ and $q\_mean_{i,t+1}$ varies considerably across observations. For example, its standard deviation (interquartile range) is 0.237 (0.210). Second, $q\_std_{i,t+1}$ is large. Specifically, the mean (median) of $q\_cv_{i,t+1}$, which is the coefficient of variation and equals the ratio of $q\_std_{i,t+1}$ to $|q\_mean_{i,t+1}|$, is 2.366 (0.716). There is also considerable cross-sectional variation in firm-level dispersion of *ROE*. For example, the interquartile range of $q\_cv_{i,t+1}$ is 0.975. Finally, the median of $q\_skew_{i,t+1}$ ($q\_kurt_{i,t+1}$) is −0.590 (1.748). Moreover, untabulated results show that 65.2 (82.7) percent of the observations have distributions of lead *ROE* that are negatively skewed (exhibit positive excess kurtosis). Hence, for the typical observation in our sample, lead *ROE* is drawn from a fat-tailed distribution with a long, left tail.

**TABLE 3**

**Descriptive Statistics for Quantile-Based Out-of-Sample Forecasts**

**Panel A: Descriptive Statistics**

| | Mean | Std. Dev. | Min. | p1 | p10 | p25 | p50 | p75 | p90 | p99 | Max. | n |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $q\_mean_{i,t+1}$ | 0.04 | 0.24 | −1.33 | −0.85 | −0.23 | −0.04 | 0.10 | 0.17 | 0.23 | 0.52 | 2.05 | 170,522 |
| $q\_std_{i,t+1}$ | 0.12 | 0.13 | 0.00 | 0.01 | 0.02 | 0.04 | 0.08 | 0.16 | 0.28 | 0.66 | 1.23 | 170,522 |
| $q\_cv_{i,t+1}$ | 2.37 | 221.96 | 0.01 | 0.04 | 0.14 | 0.29 | 0.72 | 1.27 | 2.24 | 13.00 | 90,342.54 | 170,522 |
| $q\_skew_{i,t+1}$ | 0.19 | 2.03 | −8.42 | −4.15 | −1.38 | −0.88 | −0.59 | 0.59 | 3.78 | 5.23 | 8.10 | 170,522 |
| $q\_kurt_{i,t+1}$ | 6.24 | 9.21 | −1.57 | −1.04 | −0.60 | 0.66 | 1.75 | 8.99 | 20.70 | 36.37 | 85.84 | 170,522 |

**Panel B: Cross-Sectional Correlations**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| (1) $q\_mean_{i,t+1}$ | | −0.62 | 0.20 | 0.27 |
| | | (−9.97) | (6.56) | (3.96) |
| (2) $q\_std_{i,t+1}$ | −0.47 | | −0.26 | −0.38 |
| | (−6.90) | | (−9.50) | (−14.06) |
| (3) $q\_skew_{i,t+1}$ | 0.21 | −0.34 | | 0.67 |
| | (3.70) | (−9.03) | | (4.21) |
| (4) $q\_kurt_{i,t+1}$ | 0.38 | −0.63 | 0.14 | |
| | (2.83) | (−7.93) | (1.24) | |

Please refer to Table 1 for variable definitions and descriptions. Pearson product moment (Spearman rank order) correlations are shown above (below) the diagonal. Correlations are calculated as the means of annual the correlations. t-statistics are shown in parentheses. A particular t-statistic equals the mean of the annual correlations divided by the standard error of the mean. We use Newey-West adjusted standard errors assuming a lag-length of ten years.

In Panel B of Table 3 we show the correlation structure of the variables. The Pearson correlations between $q\_mean_{i,t+1}$ and $q\_std_{i,t+1}$, $q\_skew_{i,t+1}$ and $q\_kurt_{i,t+1}$ are –0.62, 0.20, and 0.27, respectively. Hence, firms with high expected *ROE* also tend to have less volatile, more positively skewed and more extreme *ROE*. The Pearson correlation between $q\_std_{i,t+1}$ and $q\_skew_{i,t+1}$ $q\_kurt_{i,t+1}$ is –0.26 (–0.38), which implies that when the distribution of *ROE* is more disperse it also tends to be more negatively skewed (have thinner tails). Finally, the Pearson correlation between $q\_skew_{i,t+1}$ and $q\_kurt_{i,t+1}$ is 0.67. Hence, when extreme deviations are likely, extreme positive deviations tend to be more likely than extreme negative deviations.

## V. EVALUATING CONSTRUCT VALIDITY

We begin by providing graphs of the relations between our forecasts of the moments of *ROE* and the location, dispersion, and tails of the distribution of lead *ROE*. These graphs are intuitive; but they can only be evaluated via visual inspection, and thus we cannot use them to compare our forecasts to other forecasts. Hence, we also conduct industry-level tests in which we compare realized industry-year moments in year $t$+1 to forecasts of industry-year moments that are based on year $t$ out-of-sample, firm-year forecasts. The advantage of these tests is that they yield well-defined statistics that can be used to objectively compare our forecasts to other forecasts.

### Graphical Evidence

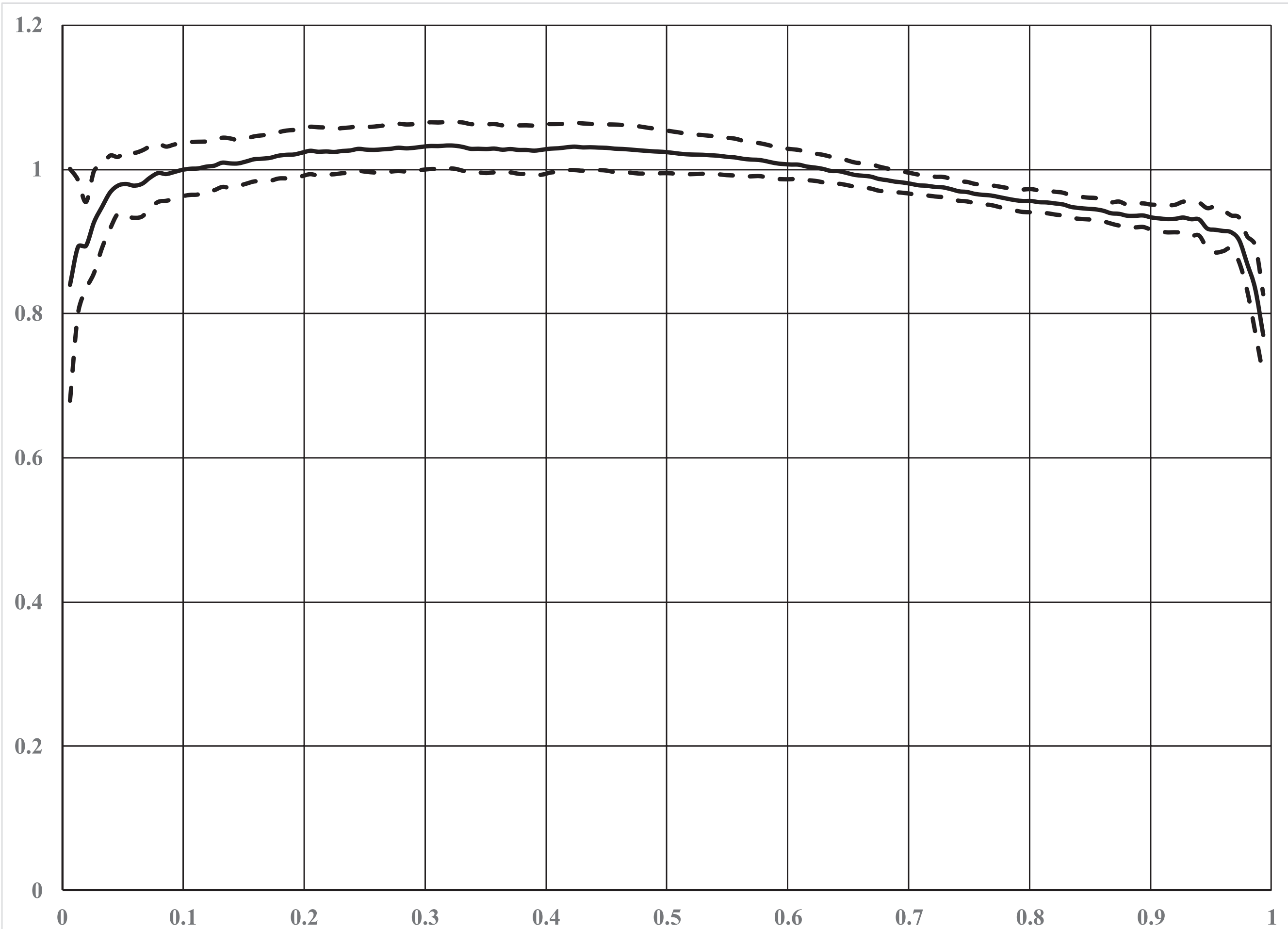
To create our graphs, we first estimate the quantile regression shown below. We estimate a separate regression for each cross-section in the prediction sample and for each value of $q$ in the set $Z$, which is described in Section III above.

$$quant_q\left(ROE_{i,t+1}|\cdot\right) = a^q_{0,t} + a^q_{1,t}q\_mean_{i,t+1} + a^q_{2,t}q\_std_{i,t+1} + a^q_{3,t}q\_skew_{i,t+1} + a^q_{4,t}q\_kurt_{i,t+1} + \delta^q_{i,t+1} \quad (8)$$

Next, we compute the time-series average of $a^q_{j,t}$ for each $j \in [1,4]$, which we refer to as $a^q_{j,AVG}$, and the standard error of $a^q_{j,AVG}$. When calculating the standard error, we make the Newey-West adjustment assuming a ten-year lag length. We then use the standard error to calculate a 95 percent confidence interval around the average. Finally, we graph $a^q_{j,AVG}$ and its confidence interval on $q$.

**FIGURE 1**
**Estimated Slope Coefficients from Equation (8)**

**Panel A: $a^q_{1,AVG}$**




$a^q_{1,AVG}$ is the average slope coefficient on $q\_mean_{i,t+1}$.

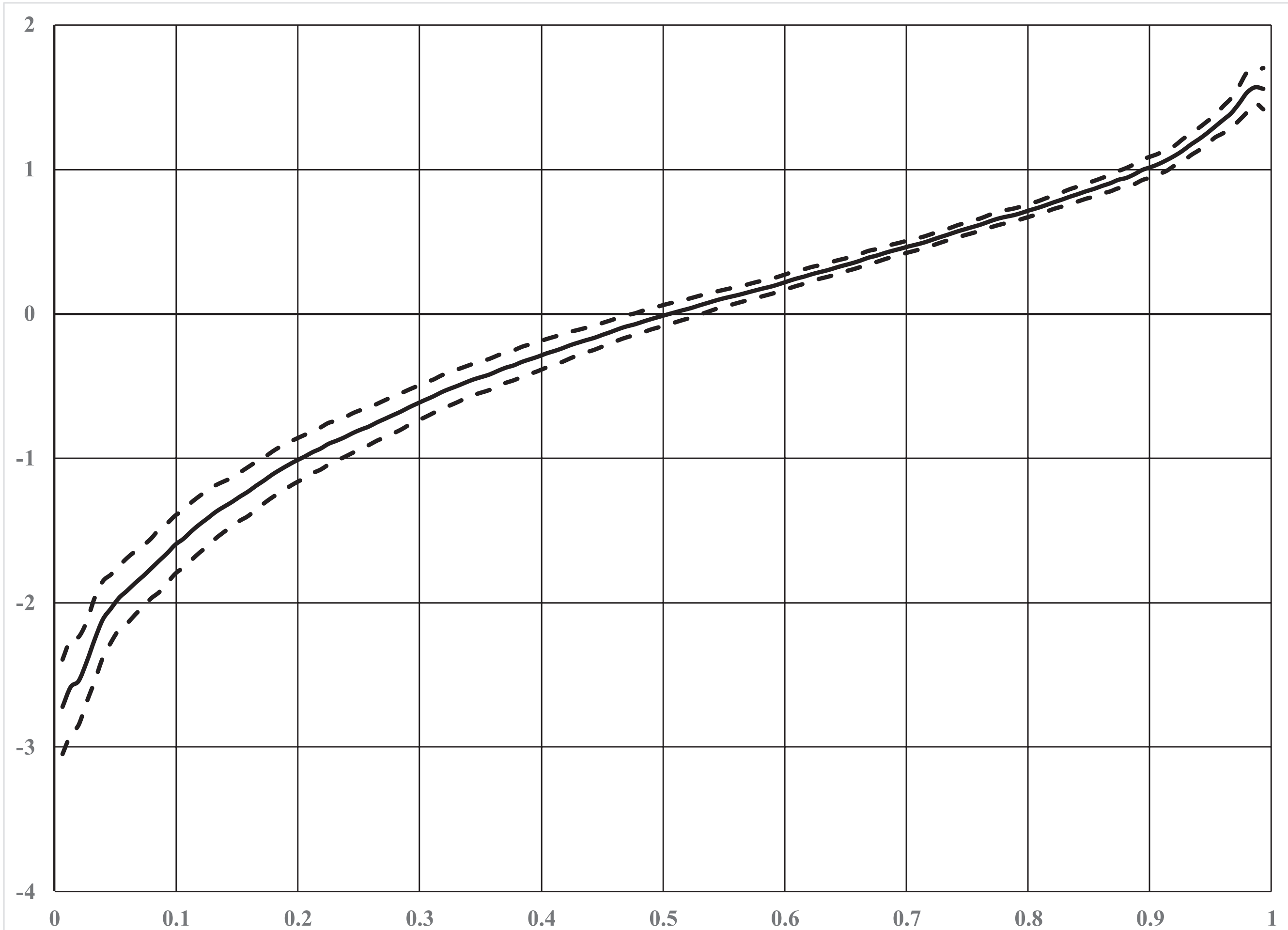
*(continued on next page)*

To interpret the graphs described above, we note that, as shown in Buchinsky (1998), the slope coefficient from a quantile regression is a consistent estimate of the marginal effect of a one-unit change in the independent variable on the relevant quantile of the dependent variable—e.g., $a^q_{1,t}$ is a consistent estimator of $\frac{\partial quant_q(ROE_{i,t+1}|\cdot)}{\partial q\_mean_{i,t+1}}$. Hence, our graphs illustrate the relations between our forecasts of the moments of *ROE* and the location, dispersion and tails of the distribution of *ROE*. To see this more clearly, consider Panel A of Figure 1. This subfigure contains the graph of the slope coefficients on $q\_mean_{i,t+1}$, which is our forecast of the mean of $ROE_{i,t+1}$. This graph shows that, for most values of $q$, $a^q_{1,t}$, is close to 1. Hence, a one-unit increase in $q\_mean_{i,t+1}$ is associated with a one-unit increase in *each* of the quantiles—i.e., the entire distribution shifts to the right by one unit. This implies that $q\_mean_{i,t+1}$ measures what it is designed to measure: The *location* of the distribution of $ROE_{i,t+1}$.

Turning to the graph shown in Panel B of Figure 1, we conclude that our forecast of the standard deviation is also a valid construct. In particular, the slope coefficients on our forecasts of the standard deviation are monotonically increasing in $q$; and untabulated results show that 51 (49) percent of the slope coefficients are negative (positive). Hence, larger values of $q\_std_{i,t+1}$

**FIGURE 1 (continued)**

**Panel B: $a^q_{2,AVG}$**




$a^q_{2,AVG}$ is the average slope coefficient on $q\_std_{i,t+1}$.

*(continued on next page)*

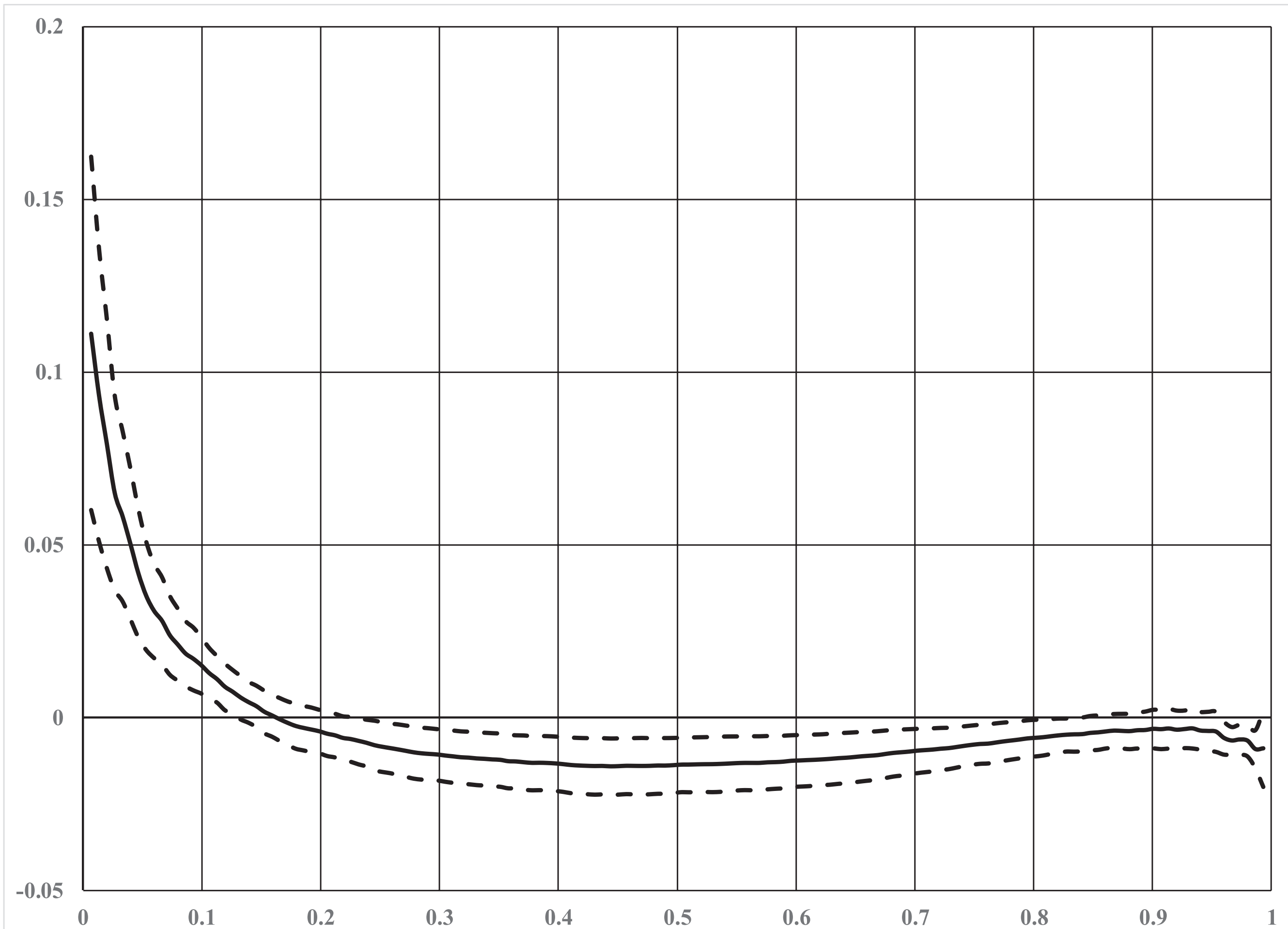
are associated with distributions that have larger upper quantiles and smaller lower quantiles (i.e., distributions that are more spread out). Hence, $q\_std_{i,t+1}$ measures what it is designed to measure: The *dispersion* of the distribution of $ROE_{i,t+1}$.

Panel C of Figure 1 contains the graph of the slope coefficients on our forecasts of skewness. We observe that for values of $q > 0.15$, the slope coefficients are all approximately equal to 0. However, for the remaining values of $q$, the slope coefficients are a decreasing, convex function of $q$. That is, for all quantiles below quantile 0.15, increases in $q\_skew_{i,t+1}$ are associated with increases in the left tail of the distribution of $ROE_{i,t+1}$ and these increases get larger in absolute value as $q$ approaches 0. Hence, higher (lower) values of $q\_skew_{i,t+1}$ are associated with distributions that have shorter (longer) left tails. This implies that $q\_skew_{i,t+1}$ captures extreme downside risk.

Finally, we consider Panel D of Figure 1, which contains the graph of the slope coefficients on our forecasts of kurtosis. We characterize the graph as being a "lop-sided frown." For values of $q$ between 0.16 and 0.77, the slope coefficients are approximately equal to 0 whereas the slopes that relate to values of $q < 0.16$ and values of $q > 0.76$ are all negative and they become more negative as $q$ becomes more extreme—i.e., closer to either 0 or 1. This "frown shape" implies that higher (lower) values of $q\_kurt_{i,t+1}$ are associated with distributions that have longer (shorter) left tails but shorter (longer) right tails. Hence, the evidence is mixed: $q\_kurt_{i,t+1}$ is positively associated with variation in the extremity of the left tail of $ROE_{i,t+1}$ but it is negatively associated with variation in the extremity of the right tail of $ROE_{i,t+1}$. That said, the frown is "lop sided."

**FIGURE 1 (continued)**

**Panel C: $a_{3,AVG}^{q}$**




$a_{3,AVG}^{q}$ is the average slope coefficient on $q\_skew_{i,t+1}$.

*(continued on next page)*

Specifically, as $q$ approaches 0 the left tail decreases very rapidly *vis-à-vis* the speed at which the right tail decreases as $q$ approaches 1. Overall, we conclude that, similar to $q\_skew_{i,t+1}$, $q\_kurt_{i,t+1}$ captures extreme downside risk but not extreme upside potential.

### Industry-Level Tests

We use the law of total moments to develop year $t$ forecasts of the within-industry-year standard deviation, skewness, and kurtosis of *ROE* in year $t$+1. For example, the law of total variance implies that the within-industry standard deviation of *ROE* can be expressed in the following manner:[16]

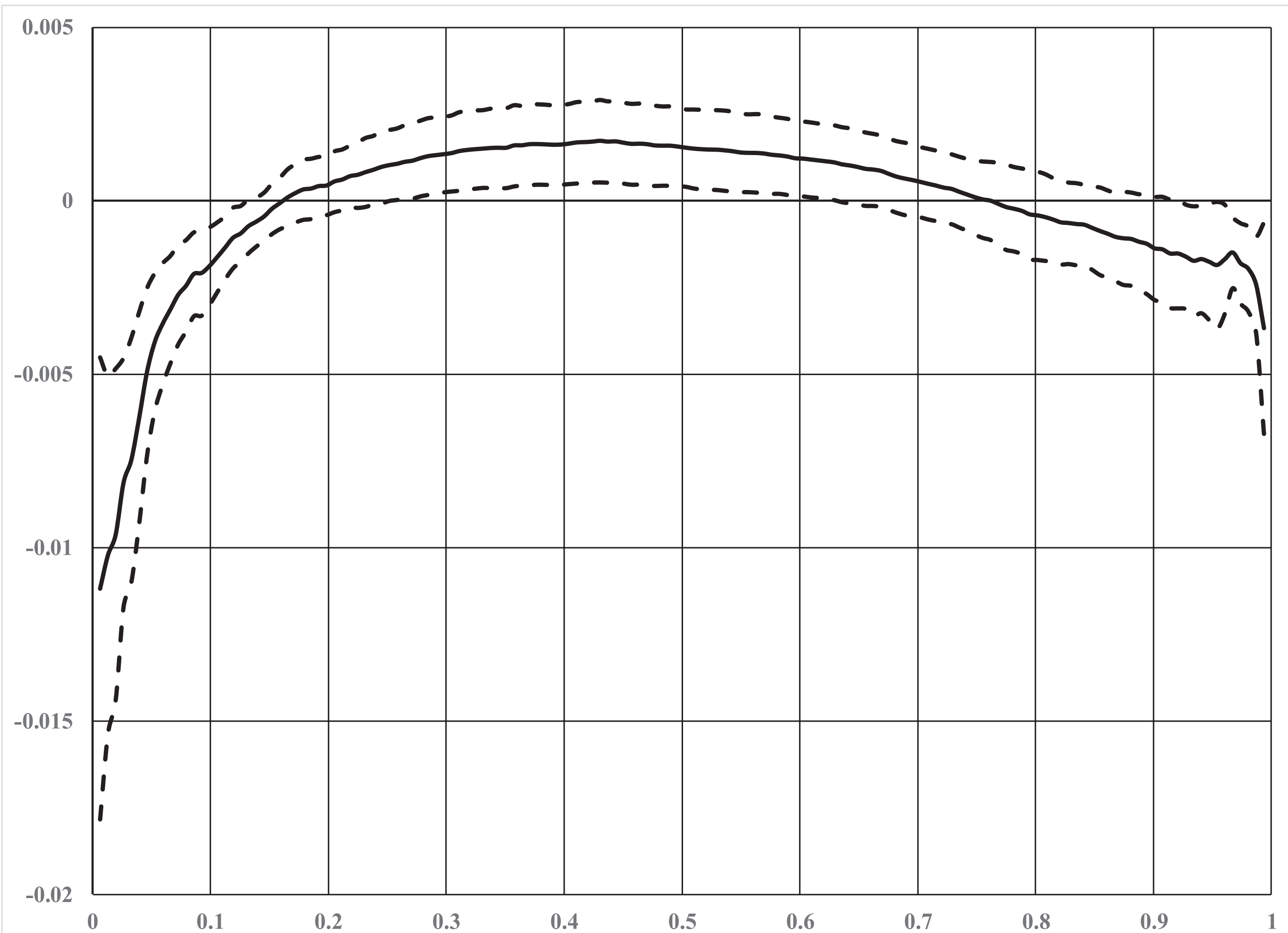
$$STD\left(ROE_{IND,t+1}|\cdot\right) = \sqrt{VAR\left(\mathbb{E}\left[ROE_{i,t+1}|\cdot\right]\right) + \mathbb{E}\left[VAR\left(ROE_{i,t+1}|\cdot\right)\right]} \tag{9}$$

In Equation (9), $VAR(\cdot)$ denotes the variance and $\mathbb{E}[\cdot]$ is the expected value.

[16] We describe the formulas that we use to calculate our industry-level forecasts of skewness and kurtosis in the Online Appendix.

**FIGURE 1 (continued)**

**Panel D: $a^{q}_{4,AVG}$**




$a^{q}_{4,AVG}$ is the average slope coefficient on $q\_kurt_{i,t+1}$.
Values of $q \in Z \subset (0,1)$ are shown on the x-axis and values of $a^{q}_{j,AVG}$ are shown on the y-axis. The solid line is the average of the annual estimates of $a^{q}_{j,t}$. Dashed lines equal the average coefficient $\pm 1.96$ multiplied by the standard error of the average. We use Newey-West adjusted standard errors assuming a lag-length of ten years.

With Equation (9) in mind, we do the following. First, for each firm $i$ and year $t$ we obtain firm-specific forecasts of the mean and the variance of $ROE_{i,t+1}$. Next, for each industry-year, we forecast the within-industry standard deviation of *ROE*. We do this by taking the square root of the sum of: (1) the within-industry variance of the forecasts of the mean of $ROE_{i,t+1}$ and (2) the industry mean of the forecasts of the variance of $ROE_{i,t+1}$. Finally, we calculate the realized cross-sectional standard deviation of *ROE* in year $t+1$, which we refer to as $R\_STD_{IND,t+1}$. (We refer to the realized cross-sectional skewness and kurtosis of *ROE* in year $t+1$ as $R\_SKEW_{IND,t+1}$, and $R\_KURT_{IND,t+1}$, respectively.)

We compare our forecasts to forecasts based on: (1) the approach used by KP (i.e., KP's approach); (2) an approach that uses historical matched samples (i.e., the historical matched-sample approach); and (3) an approach that uses the firm's historical *ROE* (i.e., the historical firm-level approach). We also compare our forecasts to an approach that does not rely on the law of total moments. We refer to it as the historical industry-level approach because it involves setting the year $t$ forecast of an industry-level moment in year $t+1$ equal to the industry-level moment of realized *ROE* in year $t$.[17]

When implementing KP's approach, we use the predictors and formulas described in their paper. The historical matched sample approach is an extension of the approach used by Donelson and Resutek (2015) to forecast the volatility of *ROE*. It sets the year $t$ forecast of a particular moment of firm $i$'s *ROE* in year $t+1$ equal to the sample moment for a set of firm-years between years $t-4$ and $t$. The firms in this set are matched to firm $i$ on the basis of total assets, *ROE* and $\Delta ROE$ in year $t$. The historical firm-level approach sets the year $t$ forecast of a particular moment of firm $i$'s *ROE* in year $t+1$ equal to the sample moment of its realized *ROE* in years $t-9$ through $t$. We provide additional details about how we implement the alternative approaches in the Online Appendix.

We refer to our year $t$ forecasts of the standard deviation, skewness, and kurtosis of industry *IND's ROE* in year $t+1$ as $q\_std_{IND,t+1}$, $q\_skew_{IND,t+1}$ , and $q\_kurt_{IND,t+1}$, respectively.[18] We use a similar naming convention for the alternative forecasts. However, when referring to forecasts based on KP's approach, the historical matched-sample approach, the historical firm-level approach, and the historical industry-level approach, we replace the letter $q$ with the letters *kp*, *hms*, *hfl*, and *hil*, respectively. We assign firm-years to industries on the basis of their two-digit Standard Industrial Classification (i.e., SIC) codes. We delete industry-years that have less than ten members.

In Tables 4, 5 and 6 we show the results of regressing realized industry-level moments on our forecasts and the forecasts obtained from the alternative approaches. As shown in columns (1), (4), (7), and (10) of Panels A and B of Table 4, $q\_std_{IND,t+1}$ has a significant positive association with $R\_STD_{IND,t+1}$ and it explains more than 20 percent of the cross-sectional variation in $R\_STD_{IND,t+1}$. Hence, it is a reliable predictor on an absolute basis. Per columns (3), (6), (9), and (12), $q\_std_{IND,t+1}$ is incrementally informative *vis-à-vis* each of the alternative forecasts. Moreover, Vuong test results show that it is a better forecast of $R\_STD_{IND,t+1}$ than any of the alternative forecasts.

Results related to $q\_skew_{IND,t+1}$ are similar to those for $q\_std_{IND,t+1}$. As shown in columns (1), (4), (7), and (10) of Panels A and B of Table 5, $q\_skew_{IND,t+1}$ has a significant positive association with $R\_SKEW_{IND,t+1}$ and it explains approximately 14 percent of the cross-sectional variation in $R\_SKEW_{IND,t+1}$. Per columns (3), (6), (9), and (12), these results remain after controlling for the forecasts obtained from the alternative approaches. Moreover, Vuong test results show that $q\_skew_{IND,t+1}$ is a better forecast of $R\_SKEW_{IND,t+1}$ than any of the alternative forecasts.

Finally, as shown in columns (1), (4), (7), and (10) of Panels A and B of Table 6, $q\_kurt_{IND,t+1}$ is positively associated with $R\_KURT_{IND,t+1}$ and it explains more than 14 percent of the variation in $R\_KURT_{IND,t+1}$. As shown in columns (3), (6), (9), and (12), $q\_kurt_{IND,t+1}$ has a positive association with $R\_KURT_{IND,t+1}$ after controlling for each of the alternative forecasts. However, the association is insignificant when we control for the forecast of kurtosis generated by KP's approach. The results of the Vuong tests show that $q\_kurt_{IND,t+1}$ is as good of a forecast of $R\_KURT_{IND,t+1}$ as any of the alternative forecasts. Overall, the tests in this section provide evidence that our forecasts of the higher moments of future earnings are reliable.

## VI. ANALYSES OF EQUITY PRICES AND CREDIT SPREADS

### Analyses of Equity Prices

In Table 7 we present the results obtained from regressing the earnings-to-price ratio, $EP_{i,t}$, and the book-to-price ratio, $BP_{i,t}$, on our forecasts of the moments of lead *ROE* and different sets of control variables. The results in columns (1) through (4) ((5) through (8)) relate to regressions in which $EP_{i,t}$ ($BP_{i,t}$) is the dependent variable. Columns (1) and (5) relate to results in which our out-of-sample forecasts of the moments of lead *ROE* are the only independent variables. In columns (2) and (6), we show results in which we control for the moments of historical, firm-level *ROE*. In columns (3) and (7), we show results in which we control for a number of market-based variables including size, equity beta, and the moments of historical firm-level stock returns. Finally, in columns (4) and (8), we show results in which all the control variables are included. A list containing the names and definitions of all the dependent and control variables is provided in Panel D of Table 1. We remove observations for which the value of any variable in the regression falls in either the top or bottom percentile of its annual distribution.

We make five comments about the results in Table 7. First, firms with higher standard deviations of lead *ROE* have lower values of $EP_{i,t}$ and $BP_{i,t}$. Hence, consistent with results in PV, equity prices are *increasing* in the volatility of future *ROE*. Second, as the skewness of lead *ROE* increases both $EP_{i,t}$ and $BP_{i,t}$ decrease, which suggests that equity investors seek exposure to upside

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[17] In a set of ancillary analyses, we evaluate three other alternative approaches in which we set the year $t$ forecast of a particular moment in year $t+1$ equal to: (1) the industry-level moment of the year $t$ residuals obtained from the OLS version of Equation (7); (2) the industry-level moments of analysts' forecasts made in year $t$; and (3) the industry-level moments of analysts' forecast errors in year $t$ (i.e., the difference between realized $ROE_{i,t}$ and year $t-1$ forecasts of $ROE_{i,t}$). Untabulated results in which we compare our forecasts to these alternative forecasts lead to similar conclusions as the results shown in Tables 4 through 6.

[18] When calculating realized moments for industry *IND* in year $t+1$ we exclude firms for which we are unable to develop a forecast in year $t$.

**TABLE 4**

**Regressions of $R\_STD_{IND,t+1}$ on $q\_std_{IND,t+1}$ and Alternative Forecasts**

**Panel A: KP and Historical Matched-Sample**

| | *a* = *KP* | | | *a* = *hms* (Historical Matched-Sample) | | |
|---|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| $q\_std_{IND,t+1}$ | 2.28*** | | 1.61*** | 1.49*** | | 1.33*** |
| | (3.18) | | (4.24) | (18.46) | | (11.53) |
| $a\_std_{IND,t+1}$ | | 2.05*** | 0.93* | | 0.62*** | 0.14 |
| | | (4.56) | (2.42) | | (6.56) | (1.76) |
| Intercept | −0.16 | 0.09* | −0.15 | −0.01 | 0.17 *** | −0.01 |
| | (−1.08) | (2.11) | (−1.13) | (−0.52) | (4.47) | (−1.17) |
| $R^2$ | 0.22 | 0.15 | 0.25 | 0.33 | 0.22 | 0.37 |
| Vuong | | 3.62*** | | | 4.27*** | |
| Industry-Years | | 2,017 | | | 1,579 | |
| Years | | 38 | | | 38 | |

**Panel B: Historical Firm-Level and Historical Industry-Level**

| | *a* = *hfl* (Historical Firm-Level) | | | *a* = *hil* (Historical Industry-Level) | | |
|---|---|---|---|---|---|---|
| | **(7)** | **(8)** | **(9)** | **(10)** | **(11)** | **(12)** |
| $q\_std_{IND,t+1}$ | 1.41*** | | 1.39*** | 2.20*** | | 2.14*** |
| | (16.39) | | (14.56) | (3.63) | | (3.24) |
| $a\_std_{IND,t+1}$ | | 0.13 | −0.01 | | 0.09 | 0.03 |
| | | (1.87) | (−0.23) | | (1.99) | (1.64) |
| Intercept | 0.01 | 0.31*** | 0.01 | −0.15 | 0.39*** | −0.14 |
| | (1.04) | (7.63) | (1.50) | (−1.18) | (4.15) | (−1.12) |
| $R^2$ | 0.29 | 0.04 | 0.31 | 0.25 | 0.07 | 0.28 |
| Vuong | | 5.68*** | | | 6.11*** | |
| Industry-Years | | 1,960 | | | 2,046 | |
| Years | | 38 | | | 38 | |

*, **, *** Represent rejection of a two-sided test at the 5 percent, 1 percent, and 0.50 percent levels, respectively.
Reported regression coefficients equal the average of the coefficients obtained from annual cross-sectional regressions. t-statistics are shown in parentheses. A particular t-statistic equals the mean of the annual coefficients divided by the standard error of the mean. Vuong statistics are obtained by computing the average of the annual slope coefficients obtained from the regression described in Vuong (1989, 318), and then dividing the average by its standard error. All standard errors reflect the Newey-West adjustment assuming a ten-year lag length.
Please refer to Table 1 for variable definitions and descriptions.

potential and avoid exposure to downside risk. This is both intuitive and consistent with results in Brunnermeier et al. (2007), Mitton and Vorkink (2007), Barberis and Huang (2008), and Conrad et al. (2013), who evaluate the relation between stock prices and the skewness of stock returns. Third, $EP_{i,t}$ and $BP_{i,t}$ are each increasing in the kurtosis of future earnings, which suggests that the negative price-effect associated with downside risk outweighs the positive price-effect of upside potential. This is consistent with results in Conrad et al. (2013), who evaluate the relation between stock prices and the kurtosis of stock returns.

Fourth, the associations described above are robust. The results regarding $EP_{i,t}$ and $BP_{i,t}$ remain when the moments of historical, firm-level *ROE* are included in the regression model. Moreover, although the association between $BP_{i,t}$ and both $q\_skew_{i,t+1}$ and $q\_kurt_{i,t+1}$ become statistically insignificant when the market-based controls are added, the results regarding $EP_{i,t}$ are insensitive to the inclusion of these controls. Hence, our forecasts of the higher moments of a firm's *ROE* capture information that is incremental to the information contained in the historical distributions of the firm's *ROE* and its stock returns.

Finally, per the Vuong test results, models that use our forecasts of the moments of lead *ROE* are closer to the true data-generating process than models that use forecasts based on the historical, firm-level approach.

**TABLE 5**

**Regressions of $R\_SKEW_{IND,t+1}$ on $q\_skew_{IND,t+1}$ and Alternative Forecasts**

**Panel A: KP and Historical Matched-Sample**

| | $a = KP$ | | | $a = hms$ (Historical Matched-Sample) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $q\_skew_{IND,t+1}$ | 0.57*** | | 0.46*** | 0.56*** | | 0.53*** |
| | (10.79) | | (11.63) | (7.19) | | (7.47) |
| $a\_skew_{IND,t+1}$ | | 0.52*** | 0.33*** | | 0.28*** | 0.08*** |
| | | (9.05) | (12.13) | | (13.18) | (3.62) |
| Intercept | −0.60*** | −0.83*** | −0.26*** | −0.30*** | −1.14*** | −0.27*** |
| | (−5.38) | (−6.55) | (−3.56) | (−5.47) | (−9.02) | (−6.41) |
| $R^2$ | 0.12 | 0.08 | 0.15 | 0.16 | 0.08 | 0.18 |
| Vuong | | 2.33* | | | 2.86** | |
| Industry-Years | | 2,017 | | | 1,579 | |
| Years | | 38 | | | 38 | |

**Panel B: Historical Firm-Level and Historical Industry-Level**

| | $a = hfl$ (Historical Firm-Level) | | | $a = hil$ (Historical Industry-Level) | | |
|---|---|---|---|---|---|---|
| | (7) | (8) | (9) | (10) | (11) | (12) |
| $q\_skew_{IND,t+1}$ | 0.56*** | | 0.56*** | 0.57*** | | 0.54*** |
| | (14.70) | | (14.88) | (19.51) | | (17.25) |
| $a\_skew_{IND,t+1}$ | | 0.01 | 0.00 | | 0.11** | 0.04*** |
| | | (1.61) | (−0.10) | | (2.76) | (3.86) |
| Intercept | −0.51*** | −1.43*** | −0.50*** | −0.55*** | −1.52*** | −0.57*** |
| | (−4.42) | (−7.19) | (−4.42) | (−3.68) | (−9.47) | (−4.31) |
| $R^2$ | 0.14 | 0.00 | 0.15 | 0.13 | 0.03 | 0.14 |
| Vuong | | 10.77*** | | | 7.01*** | |
| Industry-Years | | 1,960 | | | 2,046 | |
| Years | | 38 | | | 38 | |

*, **, *** Represent rejection of a two-sided test at the 5 percent, 1 percent, and 0.50 percent levels, respectively.
Reported regression coefficients equal the average of the coefficients obtained from annual cross-sectional regressions. t-statistics are shown in parentheses. A particular t-statistic equals the mean of the annual coefficients divided by the standard error of the mean. Vuong statistics are obtained by computing the average of the annual slope coefficients obtained from the regression described in Vuong (1989, 318), and then dividing the average by its standard error. All standard errors reflect the Newey-West adjustment assuming a ten-year lag length.
Please refer to Table 1 for variable definitions and descriptions.

## Analyses of Credit Spreads

We analyze three credit-spread proxies: (1) CDS spreads in year $t$, $CDS_{i,t}$; (2) bond yields in year $t$, $BY_{i,t}$; and (3) credit ratings in year $t$, $BR_{i,t}$.[19] Higher values of these three variables correspond to higher credit risk. We evaluate the relation between each of these variables and year $t$ forecasts of the moments of lead $ROA$ and two sets of control variables.[20] We continue to refer to our year $t$ forecasts of the mean, standard deviation, skewness, and kurtosis as $q\_mean_{i,t+1}$, $q\_std_{i,t+1}$, $q\_skew_{i,t+1}$ and $q\_kurt_{i,t+1}$. However, within the context of this subsection and Table 8, these names refer to forecasts of the moments of lead $ROA$ not lead $ROE$.

[19] We have CDS spread data, bond yield data, and credit ratings for the years spanning 2000 through 2009, 1984 through 2010, and 1985 through 2011, respectively.

[20] To forecast the moments of lead $ROA$ we make three modifications to Equation (7). First, we replace $ROE$ with return on assets, $ROA$. We compute $ROA_{i,t+1}$ ($ROA_{i,t}$) as the ratio of the sum of year $t+1$ ($t$) earnings and net interest expense to total assets in year $t$. Second, we omit the variable $LEV_{i,t}$ from the model to avoid mechanical associations between our forecasts of the moments and the credit market variables. Finally, except for the indicator variables, we deflate the remaining independent variables by total assets in year $t$ instead of equity book value in year $t$.

**TABLE 6**

**Regressions of $R\_KURT_{IND,t+1}$ on $q\_kurt_{IND,t+1}$ and Alternative Forecasts**

**Panel A: KP and Historical Matched-Sample**

| | *a* = *KP* | | | *a* = *hms* (Historical Matched-Sample) | | |
|---|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| $q\_kurt_{IND,t+1}$ | 0.46*** | | 0.24 | 0.41*** | | 0.25** |
| | (3.08) | | (1.48) | (4.64) | | (3.09) |
| $a\_kurt_{IND,t+1}$ | | 0.64*** | 0.46*** | | 0.46*** | 0.40*** |
| | | (5.09) | (9.93) | | (6.35) | (5.34) |
| Intercept | 7.35** | 7.76*** | 5.35* | 4.91*** | 5.94*** | 3.40*** |
| | (2.90) | (7.02) | (2.22) | (5.41) | (10.18) | (4.13) |
| $R_2$ | 0.11 | 0.11 | 0.16 | 0.17 | 0.18 | 0.25 |
| Vuong | | -0.08 | | | 0.17 | |
| Industry-Years | | 2,017 | | | 1,579 | |
| Years | | 38 | | | 38 | |

**Panel B: Historical Firm-Level and Historical Industry-Level**

| | *a* = *hfl* (Historical Firm-Level) | | | *a* = *hil* (Historical Industry-Level) | | |
|---|---|---|---|---|---|---|
| | **(7)** | **(8)** | **(9)** | **(10)** | **(11)** | **(12)** |
| $q\_kurt_{IND,t+1}$ | 0.67*** | | 0.64*** | 0.60*** | | 0.50*** |
| | (4.43) | | (4.54) | (3.77) | | (3.70) |
| $a\_kurt_{IND,t+1}$ | | 0.03* | 0.03 * | | 0.22*** | 0.19*** |
| | | (2.06) | (2.03) | | (3.89) | (4.04) |
| Intercept | 3.77*** | 10.92*** | 2.80 ** | 5.33* | 8.68*** | 2.46* |
| | (3.66) | (17.97) | (2.82) | (2.44) | (16.07) | (2.12) |
| $R_2$ | 0.17 | 0.08 | 0.24 | 0.15 | 0.18 | 0.29 |
| Vuong | | 1.17 | | | −0.64 | |
| Industry-Years | | 1,960 | | | 2,046 | |
| Years | | 38 | | | 38 | |

*, **, *** Represent rejection of a two-sided test at the 5 percent, 1 percent, and 0.50 percent levels, respectively.
Reported regression coefficients equal the average of the coefficients obtained from annual cross-sectional regressions. t-statistics are shown in parentheses. A particular t-statistic equals the mean of the annual coefficients divided by the standard error of the mean. Vuong statistics are obtained by computing the average of the annual slope coefficients obtained from the regression described in Vuong (1989, 318), and then dividing the average by its standard error. All standard errors reflect the Newey-West adjustment assuming a ten-year lag length.
Please refer to Table 1 for variable definitions and descriptions.

Table 8 contains results obtained from regressions of the credit-risk proxies on our forecasts of the moments of *ROA* and two different sets of control variables. The results in the first four columns relate to regressions in which CDS spreads are the dependent variable. In columns (5) through (8), we show results that relate to regressions in which bond yields are the dependent variable, whereas in columns (9) through (12) we show regressions in which bond ratings are the dependent variable. Columns (1), (5), and (9) relate to results in which our out-of-sample forecasts of the moments of lead *ROA* are the only independent variables. In columns (2), (6), and (10) we show results in which we control for the moments of historical, firm-level *ROA*.[21] In columns (3), (7), and (11), we show results in which we control for a set of ten market- and bond-based variables This set includes the moments of historical firm-level stock returns and six variables that are based on the default prediction model described in Beaver, Correia, and McNichols (2012).[22] Finally, in columns (4), (8), and (12), we show results

[21] We continue to refer to these variables as $hfl\_mean_{i,t+1}$, $hfl\_std_{i,t+1}$, $hfl\_skew_{i,t+1}$, and $hfl\_kurt_{i,t+1}$. However, within the context of this subsection and Table 8, these names refer to the moments of historical *ROA* not historical *ROE*.

[22] Our results are not sensitive to the choice of controls. In untabulated results we consider a number of alternative control variables inspired by extant studies such as Kaplan and Urwitz (1979), Chava and Jarrow (2004), and Hann, Heflin, and Subramanayam (2007).

**TABLE 7**

**Regressions of Equity-Market Variables on Quantile-Based Forecasts**

| | Earnings-to-Price Ratio ($EP_{i,t}$) | | | | Book-to-Price Ratio ($BP_{i,t}$) | | | |
|---|---|---|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** |
| $q\_mean_{i,t+1}$ | 0.58*** | 0.59*** | 0.58*** | 0.58*** | −2.19*** | −2.11*** | −1.71** | −1.57** |
| | (10.74) | (10.27) | (7.33) | (7.67) | (−3.00) | (−3.14) | (−2.86) | (−2.91) |
| $q\_std_{i,t+1}$ | −0.56*** | −0.55*** | −0.56*** | −0.56*** | −1.74*** | −1.76*** | −2.38*** | −2.37*** |
| | (−5.43) | (−5.29) | (−3.98) | (−3.74) | (−5.87) | (−6.23) | (−6.18) | (−5.69) |
| $q\_skew_{i,t+1}$ | −0.03*** | −0.03*** | −0.03*** | −0.03*** | −0.07*** | −0.05*** | −0.02 | −0.01 |
| | (−5.07) | (−5.24) | (−5.85) | (−5.89) | (−5.29) | (−4.85) | (−1.51) | (−1.21) |
| $q\_kurt_{i,t+1}$ | 0.01*** | 0.01*** | 0.01*** | 0.01*** | 0.02* | 0.01* | 0.00 | 0.00 |
| | (4.01) | (4.05) | (4.31) | (4.33) | (2.55) | (2.44) | (1.35) | (1.30) |
| $hfl\_mean_{i,t+1}$ | | −0.13* | | −0.07** | | −1.98*** | | −1.43** |
| | | (−2.15) | | (−2.80) | | (−3.36) | | (−2.89) |
| $hfl\_std_{i,t+1}$ | | −0.06 | | −0.08** | | −0.26 | | −0.33 |
| | | (−1.50) | | (−2.73) | | (−1.20) | | (−1.92) |
| $hfl\_skew_{i,t+1}$ | | 0.00* | | 0.01* | | 0.03 | | 0.05*** |
| | | (2.33) | | (2.63) | | (1.83) | | (3.11) |
| $hfl\_kurt_{i,t+1}$ | | 0.00 | | 0.00 | | 0.01* | | 0.02 |
| | | (0.62) | | (−0.24) | | (2.32) | | (1.62) |
| $SIZE_{i,t}$ | | | 0.00 | 0.00 | | | −0.11*** | −0.10*** |
| | | | (−1.25) | (−1.15) | | | (−6.59) | (−6.98) |
| $BETA_{i,t}$ | | | 0.00 | 0.00 | | | 0.10*** | 0.10*** |
| | | | (−0.85) | (−0.81) | | | (7.98) | (8.66) |
| $ANNRET_{i,t}$ | | | 0.01** | 0.01* | | | −0.07 | −0.08 |
| | | | (2.97) | (2.56) | | | (−1.29) | (−1.51) |
| $RET\_STD_{i,t}$ | | | −0.10*** | −0.09*** | | | −1.32*** | −1.21*** |
| | | | (−6.03) | (−8.30) | | | (−3.28) | (−3.08) |
| $RET\_SKEW_{i,t}$ | | | 0.00*** | 0.00*** | | | 0.02*** | 0.02*** |
| | | | (3.58) | (3.29) | | | (3.91) | (4.62) |
| $RET\_KURT_{i,t}$ | | | 0.00 | 0.00 | | | 0.01 | 0.01 |
| | | | (0.86) | (0.55) | | | (1.80) | (1.64) |
| Intercept | −0.01 | 0.01 | 0.02 | 0.03 | 1.12*** | 1.38*** | 1.64*** | 1.77*** |
| | (−0.98) | (0.67) | (0.86) | (1.29) | (4.80) | (4.87) | (7.01) | (6.30) |
| $R^2$ | 0.57 | 0.60 | 0.62 | 0.62 | 0.15 | 0.20 | 0.34 | 0.36 |
| Vuong | | 25.64*** | | 29.00*** | | 8.17*** | | 8.22*** |
| Firm-Years | 151,341 | 122,564 | 111,836 | 105,443 | 151,341 | 122,564 | 111,836 | 105,443 |
| Years | 39 | 39 | 39 | 39 | 39 | 39 | 39 | 39 |

*, **, *** Represent rejection of a two-sided test at the 5 percent, 1 percent, and 0.50 percent levels, respectively.
Reported regression coefficients equal the average of the coefficients obtained from annual cross-sectional regressions. t-statistics are shown in parentheses. A particular t-statistic equals the mean of the annual coefficients divided by the standard error of the mean. Vuong statistics are obtained by computing the average of the annual slope coefficients obtained from the regression described in Vuong (1989, 318), and then dividing the average by its standard error. All standard errors reflect the Newey-West adjustment assuming a ten-year lag length.
Please refer to Table 1 for variable definitions and descriptions.

in which all the control variables are included. Each regression includes industry fixed effects based on the Fama-French 12 classifications. A list containing the names and precise definitions of all the dependent and control variables is provided in Panel D of Table 1. We follow Beaver et al. (2012) and winsorize each variable to its 1st and 99th percentiles.

We make four comments about the results shown in Table 8. First, per the results in columns (1), (5), and (9), credit spreads are increasing in the volatility and kurtosis of *ROA* and decreasing in the skewness of *ROA*. Hence, creditors demand higher premiums when they are exposed to volatility, downside risk, and/or extreme outcomes, which is consistent with the analytical results in Black and Scholes (1973) and Merton (1974), and with arguments made in practitioner articles (e.g., Dynkin et al. 2007). These results are also intuitive given that credit securities have asymmetric payoffs. That is, if a firm's performance is sufficiently poor, creditors can lose part or all of their initial investment. However, if a firm's performance is extraordinarily good, creditors do not share in the upside. Rather, they only receive the face value of their claim and the interest owed to them.



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**TABLE 8**

**Regressions of Credit Spreads on Quantile-Based Forecasts**

| | CDS Spread ($CDS_{i,t}$) | | | | Bond Yield ($BY_{i,t}$) | | | | Bond Rating ($BR_{i,t}$) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| $q\_mean_{i,t+1}$ | −12.75*** | −10.50*** | −6.28*** | −3.59** | −9.79*** | −7.85*** | −2.54 | −1.22 | −17.89*** | −14.90*** | −3.19*** | −0.92 |
| | (−16.22) | (−11.28) | (−7.77) | (−3.65) | (−10.08) | (−10.11) | (−1.41) | (−1.42) | (−5.67) | (−8.13) | (−5.17) | (−1.69) |
| $q\_std_{i,t+1}$ | 9.27*** | 0.38 | 3.04* | 0.34 | 15.83*** | 4.45 | 5.74* | 3.46 | 8.18*** | 1.11 | 2.90 | 3.26 |
| | (10.40) | (0.25) | (2.95) | (0.44) | (4.80) | (1.20) | (2.29) | (1.24) | (3.78) | (0.37) | (1.52) | (1.27) |
| $q\_skew_{i,t+1}$ | −1.17*** | −0.71*** | −0.91*** | −0.67*** | −0.85*** | −0.36*** | 0.01 | 0.16 | −1.76*** | −1.41*** | −1.08*** | −1.05*** |
| | (−8.24) | (−7.30) | (−11.37) | (−13.66) | (−4.91) | (−4.18) | (0.05) | (0.36) | (−6.00) | (−8.09) | (−7.23) | (−8.12) |
| $q\_kurt_{i,t+1}$ | 0.19*** | 0.12*** | 0.18*** | 0.13*** | 0.09*** | 0.01 | 0.00 | −0.04 | 0.17** | 0.15*** | 0.13*** | 0.13*** |
| | (9.72) | (9.14) | (13.07) | (13.88) | (3.73) | (0.38) | (−0.05) | (−0.38) | (3.02) | (4.98) | (3.56) | (4.45) |
| $hfl\_mean_{i,t+1}$ | | −1.97*** | | −0.60*** | | −2.84*** | | 0.62 | | −9.42*** | | −4.49*** |
| | | (−31.66) | | (−4.95) | | (−6.20) | | (1.37) | | (−46.35) | | (−23.49) |
| $hfl\_std_{i,t+1}$ | | 1.89*** | | 0.65*** | | 2.04*** | | 1.64*** | | 8.67*** | | 5.48*** |
| | | (13.41) | | (5.21) | | (3.47) | | (4.64) | | (3.61) | | (3.53) |
| $hfl\_skew_{i,t+1}$ | | 0.08*** | | 0.02 | | 0.30*** | | 0.13* | | 0.08 | | 0.00 |
| | | (7.48) | | (1.04) | | (3.63) | | (2.53) | | (0.61) | | (0.03) |
| $hfl\_kurt_{i,t+1}$ | | −0.02 | | 0.01* | | −0.10*** | | −0.11 | | −0.12* | | −0.07** |
| | | (−1.24) | | (2.50) | | (−4.75) | | (−1.84) | | (−2.70) | | (−2.84) |
| $BP_{i,t}$ | | | 0.74*** | 1.18*** | | | 0.91** | 2.25*** | | | 0.19* | 0.48*** |
| | | | (6.84) | (24.38) | | | (3.17) | (3.90) | | | (2.39) | (3.59) |
| $LN\_SIZE_{i,t}$ | | | −0.14* | −0.08* | | | −0.41*** | −0.19 | | | −0.75*** | −0.69*** |
| | | | (−2.30) | (−2.92) | | | (−5.83) | (−2.05) | | | (−11.15) | (−8.97) |
| $LIAB\_ASST_{i,t}$ | | | 4.39*** | 3.42*** | | | 3.40*** | 3.07*** | | | 2.42*** | 2.41*** |
| | | | (9.36) | (8.07) | | | (12.49) | (7.74) | | | (3.36) | (3.77) |
| $EBITDA\_LIAB_{i,t}$ | | | 0.77* | 0.39 | | | 1.25*** | 1.15*** | | | −3.05*** | −2.50*** |
| | | | (2.87) | (2.26) | | | (5.98) | (4.73) | | | (−12.79) | (−11.82) |
| $ANNRET_{i,t}$ | | | −1.27*** | −0.66*** | | | −0.98*** | −0.26 | | | 0.40*** | 0.47*** |
| | | | (−5.38) | (−6.31) | | | (−3.29) | (−1.84) | | | (8.64) | (8.86) |
| $RET\_STD_{i,t}$ | | | 18.79*** | 14.60*** | | | 15.47*** | 11.26*** | | | 18.96*** | 19.47*** |
| | | | (23.71) | (32.24) | | | (5.22) | (4.14) | | | (13.75) | (17.74) |
| $RET\_SKEW_{i,t}$ | | | −0.09 | −0.02 | | | −0.14 | −0.05* | | | −0.10*** | −0.11*** |
| | | | (−1.39) | (−0.80) | | | (−1.93) | (−2.21) | | | (−3.44) | (−5.58) |
| $RET\_KURT_{i,t}$ | | | −0.03 | −0.01 | | | −0.03 | −0.06 | | | −0.10*** | −0.08*** |
| | | | (−2.05) | (−0.51) | | | (−1.58) | (−1.21) | | | (−11.11) | (−5.24) |
| $T2MAT_{i,t}$ | | | | | | | −0.04 | −0.03 | | | | |
| | | | | | | | (−1.02) | (−0.85) | | | | |
| $BOND\_SIZE_{i,t}$ | | | | | | | −0.32 | −0.50 | | | | |
| | | | | | | | (−1.08) | (−1.20) | | | | |

*(continued on next page)*

**TABLE 8 (continued)**

| | CDS Spread ($CDS_{i,t}$) | | | | Bond Yield ($BY_{i,t}$) | | | | Bond Rating ($BR_{i,t}$) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| $R^2$ | 0.32 | 0.31 | 0.57 | 0.57 | 0.14 | 0.10 | 0.27 | 0.24 | 0.49 | 0.50 | 0.69 | 0.68 |
| Vuong | | 11.40*** | | 5.83*** | | 5.37*** | | 2.58** | | 10.61*** | | 5.93*** |
| Firm-Years | 5,664 | 4,916 | 5,213 | 4,876 | 10,602 | 9,189 | 10,061 | 9,141 | 29,245 | 24,256 | 26,868 | 24,102 |
| Years | 10 | | | | 17 | | | | 27 | | | |

*, **,*** Represent rejection of a two-sided test at the 5 percent, 1 percent, and 0.50 percent levels, respectively.
Reported regression coefficients equal the average of the coefficients obtained from annual cross-sectional regressions. t-statistics are shown in parentheses. A particular t-statistic equals the mean of the annual coefficients divided by the standard error of the mean. Vuong statistics are obtained by computing the average of the annual slope coefficients obtained from the regression described in Vuong (1989, 318), and then dividing the average by its standard error. All standard errors reflect the Newey-West adjustment assuming a ten-year lag length.
Please refer to Table 1 for variable definitions and descriptions.

Second, the results regarding $q\_skew_{i,t+1}$ and $q\_kurt_{i,t+1}$ are robust. Specifically, both CDS spreads and bond ratings have a negative (positive) association with $q\_skew_{i,t+1}$ ($q\_kurt_{i,t+1}$) for all the specifications considered. The results regarding kurtosis are similar to results in KP; however, the results regarding skewness are not. Rather, KP do not find any relation between the skewness of earnings and bond yields.[23] This result is counterintuitive because it implies that, *ceteris paribus*, creditors do not price extreme downside risk. Our results, on the other hand, imply that the opposite and more intuitive interpretation is descriptive: Creditors demand compensation for taking on exposure to extreme downside risk.

Third, the results regarding $q\_std_{i,t+1}$ are sensitive to the set of control variables included in the regression model. In particular, the positive association between $q\_std_{i,t+1}$ and either CDS spreads or bond yields disappears when controls for the historical, firm-level moments of *ROA* are included in the model. Moreover, the positive association between $q\_std_{i,t+1}$ and bond ratings is present only when there are *no* control variables included in the model. Although the reasons for the weak results regarding $q\_std_{i,t+1}$ are unclear, one possibility is that investors and rating agencies rely too much on the historical, firm-level volatility of *ROA* when evaluating credit risk.

Finally, per the Vuong test results, models that use our forecasts of the moments of lead *ROA* are closer to the true data-generating process than models that use forecasts based on the historical, firm-level approach.

**Summary**

The results in this section imply that earnings uncertainty is priced; and that the manner in which it is priced depends on the type of uncertainty and the type of security being priced. Equity investors put a positive price on skewness and a negative price on kurtosis while credit investors demand lower (higher) credit risk premiums when earnings are positively skewed (kurtosis is high). Hence, both types of investors either seek exposure to extreme upside potential or avoid being exposed to extreme downside risk. And their aversion to extreme downside risk outweighs their preference for extreme upside potential. That said, the pricing of earnings volatility depends on the security being priced. *Ceteris paribus*, equity investors put a positive price on the volatility of *ROE*. This is consistent with the fact that, as discussed in PV, equity market value is an increasing, *convex* function of future growth in equity book value, which is increasing in *ROE*. Consequently, more volatile *ROE* implies more upside potential; and given they are the residual claimants, equity investors are the primary beneficiaries of higher upside potential. Creditors, on the other hand, require higher credit risk premiums as the volatility of *ROA* increases. This follows from the fact that credit securities have asymmetric payoffs. If a firm's performance is sufficiently poor, creditors can lose part or all of their initial investment. However, if a firm's performance is extraordinarily good, creditors only receive the face value of their claim and the interest owed to them.

## VII. CONCLUSION

Providing information to investors and other stakeholders that they can use to assess earnings uncertainty is a fundamental objective of financial reporting. However, extant research provides limited evidence about: (1) whether historical accounting numbers are informative about earnings uncertainty and (2) whether earnings uncertainty is priced by investors. In this study, we begin to fill this gap in the literature. We first develop and validate an empirical approach that yields reliable out-of-sample, firm-level forecasts of the dispersion, skewness, and kurtosis of future earnings. We then show that our forecasts are related to equity prices and credit spreads. Hence, we demonstrate that historical financial reports do provide investors with information that they can use to assess earnings uncertainty and that earnings uncertainty is priced.

In addition to its immediate contribution to the extant literature, our study paves the way for future research. First, our equity- and credit-market results suggest that earnings uncertainty may be relevant to other stakeholders, especially those stakeholders who, unlike capital-market participants, are unable to diversify away their exposure to idiosyncratic shocks (e.g., owners of private firms, auditors, executives and employees who receive earnings-based bonuses). Hence, when exposed to extreme downside risk (or extreme upside potential), these agents are especially likely to alter either their behavior or the institutional arrangements in which they participate.

Second, the approach we develop for forecasting higher moments of earnings can be used in other economic contexts such as the evaluation and prediction of the higher moments of return on invested capital, earnings growth, accruals, etc. Third, our

[23] Our evidence regarding the association between bond yields and skewness and kurtosis is also weak. In particular, the negative (positive) association between $q\_skew_{i,t+1}$ ($q\_kurt_{i,t+1}$) and bond yields disappears once we include either set of control variables in the regression. However, we place less weight on these results and more weight on the results pertaining to CDS spreads. We do this because, *vis-à-vis* bond yields, CDS spreads are a better indicator of priced credit risk. There are two reasons for this. First, the primary purpose of CDS contracts is to put a price on credit risk so that it can be traded and hedged. Hence, credit risk is the primary determinant of CDS spreads whereas bond yields are affected by numerous other phenomena (e.g., interest rate risk, debt contract characteristics, illiquidity in the secondary market) that are difficult to observe, measure, and control for. Second, as shown in Acharya and Johnson (2007), the CDS market is more liquid than the bond market and CDS spreads reflect information in a timelier manner than bond yields.

approach for evaluating construct validity serves as a useful tool for researchers who want to evaluate the usefulness of new approaches for forecasting higher moments.

Finally, our results are predicated on the assumption that earnings reflect economic performance. However, earnings also reflect accounting choices; and these choices may affect both: (1) the higher moments of earnings and (2) firm value. For example, Givoly and Hayn (2000) show that, *ceteris paribus*, higher conditional conservatism implies more negatively skewed earnings. Conditional conservatism may also have a disciplining effect on managers. That is, when conditional conservatism is high, managers may realize that it is more difficult to withhold bad news *ex post*. Hence, to avoid negative *ex post* consequences, managers may make better investment decisions *ex ante*. This implies that, *ceteris paribus*, higher conditional conservatism may lead to more negative skewness and *higher* firm value. Consequently, the positive relation that we document between earnings skewness and security prices may be partially offset by a second-order accounting effect that we do not investigate. We believe that whether this accounting effect and/or similar accounting effects exist is a promising topic for future research.[24]

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## APPENDIX A

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