# Tail-Heaviness, Asymmetry, and Profitability Forecasting by Quantile Regression[†]

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***Abstract*****.** We show that quantile regression is better than ordinary-least-squares (OLS) regression in forecasting profitability for a range of profitability measures following the conventional setup of the accounting literature, including the mean absolute forecast error (MAFE) evaluation criterion. Moreover, we perform both a simulated-data and an archival-data analysis to examine how the forecasting performance of quantile regression against OLS changes with the shape of the profitability distribution. Considering the MAFE and mean squared forecast error (MSFE) criteria together, quantile regression is more accurate relative to OLS when the profitability to be forecast has a heavier-tailed distribution. In addition, the asymmetry of the profitability distribution has either a U-shape or an inverted-U-shape effect on the forecasting accuracy of quantile regression. An application of the distributional shape analysis framework to cash flows forecasting demonstrates the usefulness of the framework beyond profitability forecasting, providing additional empirical evidence on the positive effect of tail-heaviness and supporting the notion of an inverted-U-shape effect of asymmetry. (JEL L25, G17, M21, M41, C53)

*Keywords: Heavy tails, distributional shape, profitability forecast, quantile regression*

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## 1. Introduction

It is in the interest of different parties, including investors, analysts, and companies themselves, to obtain more accurate profitability forecasts. Companies have experienced extreme profits and losses more often in recent decades.[1] This is likely to impact the distributional shape of profitability, increasing the difficulty in forecasting profitability accurately.

To formulate forecasts as accurately as possible, sophisticated market participants are likely to resort to statistical methods. Ordinary-least-squares (OLS) regression is a very popular choice, if not the prevalent choice. The least squares method has a very long history dating back to 1795 (Courgeau 2012). In contrast, quantile regression (QR), an alternative approach based on the least absolute deviation (LAD) method, was developed only four decades ago by Koenker and Bassett (1978). Unlike the least squares method, the LAD method is not sensitive to outliers (Chen et al. 2008). Despite this advantage, quantile regression applications in finance and accounting remain not popular.[2] However, quantile regression has long been considered an attractive method in areas such as medicine, survival analysis, and economics (Yu et al. 2003).

In this study, we conduct a series of analyses to examine whether the quantile regression approach to profitability forecasting can be more accurate than the OLS approach, and if so, under what distributional shape of profitability, quantile regression is likely to have higher forecasting accuracy relative to OLS. The findings of this study will help investors, analysts, and other market participants to make better decisions on adopting statistical methods to forecast profitability and guide investment.

Our first analysis, a forecasting analysis, uses archival data to show that quantile regression profitability forecasts are more accurate than OLS forecasts. We follow the conventional setup of the accounting literature, including the mean absolute forecast error (MAFE) evaluation criterion (Fairfield et al. 2009; Schröder and Yim 2018). We consider four new profitability measures in this analysis. They are the gross profitability (GP) defined by Novy-Marx (2013), operating profitability (OP) defined by

[1] List of largest corporate profits and losses, 2019. Wikipedia. URL https://en.wikipedia.org/wiki/List_of_largest_corporate_profits_and_losses (accessed 10.8.19).
[2] The applications in finance that we are aware of include return forecasting, portfolio analysis, and risk measurement (Pohlman and Ma 2010; Bassett Jr and Chen 2001; Lauridsen, 2000). Recent applications in accounting include forecasting risk in earnings (Konstantinidi and Pope 2016).

Ball et al. (2015) and two versions of cash-based operating profitability (CbOP) defined by Ball et al. (2016).

Besides the new profitability measures above, we also include the return on equity (ROE) and return on net operating assets (RNOA) in our comparison. Prior research on profitability forecasting examines these traditional measures of profitability because they are the inputs to accounting-based valuation models (Fairfield et al. 2009; Schröder and Yim 2018). Their inclusion here facilitates the comparison of our results with prior research findings. It is also interesting to include ROE in its own right. This is the profitability measure used in the Hou et al. (2015) *q*-factor asset pricing model, whose performance is comparable to and sometimes even better than that of the Fama and French (1993) three-factor model and the Carhart (1997) four-factor model.

Next, we conduct a large number of simulated experiments (500 for each set of distribution types and parameter combinations) to understand why quantile regression forecasts are more accurate and to what extent this continues to hold under the mean squared forecast error (MSFE) evaluation criterion, as opposed to the conventional MAFE criterion. Using the simulated data, we perform a regression analysis to examine how the accuracy of quantile regression forecasts relative to OLS forecasts varies with the shape of the profitability distribution. In line with the statistics literature, we focus on the tails and the asymmetry of the distribution in characterizing its shape. To ensure the robustness of our results, we consider altogether three tail-heaviness measures and five asymmetry measures (including the widely used kurtosis and skewness coefficients). The results are highly similar across the measures. In the interest of space, we report only two of the tail-heaviness measures and three of the asymmetry measures.

A key finding of our simulated-data distributional shape analysis is that the accuracy of quantile regression forecasts relative to OLS forecasts increases as the sampling distribution's tails become heavier. This finding is very consistent across the 16 × 16 parameter combinations (varying from light to heavy tails or from low to high asymmetry, holding constant the other aspect) and the four distribution types examined and the different tail-heaviness measures considered, controlling for the asymmetry of the sampling distribution, as well as its dispersion (in terms of standard deviation). The finding is also robust to whether the Wilcoxon (signed-rank) test or the t test is based on to determine the prevalence of a forecasting approach under a given evaluation criterion.

We also find that the accuracy of quantile regression forecasts varies with different measures of asymmetry, however, in a less consistent manner. Note that we allow for positive and negative asymmetry, which is like positive and negative skewness that represent a right tail longer than the left and the other way around, respectively. The simulated-data analysis shows that according to one of our forecasting accuracy measures, asymmetry always has a U-shape effect on the forecasting performance of quantile regression, i.e., becoming more accurate relative to OLS when the profitability distribution is more asymmetric (in either direction). However, under a second forecasting accuracy measure, the effect has an inverted-U shape if the prevalence is determined by the t test but again a U shape if the Wilcoxon test is used. This is in sharp contrast to the very consistent effect of tail-heaviness.

The robust effect of tail-heaviness is in line with a wisdom, from the statistics literature, that is often forgotten: The inclusion of even a few extreme observations can increase the sampling variance of the mean much more than the median's. Thus, moving away from normality toward a distribution with heavy tails, the sample *median* can be more efficient than the sample mean as an estimator of the population *mean* (Myers et al. 2010; Wilcox and Rousselet 2018). In light of this, it becomes clear why the median forecasts from quantile regression can be more accurate than the mean forecasts from OLS when the profitability distribution in concern has heavy tails.

The robust effect of tail-heaviness is also consistent with a key insight from the machine learning literature. Regularization is an important step in machine learning used to prevent overfitting a forecasting model. Overfitting occurs when the estimation method works too hard to find patterns in the training data and mistakes those patterns due to random chance as though they were highly representative features of the underlying true model (James et al. 2013). When this happens, the forecast error on the hold-out sample will be quite large because the learned patterns caused by random chance are unlikely to reappear.

Comparing quantile regression to OLS in the forecasting context, the former is likely to mitigate overfitting better when the profitability distribution has heavy tails. Extreme values of such distributions are observed more often than those of the Gaussian. Yet, extreme-value observations still occur quite rarely and are unrepresentative of other observations much closer to the center. The OLS forecasting approach will work hard to adjust its in-sample coefficient estimates to reduce the quadratic loss of deviating from the extreme-value observations. In contrast, the absolute loss of quantile regression forecasting is less affected by such observations and hence likely to give more accurate forecasts when assessed based on out-of-sample data. Thus, the robust nature of quantile regression may be viewed as a kind of regularization built into its design.

To summarize, quantile regression's advantage in constructing firm-specific forecasts based on samples pooled across firms lies in the ability to mitigate the influence of extreme-value observations. The advantage is not on forecasting these extreme-value observations but on forecasting the non-extreme-value observations, which constitute the vast majority of a sample.

To corroborate the insight from the simulated experiments, we run the same regression relating the accuracy of quantile regression to tail-heaviness and asymmetry using archival data. The data used comes from the sample we use for the out-of-sample testing in the forecasting analysis. Unlike the simulated experiments, where it is straightforward to compute distributional shape measures based on many draws of simulated profitability, archival data does not allow this luxury. Even when some firms have sufficiently long time series to give reliable estimates, the data requirement would induce a severe survivorship bias. Therefore, we estimate the tail-heaviness and asymmetry measures based on the profitability distribution across different firms of each industry-year. This is consistent with the cross-sectional approach to forecasting, which assumes that there is enough similarity across different firms to warrant pooling them together for forecasting,

The above is not the only difference between the simulated and archival data. There are several. For example, in the archival data, the individual firms' absolute and squared forecast errors used for computing the forecasting accuracy measures are based on a full model consistent with Fairfield et al. (2009), instead of the simple first-order autoregressive model assumed in the simulated experiments. Moreover, the archival data comes from an in-sample estimation step using a rolling window of data available in the previous ten years, whereas the corresponding step in the simulated experiments uses only one prior period of simulated data.

Given such differences, it is not obvious that the insights from the simulated experiments would be robust enough to hold also in the archival data. We, however, find a varying degree of support for the insights. In both the unweighted and the weighted regressions pooling all profitability measures together, the effect of tail-heaviness on the accuracy of quantile regression forecasts relative to OLS is significantly positive across all the tail-heaviness measures controlling for any one of the asymmetry measures. There is also clear support for a positive effect of tail-heaviness from the individual-profitability regressions for CbOP (cash-flow approach) and ROE and moderate support from those for OP, CbOP (balance-sheet approach), and RNOA.

Considering the differences between the simulated and archival data, we view the above finding from the archival data as generally corroborating the simulation results of the tail-heaviness effect. Similarly, in the archival-data analysis, the pooled regression and the ROE results show strong support for an inverted-U-shape effect of asymmetry, whereas three of the six profitability measures provide strong to moderate support for a U-shape effect, with the remaining two having no significant effect whatsoever. These results echo the not-so-consistent effect of asymmetry found in the simulated-data analysis.

To demonstrate the usefulness of the distributional shape analysis framework beyond profitability forecasting, we apply the framework to examine the out-of-sample forecasting of cash flows from 1990 to 2015 studied by Nallareddy et al. (2020). We show that the tail-heaviness, measured by the kurtosis, of the yearly cash flows distribution across all firms has a positive effect on the incremental forecasting accuracy of quantile regression while the asymmetry, measured by the skewness coefficient, has an inverted-U-shape effect. We also analyze various subsamples that exclude firms likely to have contributed to the tail-heaviness and asymmetry of the cash flows distribution. By confining to these subsamples, we expect to see a somewhat weaker relation between the incremental forecasting accuracy and the distributional properties. The subsample findings are largely consistent with our expectation. All in all, the results of the cash flows distributional shape analysis for the full sample and the various subsamples are in line with the earlier findings for profitability forecasting.

To our knowledge, we are the first to provide large-sample evidence of the effects of the profitability distributional shape on the accuracy of quantile regression forecasts relative to OLS using both simulated and archival data. Related prior simulation studies were done twenty to thirty years ago. They primarily focus on the least absolute deviation (LAD) estimators, rather than out-of-sample forecasts, or otherwise on the small-sample forecasting performance or use a simulation setup that has a maximum of 1,000 draws repeated for only 20 times (Mitra 1987; Dielman 1986; Dielman and Rose 1994). In contrast, our setup has 2,500 draws repeated for 500 times for each set of the distribution types and parameter combinations. Most importantly, none of the prior studies has considered asymmetry jointly with tail-heaviness. We examine both aspects of the distributional shape using two four-parameter distribution families that allow controlling not only the location and scale but also the tail and skewness properties separately. These families are the stable and the inverse hyperbolic sine (IHS) distributions (Nolan 2013; Nolan 2019; McDonald and Turley 2011).

In making the contribution above, we develop a framework of conducting simulated-data and archival-data analysis of the profitability distributional shape and its relation to forecasting accuracy under both the MAFE and MSFE criteria. This includes the use of various new measures, such as the incremental and relative forecasting accuracy measures (both the simulated- and archival-data versions) and the Mean%Extremes and Tails Asymmetry measures of tail-heaviness and asymmetry, respectively (see section 4 for details). To our knowledge, the use of stable and IHS distributions for analysis is also new in the accounting literature.

We are also the first to document the higher accuracy of quantile regression forecasts, compared to OLS forecasts, across four new profitability measures and two traditional measures (including ROE). In contrast, a recent paper by Evans et al. (2017) focuses on comparing model-based forecasts of ROE (both LAD and OLS) to analysts' explicit forecasts of ROE. They do not at the same time examine the profitability distributional shape's effects on the accuracy of quantile regression forecasts nor consider both the MAFE and MSFE criteria.

This study also adds to the debate on the reasons behind analyst forecast bias (Gu and Wu 2003; Basu and Markov 2004) by clarifying the roles of earnings skewness and the assumption of an absolute loss function (or MAFE minimization objective) for analysts. An MAFE minimization objective is very plausible, and the distributions of profitability (as a kind of scaled earnings) indeed are often skewed.[3] However, neither of these is necessary to explain why analysts are likely to have formulated their forecasts based on a median rather than a mean forecast (estimated with quantile and OLS regressions, respectively). Even when analysts have a quadratic loss function and the objective is to minimize MSFE, they can still find it gainful to use a quantile regression forecasting approach under the circumstances of heavy-tailed distributions, even without skewness.

## 2. Related Literature

### *2.1. Firm profitability forecasts*

Profitability is a key indicator of company performance and widely used as an input for valuation. Traditional measures of profitability include ROE and RNOA. Freeman et al. (1982) show that there is regression toward the mean in ROE and establish that extreme ROEs are more transitory than moderate ones. Fama and French (2000) provide evidence that mean reversion in firm profitability is a robust phenomenon and suggest that changes in profitability and earnings are to some degree predictable. In a simple partially adjusted model using US data, they find an estimated rate of mean reversion around 38% p.a.. Similar results are documented by Allen and Salim (2005) who report a mean reversion rate of 25% p.a. in the UK market. We follow Fairfield et al. (2009) in using a forecasting model that captures the mean-reversion pattern of profitability conditional on the deviation of a firm's profitability from the median profitability benchmark (Fama and French 2000; Freeman et al. 1982).

Besides ROE and RNOA, we consider several alternative measures of profitability: GP, OP, and CbOP. They are the gross profit, operating profit, and cash-based operating profit, deflated by the total assets lagged by one year. *Gross profit* is the sales minus the cost of goods sold. *Operating profit* is defined as the gross profit minus the selling, general, and administrative expenses reported (i.e., the Compustat-adjusted selling, general, and administrative expenses with the expenditures on research and development subtracted in order to undo this adjustment by Compustat). Two versions of *Cash-based*

[3] Forecasting earnings in practice is often equivalent to forecasting profitability (e.g., Li 2011; Chang et al. 2016). Data samples used to forecast earnings typically include firms of different sizes. Deflation is a technique to control for the size differences. Deflating an earnings measure by certain size variable, such as book value of equity, net operating assets, or total assets, gives a profitability measure (Li et al. 2014; Schröder and Yim 2018).

*operating profit* are obtained by purging accruals from the operating profit, with the accruals constructed using the cash-flow approach or the Sloan (1996) balance-sheet approach (see Ball et al. 2016, p. 44). Panel A of table 1 summarizes the definitions of the profitability measures examined in this study, which are consistent with prior literature (Novy-Marx, 2013; Ball et al. 2015, 2016; Fairfield et al. 2009).

The GP, OP, and CbOP have received considerable attention because of their predictive power in explaining the cross section of stock returns (Novy-Marx 2013; Ball et al. 2015, 2016; Fama and French 2015, 2016, 2017; Akbas et al. 2017). Novy-Marx (2013) find that GP can explain most earnings related cross-sectional anomalies in stock returns. Ball et al. (2015), however, show that OP has a much stronger link with stock returns than GP. The usefulness of OP in explaining the cross section of stock returns has led to its inclusion as a new factor in the latest five-factor asset pricing model (Fama and French 2015; 2016; 2017). Adding to the success of OP, Ball et al. (2016) show that CbOP outperforms OP in predicting the cross section of stock returns, explaining two anomalies related to accruals and profitability measures that include accruals.

The literature above relates the current profitability to the stock return of the following year. Our interest in the profitability measures comes from their potential for valuation. Because valuation is forward-looking in nature, this study focuses on the forecasts of the measures, rather than their realized current levels.

### *2.2. Quantile regression versus OLS*

We propose constructing point forecasts of profitability using quantile regression, as opposed to the common practice of using OLS regression.[4] Specifically, we focus on the quantile regression for $\tau$ = 0.5 (i.e., the 50$^{th}$ percentile), which is also referred to as the median regression. This special case of quantile regression uses the absolute error loss criterion, as opposed to the squared error loss criterion upon which OLS regression is based. Median regression has the advantage of being more robust to outliers than OLS regression (Cameron and Trivedi 2005).

[4] We focus on point forecasts in this study. Despite the availability of methods to produce interval and density forecasts, point forecasts remain the most commonly used in practice. They are often easier to understand and act upon and are less costly to produce (Diebold 2015).

Similarly, quantile regression is a more robust alternative for accommodating dependent variables with skewed distributions (Olsen et al. 2012). It is well-documented that firm earnings are skewed (Basu 1997; Givoly and Hayn 2000; Konstantinidi and Pope 2016). This makes the mean estimation by OLS regression less appropriate for capturing the central tendency of the earnings distribution.

Our analyses show that while both tail-heaviness (reflecting outliers in a sample) and asymmetry (as what skewness tries to measure) have effects on the accuracy of quantile regression profitability forecasts, the former's effect is much more consistent than the latter across the different settings examined.

## 3. Forecasting Analysis

### *3.1. Research Design*

Consistent with prior studies such as Fairfield et al. (2009) and Li and Mohanram (2014), we construct the profitability forecast for each firm-year in two steps. First, we estimate in-sample a forecasting model on a rolling basis using the data of all the firms available in the previous ten years. For example, to forecast the profitability of a firm for year $T$, we first estimate the coefficients of a forecasting model using the data of all the firms available from year $T$−10 to year $T$−1. Next, we apply the estimated coefficients from the in-sample regression to the current-year data of a firm to obtain the one-year-ahead profitability forecast of the firm.

The first forecasting approach considered by us uses the following forecasting model based on the *economy-wide OLS regression* specification studied in Fairfield et al. (2009):

$$x_{i,t} = \alpha_T + \beta_T x_{i,t-1} + \gamma_T D_{i,t} * x_{i,t-1} + \lambda_T PREDGSL_{i,t} + u_{i,t}, \quad (1)$$

where $t = T-10, \ldots, T-1$. The dependent variable $x_{i,t}$, indexed by firm $i$ and year $t$, stands for one of the profitability measures considered: GP, OP, balance-sheet approach CbOP, cash-flow approach CbOP, RNOA, and ROE. $D_{i,t}$ is a dummy variable equal to one if in year $t$−1, the profitability of firm $i$ is below the threshold set at the median profitability of all observations available in the ten years for the in-sample estimation and equal to zero otherwise. $PREDGSL_{i,t}$ is the predicted growth in sales, which is found to be useful for profitability forecasting (Fairfield et al. 2009). $u_{i,t}$ is the error term. The model parameters $\alpha_T$, $\beta_T$, $\gamma_T$, and $\lambda_T$ are indexed by year $T$ to highlight that they are estimated for each year $T$ using data available in the previous ten years.

To construct *PREDGSL*, we use the following simple first-order autoregressive model estimated by OLS regression on an industry-specific basis:

$$g_{i,t} = \mu_{j,T} + \upsilon_{j,T} g_{i,t-1} + \epsilon_{i,t}, \tag{2}$$

where $g_{i,t}$ is the growth in sales of firm $i$ in year $t$, $\epsilon_{i,t}$ is the error term, and $t = T-10, \ldots, T-1$. The model parameters $\mu_{j,T}$ and $\upsilon_{j,T}$ are indexed by industry $j$ and year $T$ to highlight that the estimation is done on an industry-specific basis and for each year $T$ using the previous ten years of data. The $PREDGSL_{i,T}$ for each firm-year ($i,T$) is set to the predicted value $m_{j,T} + n_{j,T} g_{i,T-1}$, where $m_{j,T}$ and $n_{j,T}$ are the estimated coefficients of the model parameters $\mu_{j,T}$ and $\upsilon_{j,T}$. We construct *PREDGSL* by OLS regression on an industry-specific basis since Fairfield et al. (2009) find that sales growth forecasts are more accurate when constructed this way, rather than on an economy-wide basis.[5] We classify industries based on the first-digit SIC. Schröder and Yim (2018) find that a broad industry classification like this better balance the bias from model misspecification and the sample size for industry-specific estimation.

Our second forecasting approach, *economy-wide quantile regression*, uses the same model as specified in equation 1 except that the parameters ($\alpha_T$, $\beta_T$, $\gamma_T$, $\lambda_T$) are estimated by quantile regression for $\tau$ = 0.5 (i.e., by median regression). In general, quantile regression estimates are obtained by minimizing the loss function $\rho_\tau(u)$ on the error term $u$ as illustrated in Figure 1 in the online appendix. For $\tau$ = 0.5, the loss function becomes symmetric and equals $|u|$. The quantile regression estimates for this case are conditional median estimates. In our context, the estimated coefficients are given by

$$\underset{(\alpha_T,\, \beta_T,\, \gamma_T,\, \lambda_T)}{\operatorname{argmin}} \sum_{i,t} \left| x_{i,t} - (\alpha_T + \beta_T x_{i,t-1} + \gamma_T D_{i,t} * x_{i,t-1} + \lambda_T PREDGSL_{i,t}) \right|. \tag{3}$$

Following prior research such as Li et al. (2014) and Fairfield et al. (2009), we use the absolute forecast error (AFE) to measure the accuracy of a forecasting approach. Specifically, the AFE of

[5] We verify that this also holds for our sample. We discuss the robustness of our results to alternative ways to construct *PREDGSL* in appendix A in the online appendix.

forecasting approach A for a firm-year $(i,T)$ is defined as the absolute difference between the actual profitability $x_{i,T}$ and the profitability forecast $E_A[x_{i,T}]$ constructed with forecasting approach A:

$$AFE_A(i,T) = | x_{i,T} - E_A[x_{i,T}] |. \quad (5)$$

For example, the profitability forecast constructed with the first approach (i.e., economy-wide OLS) is

$$E_{ew\_OLS}[x_{i,T}] = a_T + b_T x_{i,T-1} + c_T D_{i,T} * x_{i,T-1} + l_T PREDGSL_{i,T}, \quad (6)$$

where $(a_T, b_T, c_T, l_T)$ are the economy-wide OLS estimates of the model parameters $(\alpha_T, \beta_T, \gamma_T, \lambda_T)$. Because the actual profitability is not part of the data used to construct the profitability forecast, the assessment by the AFE is said to be out-of-sample.

Like prior research, we compute the forecast improvement (FI) of an approach (say, A) over another (say, B) for a firm-year $(i,T)$ to compare the accuracy of the two forecasting approaches. This is defined as the difference in the AFE between the forecasts from the two approaches:

$$FI_{A,B}(i,T) = AFE_B(i,T) - AFE_A(i,T). \quad (7)$$

The FI would be positive if approach A has a lower AFE than approach B. To conclude on which of the two approaches is more accurate, we perform tests on the mean as well as the median FI over all firm-years. Consistent with the framework of comparing predictive accuracy in Diebold and Mariano (1995), the test on the mean FI is a regression-based t-test using robust standard errors controlling for two-way clustering by firm and year. The test on the median FI is the Wilcoxon signed-rank test.

### *3.2. Sample selection*

Profitability forecasts for the forecasting analysis are constructed for the period from 1989 to 2018 because some measures require data from the cash flow statements available only from 1987 onwards. We use data available in the previous ten years to construct the profitability forecasts for a year. As the *PREDGSL* variable in the forecasting models requires ten earlier years of data to construct, the profitability forecasts for 1989 are constructed with data as far back as in 1969.[6]

We obtain accounting data of US firms from the Compustat North America annual fundamentals

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[6] We use up to twenty earlier years of data to construct the first year of profitability forecasts in 1989. For the cash-flow approach CbOP, this first year of forecast uses only the previous two years of cash flow data because the source of the data (i.e., cash flow statements) is available only from 1987 onward. The estimated coefficients for constructing the 1989 forecasts of the cash-flow approach CbOP come from an in-sample regression that uses the 1988 *PREDGSL* variable, which requires sales data of the previous ten years to construct. For this profitability measure, the 1989 forecasts are constructed with data as far back as in 1978, whereas for the other profitability measures, as far back as in 1969.

file on Wharton Research Data Services (WRDS). Only observations with identifiable SIC codes and data available for computing the profitability measures are retained.[7] We exclude financial and utility firms (SIC from 6000 to 6799, or from 4900 to 4949) because they are highly regulated. In addition, the U.S. Postal Service (SIC 4311) and public administration (SIC 9000 or above) are excluded because of their special nature.[8]

Like Fairfield et al. (2009) and Schröder and Yim (2018), we apply a number of filters. To reduce the influence of outliers, we exclude observations with the profitability measure exceeding 1 in absolute value from the analysis of that measure. To mitigate the effect of a small denominator on the profitability or sales growth measure, observations with lagged total assets, average net operating assets, or lagged sales below USD 10 million or average book value of equity below USD 1 million are excluded from the analysis of the measure in concern. To further mitigate the effect of mergers and acquisitions on the relation between current-year and lagged variables, we exclude observations with growth in total assets, net operating assets, sales, or book value of equity exceeding 100%.

For the in-sample estimation of the forecasting models, we trim all continuous-value dependent and predictor variables to the 1st and 99th percentiles. To avoid any bias in assessing the forecast accuracy out-of-sample, there is no such trimming in the data upon which the estimated coefficients are applied to obtain the forecasts. Given the limited data availability in the early years of our sample period, we require at least 100 firm-year observations in the in-sample estimation step to avoid unreliable estimation.

Panel A of table 2 summarizes the sample selection procedure for the forecasting analysis. The forecasting models are estimated annually on a rolling basis using data available in the previous ten years. The actual number of observations used in each round of in-sample estimation can vary depending on the data availability.

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[7] A firm-year observation's SIC code is identifiable if its value is not missing or otherwise may be imputed based on the non-missing SIC code of the firm in the nearest future year.

[8] The U.S. Postal Service category comprises all establishments of the U.S. Postal Service as an agency of the executive branch of the U.S. Federal government responsible for providing postal service in the United States. The public administration category contains the executive, legislative, judicial, administrative and regulatory activities of Federal, State, local, and international governments.

Panel B of the table presents the descriptive statistics of the profitability and sales growth measures and the main variables required for constructing the measures. On average, the OP and the two versions of CbOP are in the range of 12.4% to 14.7%, in contrast to the smaller RNOA and ROE (12.6% and 2.9%, respectively). As GP only has the cost of goods sold deducted, its average value is much higher at 35.6%. The mean growth in sales is 9.2%.

A value above three in the Kurtosis column indicates that a measure is *leptokurtic*, i.e., having tails heavier than the Gaussian distribution (Westfall 2014). All of the profitability measures are leptokurtic.. The Skewness Coefficient column reports the adjusted Fisher-Pearson standardized moment coefficient of skewness. All the earnings and size measures are positively skewed (i.e., skewed to the right – with a longer right tail than the left). With the deflation by some size measures, all the profitability measures are negatively skewed.

### *3.3. Results of the forecasting analysis*

Table 3 presents the forecasting analysis results comparing the alternative approach by economy-wide quantile regression to the benchmark approach by economy-wide OLS regression. We obtain strong evidence showing significantly positive forecast improvements for all the profitability measures. This holds not only for the mean forecast improvements but also for the median. The levels of significance are consistently high (all at the 1% level).

We perform a number of additional analyses to ensure that our results are not sensitive to various methodological and sample choices and can extend beyond profitability forecasting. The analyses are summarized in appendix A in the online appendix.

## 4. Distributional Shape Analysis: Research Design

The purpose of the distributional shape analysis is to examine whether as prior research suggests, the accuracy of quantile regression forecasts relative to OLS forecasts is related to the distributional shape of profitability characterized by its tail-heaviness and asymmetry. We consider both the MAFE and the MSFE criterion in this examination.

Below, we report the research design of the analysis based on data collected from simulated experiments. We introduce two measures of forecasting accuracy for the simulated data and define different measures of tail-heaviness and asymmetry. The simulation procedure is described in appendix B in the online appendix. The results of this simulated-data analysis and the verification of the key findings using archival data are reported in the next section.

#### *4.1. Forecasting accuracy measures*

Because profitability with a more asymmetric distribution or heavier tails is likely to be harder to forecast, we do not expect quantile regression forecasts to become more accurate in those situations in an absolute sense. Instead, we focus on assessing whether quantile regression forecasts are relatively more accurate than OLS forecasts as the tail-heaviness and asymmetry change, considering both the MAFE and MSFE criteria. To do so, we consider measures that benchmark the forecasting performance of quantile regression under the MAFE criterion against that of OLS under MSFE.

To see why we consider such measures, first note that when confining to predictions within the training sample, the OLS's mean forecast is by design optimal under the MSFE criterion; similarly, the quantile regression's median forecast is by design optimal under the MAFE criterion. For a hold-out test sample, quantile regression forecasts can be more accurate than OLS forecasts even under the MSFE criterion, and the other way around under the MAFE criterion. Nonetheless, due to the ways these forecasts are designed, in out-of-sample testing we expect them to have a tendency to prevail under the criteria they are optimal for in-sample prediction. Suppose that a forecasting approach performs very competitively even under the criterion unfavorable to it and also has expectedly superior performance under the criterion favorable to it. However, the other forecasting approach cannot analogously achieve similarly strong performance under the two criteria. Then it is reasonable to consider the former forecasting approach to be relatively more accurate.

More precisely, we look at the statistical test result on the FIs in each simulated experiment. Then, out of the 500 experiments for each set of the distribution type and parameter combination, we count the percentage of the times a forecasting approach prevails under the criterion favorable to it. To determine whether quantile regression prevails in an experiment under the MAFE criterion, we compute the FIs for the 2,500 draws of next-period profitability in the experiment like what we do in the forecasting analysis reported in table 3. Then we perform a statistical test to see if the mean FI is positive at the 0.01 significance level using the t test.[9] Similarly, we do this to see whether OLS prevails in an experiment under the MSFE criterion with the FIs redefined as the SFE of the quantile regression forecast minus that of the OLS. Counting the results over the 500 experiments, we obtain the following measures for each set of the distribution type and parameter combination:

*pct.QR.Prevail* = Percentage of the times where quantile regression prevails under the MAFE criterion;

*pct.OLS.Prevail* = Percentage of the times where OLS prevails under the MSFE criterion.

We also consider the counterparts of these measures by replacing the t test with the Wilcoxon signed-rank test. This is a test on the median FI. Thus, the counterpart measures are better described as under the median AFE (MdAFE) and median SFE (MdSFE) criteria, respectively. Figure 2 in the online appendix illustrates the empirical cumulative distributions of the p-value of the Wilcoxon (signed-rank) test and the t test from the 500 experiments for a moderately heavy-tailed, highly skewed stable distribution.

We consider two forecasting accuracy measures that benchmark the performance of quantile regression under the MAFE criterion against that of OLS under MSFE. The *incremental forecasting accuracy* of quantile regression is

$$IncrAccur = pct.QR.Prevail - pct.OLS.Prevail$$

Because *pct.OLS.Prevail* represents the prevalence of OLS over quantile regression under the MSFE criterion, the lower this measure, the more competitive the forecasting performance of quantile regression under this criterion unfavorable to it. If quantile regression and OLS do similarly well under the criteria favorable to them respectively, *IncrAccur* should be close to zero. If *IncrAccur* increases above zero for experiments where profitability has heavier tails, this means quantile regression performs better in forecasting profitability of that nature relative to OLS.

Besides *IncrAccur*, we also consider the *relative forecasting accuracy* of quantile regression with a similar interpretation:[10]

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[9] We have considered also the 0.05 significance level, and the findings are highly similar.

[10] To be precise, in defining *RelAccur*, we set *pct.QR.Prevail* and *pct.OLS.Prevail* to 0.5/500 = 0.001 whenever they have a zero value. Note that for any given setup of $M$ experiments ($M$ = 500 in our case), the lowest nonzero value of *pct.QR.Prevail*

*RelAccur* = log(*pct.QR.Prevail*) – log(*pct.OLS.Prevail*)

This is simply the log ratio of the likelihood that quantile regression prevails under MAFE to the likelihood that OLS prevails under MSFE.

### *4.2. Tail-heaviness and asymmetry measures*

Skewness is a measure of distributional asymmetry (Arnold and Groeneveld 1992). Kurtosis is a measure of tail extremity, i.e., either existing outliers in a sample or the propensity of a probability distribution to produce outliers (Westfall 2014). Skewness and kurtosis are often defined as the third and the fourth standardized central moment. There are variations in the exact formulas to use for their sample measures (Cox 2010). We use the following sample measures of skewness and kurtosis, which are the $b_1$ and $g_1 + 3$ discussed in Joanes and Gill (1998):

Skewness coefficient = $\sum_i [x_i - \text{mean}(x)]^3 / n\text{sd}(x)^3$

Kurtosis = $\sum_i [x_i - \text{mean}(x)]^4 / n\text{sd}(x)^4$

where $n$ is the number of observations in the sample and sd($x$) is the sample standard deviation. Though commonly used, these moment-based statistics are not the only measures of the asymmetry and tails of a distribution (Holgersson 2010; Groeneveld 1998). We therefore consider various alternatives to ensure that our results are robust to multiple measures.

Our second asymmetry measure is the *Pearson 2nd skewness coefficient* (Doane and Seward 2011):

Mean-less-median = 3[mean($x$) – median($x$)]/sd($x$).

This is similar to Gu and Wu's (2003) MNMD measure but theirs is deflated by the lagged stock price.

*Tails asymmetry* is our third asymmetry measure. It is a simple indicator of the difference in the relative frequencies in the "tails" of the sample in concern:

Tails Asymmetry = $[1 - F(\text{Tail}_R)] - F(\text{Tail}_L)$,

where $F$ is the cumulative relative frequency distribution of the sample in concern, and $\text{Tail}_L$ = median($x$) − 2.136 sd($x$) and $\text{Tail}_R$ = median($x$) + 2.136 sd($x$) are where the left and right "tails" begin. The literature does not have a universally accepted definition of the tails of a distribution. We use Taleb's definition

and *pct.OLS.Prevail* is $1/M$. So the adjustment above avoids any undefined/infinite value due to the log transformation while maintaining the intended ranking of the *RelAccur* measure.

for its simplicity (Taleb 2018; Taleb n.d.).[11] Considering the skewed and heavy-tailed distributions in our analysis, we replace the sample mean by the sample median as a robust estimate of the central tendency, which is likely to have lower sampling variability in this context (Myers et al. 2010; Wilcox and Rousselet 2018).

Our second tail-heaviness measure is the *mean percentage in extremes*:

$$\text{Mean\%Extremes} = 100 \times [F(\text{Extreme}_L) + 1 - F(\text{Extreme}_R)]/2$$

where $\text{Extreme}_L = \text{median}(x) - 4.5\ \text{sd}(x)$ and $\text{Extreme}_R = \text{median}(x) + 4.5\ \text{sd}(x)$. The measure, in percentage points, calculates the mean percentage of the sample falling in the two extreme regions, defined as the regions outside the median minus and plus four and a half standard deviations. In our simulated-data and archival-data regression analysis, an asymmetry measure is always included as a control variable. Therefore, the coefficient of Mean%Extremes captures the effect of heavy tails over and above what could have been driven by the long left or right tail of a skewed distribution. We have also considered the range of four to five standard deviations in defining the extreme regions, all with very similar results in our simulated-data regression analysis. Therefore, we only report the results based on four and a half standard deviations.[12]

Panel B of table 1 summarizes the variable definitions of the forecasting accuracy and distributional property measures. Panel A of table 4 provides the descriptive statistics of these measures for the simulated data used in the distributional shape analysis. The forecasting accuracy measures in the panel are computed based on the Wilcoxon-test or t-test based forecasting performance of the quantile regression and OLS approaches in every 500 simulated experiments of the 4 × 256 sets of the distribution type and parameter combination. The measures of the distributional properties are computed based on the 2,500 draws of the simulated next-period firm profitability to be forecast in each experiment. Presented in the panel are these measures mean- or median-aggregated to the distribution type-parameter combination level.

[11] Nassim N. Taleb, Distinguished Professor of Risk Engineering at the New York University Tandon School of Engineering and the author of the best seller *The Black Swan: The Impact of the Highly Improbable*, defines the fat tails of a perturbed Gaussian distribution to start from the mean minus and plus approximately 2.136 times of the standard deviation.

[12] We also have considered two additional asymmetry measures and one additional tail-heaviness measure explained in appendix C in the online appendix. The inclusion of these measures does not change the highly consistent findings of the tail-heaviness effect. In the interest of space, we omit these measures from the reported tables.

It is worth a note that based on the nonparametric Wilcoxon signed-rank test, OLS prevails under the MSFE criterion (at the 0.01 significance level) for only 10.2% of the times at maximum. This does *not* necessarily mean that quantile regression prevails more often under this criterion. It can simply be that under the robust nonparametric test, it is often hard to tell whether one approach clearly prevails. Because the design of the simulated experiments is to examine the impact of asymmetric and heavy-tailed profitability distributions on the forecasting performance, most of the parameter combinations yield distributions that OLS is unlikely to handle well. Therefore, the statistics reported in the panel should not be confused with OLS's typical performance for profitability distributions close to the Gaussian.

The statistics based on the parametric t test are quite different: The percentage of the times OLS prevails under the MSFE criterion can be as high as 61.2%. This sharp difference explains why we consider both tests in this analysis in order to see the full picture.

The mean- and median-aggregated distributional properties are very similar. In either case, the mean or median Kurtosis in log scale is above the Gaussian benchmark 1.099, which is consistent with the profitability distributions in the simulated experiments typically having heavier tails than the Gaussian. In the simulated experiments, the minimum Kurtosis in log scale at 1.102 is attained when the tail parameter is close to a level giving the Gaussian as a limiting case of the simulated distribution.

Nearly all the asymmetry measures have a nonzero mean and median. This reflects the average outcome of the randomized samples simulated from population distributions that are heavy-tailed and skewed. By design, the parameter combinations used for negatively skewed distribution types are the mirror image of those for positively skewed distribution types. But it is still hard to achieve symmetric realized sample outcomes when the sampling variability is high owing to population distributions that have a high or even infinite variance (e.g., the stable distribution with the $\alpha$ parameter in a range strictly below 2; see appendix B in the online appendix for further details).

## 5. Distributional Shape Analysis: Regression Results

### *5.1. Regression analysis of simulated data*

We use the following regression model to relate the distributional shape of profitability to the forecasting accuracy of quantile regression:

$$DepVar = \alpha_0 + \alpha_1\, Heavy + \alpha_2\, Asymmetric + \alpha_3\, Asymmetric^2 + \alpha_4\, \mathrm{sd}(Profit.) + \text{Distribution type fixed effects} + \varepsilon, \quad (11)$$

where

*DepVar* = *IncrAccur* or *RelAccur*;

*Heavy* = Mean%Extremes or Kurtosis;

*Asymmetric* = Tails asymmetry, Mean-less-median, or Skewness coefficient;

sd(*Profit.*) = Standard deviation of the sample distribution of profitability;

Distribution type fixed effects = Effects of whether the distribution is positively or negatively skewed stable or IHS;

$\varepsilon$ = Error term.

Driven by goodness-of-fit consideration, the log values of Kurtosis and sd(*Profit.*) and the cube-root values of the *Asymmetric* measures are used in the regression. The cube-root transformation works much like the log transformation but accepts and maintains negative values (Cox 2011). We control for the sd(*Profit.*) because not all the measures involve the deflation by the sample standard deviation and even when some do, deflation alone is not likely to remove the influence completely.

Table 5 show the results of the simulated-data regression analysis at the mean-aggregated level for the pooled regressions. Without an exception, the effect of tail-heaviness on the incremental forecasting accuracy of quantile regression is significantly positive across all the combinations of *Heavy* and *Asymmetric* measures and for both the Wilcoxon-test and t-test based definitions of *IncrAccur*.

For asymmetry, we focus on the shape of its effect on the incremental forecasting accuracy of quantile regression. The effect has a U shape with the minimum around $-\alpha_2/2\alpha_3$ if the coefficient $\alpha_3$ of the *Asymmetric*$^2$ term is significantly positive (an inverted-U shape if significantly negative). The results in the table show that the shape of the asymmetry effect is consistently a U shape throughout.

The shape of the asymmetry effect is not as consistent throughout table 6, where the results for the relative forecasting accuracy of quantile regression for the pooled regressions are presented. However, it is still highly consistent when confining to only the Wilcoxon-test or only the t-test based results. The asymmetry effect has a U shape in the former but an inverted-U in the latter. This mixed result is in sharp contrast to the highly consistent significantly positive effect of tail-heaviness in table 6.

The individual-distribution regression results are presented in tables A1 and A2 in the online appendix. Regardless of the distributions (stable or IHS) and measures (*IncrAccur* or *RelAccur*), the results are highly consistent with the corresponding pooled-regression results. In an untabulated analysis, we have examined also the median-aggregated versions of the pooled and individual-distribution regressions, and the results are very similar.

The findings above continue to hold in the regression analysis at the experimental level where the *IncrAccur* or *RelAccur* is regressed on the experimental-level profitability distributional properties with robust standard errors adjusted for clustering by distribution type-parameter combination. The effect of tail-heaviness continues to be significantly positive without an exception. The shape of the asymmetry effect again is typically opposite for the Wilcoxon-test versus the t-test defined *RelAccur*. In the interest of space, we do not tabulate these highly similar results.

In table A3 (in the online appendix), we report the regression results of the building blocks, *pct.QR.Prevail* and *pct.OLS.Prevail*, of the incremental and relative forecasting accuracy measures defined based on the Wilcoxon (signed-rank) test. Panel A of the table shows the findings for the pooled sample of the stable and the IHS distributions. The breakdown of *IncrAccur* or *RelAccur* into its building blocks reveals that *pct.OLS.Prevail* (i.e., the percentage of the times where OLS prevails under the MSFE criterion) always decreases with the tail-heaviness measures. By contrast, *pct.QR.Prevail* (i.e., the percentage of the times where quantile regression prevails under the MAFE criterion) always increases with the tail-heaviness measures. This supports the notion that heavy-tailed profitability distributions are driving the superior forecasting performance of quantile regression under the MAFE criterion reported in table 3.

Table A4 (in the online appendix) presents the regression results of *pct.QR.Prevail* and *pct.OLS.Prevail* defined based on the t test. Panel A of the table again shows that *pct.QR.Prevail* increases with the tail-heaviness measures, whereas *pct.OLS.Prevail* decreases with the measures (except for the insignificant findings when *Asymmetric* is Tails Asymmetry). Therefore, the effect of tail-heaviness on the building blocks of the incremental and relative forecasting accuracy measures is highly consistent, regardless of the statistical test used to define the measures.

The finding of a U-shape effect of asymmetry on *pct.QR.Prevail* is also highly consistent among the regression results of the Wilcoxon-test or the t-test based measure. However, the shape of the asymmetry effect on *pct.OLS.Prevail* is opposite between the regression results reported in panels A of tables A3 and A4 (inverted-U in the former and U-shape in the latter). The difference again explains why we need both tests to see the not-so-robust effect of asymmetry and the highly robust effect of tail-heaviness.

Panels B and C of tables A3 and A4 show the findings for the stable and the IHS distribution separately, which are very similar to those for the pooled sample discussed above.

***5.2. Regression analysis of archival data***

In the archival data used for the distributional shape analysis, distributional properties are estimated for each profitability measure using all firms in each industry-year. The industry classification is based on two-digit SIC. The firm-year observations used to construct the industry-year observations come from the sample for out-of-sample testing reported in table 3. A minimum of 20 firms in each industry-year is required to avoid unreliable estimates of the distributional properties.

The regression model is

$$\begin{aligned} DepVar = {} & \alpha_0 + \alpha_1\, Heavy + \alpha_2\, Asymmetric + \alpha_3\, Asymmetric^2 + \alpha_4\, \mathrm{sd}(Profit.) \\ & + \text{Profitability fixed effects (only for the pooled all-profitability regression)} \\ & + \text{First-digit SIC industry fixed effects} + \text{Year fixed effects} + \varepsilon, \end{aligned} \tag{12}$$

where the *Heavy* and *Asymmetric* measures are the same set as in the simulated-data analysis. The two forecasting measures for *DepVar* are still referred to as *IncrAccur* and *RelAccur*. However, they are redefined as follows for the archival-data analysis:

$$IncrAccur = fir.QR.Prevail - fir.OLS.Prevail$$

$$RelAccur = \log(fir.QR.Prevail) - \log(fir.OLS.Prevail),$$

where $fir.QR.Prevail = \mathrm{mean}(AFE_{\mathrm{OLS}})/\mathrm{mean}(AFE_{\mathrm{QR}})$ is the forecast improvement ratio (FIR) of quantile regression under the MAFE criterion, and $fir.OLS.Prevail = [\mathrm{mean}(SFE_{\mathrm{QR}})/\mathrm{mean}(SFE_{\mathrm{OLS}})]^{½}$ is the forecast improvement ratio of OLS under the root mean squared forecast error (RMSFE) criterion. The mean(·) operation in the forecast improvement ratios is taken over all firms in an industry-year. We use the RMSFE criteria, which has the same ranking as MSFE, to define *fir.OLS.Prevail* so that its scale is comparable to *fir.QR.Prevail* and hence the meaning of *IncrAccur* as their difference is more intuitive.

Industry and year fixed effects are included in the regression. Robust standard errors adjusted for clustering by profitability-industry-year are reported in parentheses in the result tables. Because the observations for each profitability measure are at the industry-year level with the industry classification based on two-digit SIC, we use the broader first-digit SIC to define the industry for the industry fixed effects and robust standard errors.

Panel B of table 4 provides the descriptive statistics of the archival data used for the distributional shape analysis. The mean and median sizes of each industry-year are 82.7 and 50 firms, respectively. This variable provides the weights for the size-weighted regressions reported in table 7, in addition to the unweighted regressions.

RMSFE should be an evaluation criterion more favorable to OLS. However, the mean *fir.OLS.Prevail* is below one (0.996), whereas the mean *fir.QR.Prevail* is above one (1.027). This necessarily results in a positive mean *IncrAccur*, suggesting that on average the forecasting accuracy of quantile regression is higher relative to OLS, just like in the simulated data.

The mean and median of the asymmetry measures are nonzero, also like in the simulated data. Note that the Kurtosis reported in the panel and used in the regressions are in log scale. Therefore, its median at 1.521 is equivalent to a value of 4.577 in the original scale. This suggests that over half of the industry-years have profitability distributions with tails heavier than the Gaussian. However, with a minimum at 0.274 for Kurtosis in log scale, there should be cases with tails lighter than the Gaussian, which do not exist at all in the simulated data. This could be a reason for expecting results somewhat different from the simulated-data analysis.

Table 7 shows the results of the archival-data analysis at the industry-year level for *IncrAccur* as the dependent variable. In panel A where the results for the pooled all-profitability regressions are reported, the effect of tail-heaviness on the incremental forecasting accuracy of quantile regression is significantly positive across all the combinations of *Heavy* and *Asymmetric* measures, as well as for both the unweighted and size-weighted regressions. This highly consistent result also appears in panel E for the individual-profitability regressions for CbOP_CF (except for the Mean%Extremes-Skewness coefficient combination) and more or less so in panel G for ROE (with nine of the twelve estimated coefficients being significantly positive). There is also moderate support for this tail-heaviness effect from the regressions for OP, CbOP_BS, and RNOA in panels C, D, and F, respectively (with five to seven of the estimated coefficients being significantly positive). Across all the regressions, whenever the estimated coefficients for the tail-heaviness effect are significant, they have a positive sign (except for the Kurtosis-Skewness coefficient combination in the unweighted and size-weighted regressions for GP). Considering the differences between the simulated and archival data, we view the tail-heaviness effect found here as generally corroborating the simulation results of the tail-heaviness effect.

In table A5 (provided in the online appendix), we report the regression results of the building blocks of the archival-data incremental and relative forecasting accuracy measures. The results show that without an exception, $fir.OLS.Prevail$ = $[\text{mean}(SFE_{\text{QR}})/\text{mean}(SFE_{\text{OLS}})]^{½}$ decreases with the tail-heaviness measures, whereas $fir.QR.Prevail$ = $\text{mean}(AFE_{\text{OLS}})/\text{mean}(AFE_{\text{QR}})$ increases with the measures. This finding confirms that the heavy tails of profitability distribution are a driver behind the superior forecasting performance of quantile regression under the MAFE criterion reported in table 3. Figures 3a to 3c in the online appendix depict the archival-data based finding of the tail-heaviness effect (illustrated in terms of Kurtosis) on the incremental forecasting accuracy *IncrAccur* of quantile regression and its components *fir.QR.Prevail* and *fir.OLS.Prevail*.

The pooled regressions in panel A of table 7 support the notion of an inverted-U-shape asymmetry effect (with ten of the twelve estimated coefficients of the $Asymmetric^2$ term being significantly negative). However, this finding appears to be driven by the result for ROE in panel G. Across all the regressions for the other profitability measures, either there is no significant asymmetry effect (for CbOP_BS and CbOP_CF in panels D and E) or any significant finding is consistent with a U-shape asymmetry effect (for GP, OP, and RNOA in panels B, C, and F).

The untabulated results for *RelAccur* as the dependent variable are very similar. Nearly all of the regressions for GP and RNOA and half of those for OP have a significantly positive coefficient of the *Asymmetric*$^2$ term while the regressions for CbOP_BS and CbOP_CF show no significant effect of asymmetry. As in table 7, the inverted-U-shape asymmetry effect found in the pooled regressions appears to be driven by the regression results for ROE. Additionally, the pooled and individual regressions for the profitability measures show consistent support for a positive tail-heaviness effect. Overall, the evidence from the archival-data analysis confirms the key insight about the tail-heaviness effect from the simulated-data analysis and highlights again the mostly significant but not entirely consistent effect of asymmetry (i.e., can be U-shape or inverted-U-shape).

**6. Application to Cash Flows Forecasting**

To demonstrate the usefulness of our analysis framework beyond profitability forecasting, we apply the framework to examine the out-of-sample forecasting of cash flows studied by Nallareddy et al. (2020). They find that under the MSFE criterion and using the OLS approach, the first-order autoregressive model (i.e., using lagged cash flows to forecast cash flows) is more accurate than the forecasting-by-lagged-earnings model (i.e., using lagged earnings to forecast cash flows).

Following Nallareddy et al. (2020), we examine the out-of-sample forecasts of cash flows for the period from 1990 to 2015. We are interested to relate together the annual time series of the cash flows distributional properties and the incremental forecasting accuracy of the quantile regression approach against OLS. Prior research mentions that the cash flows distribution has changed significantly over time (Gassen 2018). In an untabulated analysis, we find a moderate upward trend in the yearly variation in the tail-heaviness of the cash flows distribution across all firms: An OLS regression of the tail-heaviness, measured as Kurtosis in log scale, on the year gives a slope coefficient of 0.027 (with a p-value of 0.053).

We compare the quantile regression approach to estimating the first-order autoregressive cash flows forecasting model against the OLS approach. Note that the forecasting-by-lagged-earnings model does not fit into the simple/extended first-order autoregressive structure upon which our analysis framework was developed. Therefore, we do not expect that the quantile regression approach would prevail for this second model or that the (perhaps non-positive) incremental forecasting accuracy would be associated with the distributional properties of cash flows. Nonetheless, we are interested to know whether to some extent the key insights of our framework might hold after controlling for the cross-sectional variability of the lagged earnings in the distributional shape analysis. Controlling for the variability of this only predictor variable of the second model is important because the variability is likely to adversely impact the forecasting accuracy of both the quantile regression and the OLS approach perhaps unevenly.

We obtain the data of US firms from the Compustat North America annual fundamentals file on WRDS. Consistent with Nallareddy et al. (2020), cash flows (*CF*) are measured as cash flows from operations adjusted for extraordinary items and discontinued operations (derived from cash flow statements). Earnings (*EARN*) are defined as income before extraordinary items and discontinued operations. Both variables are deflated by average total assets. Following them, we exclude observations meeting any of the following criteria: (i) sales of less than $10M; (ii) share price of less than $1; (iii) SIC code in the range of 6000-6999 (i.e., in the financial services sector).[13] This would yield a sample of 110,597 firm-year observations if we also followed them to winsorize all continuous independent variables of the full sample at the 1 percent and 99 percent levels. Instead, we mitigate the effects of outliers only at the in-sample estimation stage to finalize the sample used for the regression with a given rolling window of data (e.g., the most recent two years of available data as in Nallareddy et al. 2020). This alternative approach avoids a look-ahead bias. We truncate the top and the bottom one percent of all continuous variables used in the in-sample regression, rather than winsorize them, to be consistent with the literature our profitability forecasting analysis builds upon. This prevents the clustering of observations around the 1 percent and 99 percent levels. To avoid a look-ahead bias, there is no truncation on the sample of the prior-year data for constructing the out-of-sample forecasts and on the sample of the forecasts constructed.

Figure 4 in the online appendix depicts the annual time series of the incremental forecasting accuracy, its forecast improvement ratio components, and the distributional properties of cash flows. The temporal variation of the incremental forecasting accuracy (*IncrAccur*) of the quantile regression approach (against OLS) for the first-order autoregressive cash flows model is shown in the first chart

[13] If the SIC code of a firm-year observation is missing, we impute the value based on the non-missing SIC code of the firm in the nearest future year.

of the figure. The components of *IncrAccur*, namely the forecast improvement ratio of quantile regression under the MAFE criterion (*fir.QR.Prevail*) and the forecast improvement ratio of OLS under the RMSFE criterion (*fir.OLS.Prevail*), are depicted in the second and the third chart of the figure, respectively. Note that *fir.QR.Prevail* is above one nearly for all the years, whereas *fir.OLS.Prevail* is more evenly spread above and below one. In other words, the quantile regression approach clearly prevails under the MAFE criterion but the OLS approach on average cannot prevail even under the RMSFE criterion more favorable to it. Consequently, *IncrAccur* is positive for most of the years.

The fourth chart in the figure depicts the Kurtosis of the cash flows distribution, which shows a moderate upward trend. The Skewness coefficient of the distribution depicted in the fifth chart indicates that except for a few years, the cash flows distribution is negatively skewed. The last chart shows the temporal variation of the standard deviation of the cash flows distribution. The standard deviation measures the cross-sectional variability of the cash flows in a year. This is likely to affect the forecasting accuracy of both the quantile regression and the OLS approach. It is included in the distributional shape analysis regression to help identify the incremental effects of the tail-heaviness and the asymmetry, measured by the Kurtosis and the Skewness coefficient, respectively.

The first two columns in panel A of table 8 present the results of the distributional shape analysis for the first-order autoregressive cash flows model. They are based on in-sample estimation with a two-year rolling window as in Nallareddy et al. (2020). The dependent variable is *IncrAccur*. The first column in the panel shows a positive mean *IncrAccur* at the 5% significance level. The second column shows that this positive incremental forecasting accuracy of the quantile regression approach is partly driven by the tail-heaviness of the cash flows distribution (a positive coefficient for *Heavy* at the 5% significance level). The significantly negative coefficient of the $Asymmetric^2$ term means that the asymmetry has an inverted-U-shape effect on the incremental forecasting accuracy. These findings are consistent with the pooled regression archival-data results of our analysis for profitability forecasting. To assess the robustness of these findings, we also perform the analysis for different in-sample estimation windows up to ten years of available data as in our analysis for profitability forecasting.[14] The results are similar to those for the two-year window case. For brevity, we only tabulate the results for the four-year, seven-year, and ten-year cases in columns 4 to 5 and 7 to 10 in the panel.

Column 3 in the panel presents the two-year window result for the forecasting-by-lagged-earnings model. The (untabulated) corresponding mean *IncrAccur* is −0.009 (at the 10% significance level), which becomes insignificantly different from zero for any longer window up to ten years. Column 3 shows that controlling for the standard deviation of the lagged earnings distribution, the incremental forecasting accuracy of the quantile regression approach is less negative when the cash flows distribution has heavier tails. The asymmetry of the cash flows distribution has an inverted-U-shape effect on the *IncrAccur* even for this model not having a first-order autoregressive structure. These findings are robust to widening the in-sample estimation window to three or four years. For brevity, we tabulate only the four-year case in column 6 of the panel.

We also analyze various subsamples that exclude firms likely to have contributed to the tail-heaviness and asymmetry of the cash flows distribution. By confining to these subsamples, we expect to see a somewhat weaker relation between the incremental forecasting accuracy and the distributional properties. Intangible-intensive firms are excluded from the first subsample we consider. Gassen (2018) points out that "new firms from intangible intensive industries, in particular from the health sector, appear to have extremely left skewed cash flow" (Gassen 2018, p. 19). He also notices that from 2005 to 2014, a sizable fraction of the negative cash flow firms are based in the health sector. Many of them tend to be "relatively small, and invest heavily in in-process research and development" (p. 13). Following him, we define intangible-intensive firms as the firms in the Health, Business Equipment, Telecommunication, and Chemical sectors of the Fama-French 12-industry classification.[15]

The second subsample we examine excludes loss firms (i.e., *EARN* < 0) because they are likely to be associated with negative cash flows, contributing to the negative skewness of the cash flows

[14] This means that for the ten-year window case, only three years of available cash flows data (i.e., from 1987 to 1989) are used in the in-sample estimation for constructing the 1990 forecasts; only four years of available data (i.e., from 1987 to 1990) are used for constructing the 1991 forecasts; so and so forth. See also the explanation in footnote 6.

[15] We downloaded the definition of the Fama-French 12-industry classification on 31 March 2020 from https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_12_ind_port.html.

distribution. Smaller firms might also contribute to the cash flows distribution's negative skewness. They are excluded from the third subsample. It seems reasonable to expect that the firms in the tails of the cash flows distribution overlap somewhat with the firms in the tails of the firm size distribution. Excluding these firms might lighten the tails of the cash flows distribution. We investigate this case in the fourth subsample. Measuring firm size by total assets, we define smaller firms as those below the first quartile of the firm size distribution and define "size-tails" firms as those outside the 12.5$^{\text{th}}$ and the 87.5$^{\text{th}}$ percentile of the distribution.

Panel B of table 8 shows the subsample findings based on the first-order autoregressive cash flows model with a two-year in-sample estimation window. Compared to the full-sample result (columns 1 and 2 of panel A), the magnitude or statistical significance of the mean *IncrAccur* and of the estimated coefficients of the *Heavy* and the *Asymmetric*$^2$ term is generally lower. The few exceptions are the statistically more significant mean *IncrAccur* of the same magnitude in column 7 and the statistically more significant coefficients of the *Heavy* and the *Asymmetric*$^2$ term in column 8 (but both coefficients are lower in magnitude).

All in all, we conclude that the results of the distributional shape analysis for the cash flows forecasting models and for the various subsamples are in line with our earlier findings for profitability forecasting.

**7. Conclusion**

We document that quantile regression performs better than OLS in forecasting profitability for a range of profitability measures under the MAFE criterion. Considering the MAFE and the MSFE (RMSFE) criteria together, we also examine how quantile regression's forecasting performance, benchmarked against OLS's, changes with the shape of the profitability distribution. Specifically, we perform a distributional shape analysis to relate the forecasting accuracy of quantile regression against OLS to the tail-heaviness and asymmetry of profitability distribution. In the simulated-data analysis of this analysis, we find a robust positive effect of tail-heaviness on the accuracy of quantile regression relative to OLS. The finding is strongly to moderately supported by the archival-data results of the pooled and individual profitability (unweighted and size-weighted) regressions.

In the simulated-data analysis, we also find that asymmetry has either a U- or inverted-U-shape effect on the accuracy of quantile regression forecasts. Which of these holds depends on (i) whether Wilcoxon- or t-test based evidence is relied upon to determine the prevalence of a forecasting approach under a given evaluation criterion (MAFE or MSFE) and (ii) whether the accuracy measure is the incremental or the relative forecasting accuracy. The archival-data analysis also shows mixed evidence: The effect of asymmetry is mostly significant but not entirely consistent (i.e., can be U-shape or inverted-U-shape).

Applying the distributional shape analysis framework to cash flows forecasting, we demonstrate the usefulness of the framework beyond profitability forecasting. The empirical results support the notion of an inverted-U-shape effect of asymmetry and provide additional evidence on the positive effect of tail-heaviness.

In this study, we have only scratched the surface of quantile regression's usefulness by focusing on the median regression as its special case. Quantile regression in general can produce optimal estimates/forecasts for asymmetric loss functions (when $\tau \neq 0.5$). Prior research has argued that financial analysts have an asymmetric loss function (Clatworthy et al. 2011). If they do, would they find formulating their forecasts based on quantile regression with $\tau \neq 0.5$ more aligned with their forecasting objective? What is the implied $\tau$ that can be inferred from analyst earnings forecasts? Are the implied $\tau$'s similar across different types of analyst forecasts (cash flow forecasts, revenue forecasts, etc)? These are interesting questions left for future research to answer.

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**TABLE 1**
Variable definitions

**Panel A:** Forecasting analysis

| Variable | Description | Computation / WRDS mnemonic |
|---|---|---|
| (USD million) | | |
| *OPINC* | Operating income after depreciation | OIADP |
| *NI* | Income before extraordinary items - available for common equity | IBCOM |
| *TA* | Total assets | AT |
| *NOA*† | Net operating assets | Common stock (CEQ) + Preferred stock (PSTK) + Long-term debt (DLTT) + Debt in current liabilities (DLC) + Minority interest (MIB) – Cash and short-term investments (CHE) |
| *BV* | Common/Ordinary shareholder's equity | CEQ |
| *SALES* | Sales/Turnover (net) | SALE |
| *GP* | Gross profitability | [Sales (SALE) - Cost of goods sold (COGS)] scaled by Total assets (AT) lagged by one year |
| *OP*† | Operating profitability | [Gross profit (SALE - COGS) - Selling, general, and administrative expenses reported (XSGA - XRD)] scaled by Total assets (AT) lagged by one year |
| *CbOP_BS*† | Cash-based operating profitability (balance-sheet approach) | [Operating profit (SALE - COGS - (XSGA -XRD)) - △(Accounts receivable (RECT)) - △(Inventory (INVT)) - △(Prepaid expenses (XPP)) + △(Deferred revenue (DRC+DRLT)) + △(Trade accounts payable (AP)) + △(Accrued expenses (XACC))] scaled by Total assets (AT) lagged by one year |
| *CbOP_CF*† | Cash-based operating profitability (cash-flow approach) | [Operating profit (SALE - COGS - (XSGA -XRD)) + Decrease in accounts receivable (RECCH) + Decrease in inventroy (INVCH) + Increase in accounts payable and accrued liabilities (APALCH)] scaled by Total assets (AT) lagged by one year |
| *RNOA* | Return on net operating assets | $OPINC_t/(0.5*(NOA_t + NOA_{t-1}))$ |
| *ROE* | Return on equity | $NI_t/(0.5*(BV_t + BV_{t-1}))$ |
| *GSL* | Growth in sales | $(SALES_t - SALES_{t-1})/ SALES_{t-1}$ |

† If the data items from balance sheet accounts and the data items for preferred stock, long-term debt, debt in current liabilities, minority interest, cash and short-term investments, selling, general, and administrative expenses, research and development expenses, decrease in accounts receivable, decrease in inventroy, and increase in accounts payable and accrued liabilities are not available, they are assumed to equal zero.

**TABLE 1** (continued)
Variable definitions

**Panel B: S**imulated-data and achival-data distributional shape analyses

| Variable | Description | Computation |
|---|---|---|
| sd(*Profit.*)† | Standard deviation of the sample distribution of profitability | |
| Mean%Extremes | Mean percentage in extremes (in percentage points) | $= 100 \times [F(\text{Extreme}_L) + 1 - F(\text{Extreme}_R)]/2$ where $F$ is the cumulative relative frequency distribution of the sample profitability distribution in concern, $\text{Extreme}_L = \text{median}(x) - 4.5\ \text{sd}(x)$, and $\text{Extreme}_R = \text{median}(x) + 4.5\ \text{sd}(x)$ |
| Kurtosis† | Moment coefficient of kurtosis | $= \sum_i [x_i - \text{mean}(x)]^4 / n\text{sd}(x)^4$ |
| Tails Asymmetry‡ | Tails asymmetry | $= [1 - F(\text{Tail}_R)] - F(\text{Tail}_L)$, where $\text{Tail}_L = \text{median}(x) - 2.136\ \text{sd}(x)$ and $\text{Tail}_R = \text{median}(x) + 2.136\ \text{sd}(x)$ are where the left and right "tails" begin (Taleb 2018; Taleb n.d.) |
| Mean-less-median‡ | Pearson 2nd skewness coefficient | $= 3[\text{mean}(x) - \text{median}(x)]/\text{sd}(x)$ |
| Skewness Coeff.‡ | Adjusted Fisher-Pearson standardized moment coefficient of skewness | $= \sum_i [x_i - \text{mean}(x)]^3 / n\text{sd}(x)^3$ |
| Simulated-data analysis: | | |
| *pct.QR.Prevail* | Percentage of the times where QR prevails under MAFE | To determine whether QR prevails in an experiment under MAFE, compute the FIs for the 2,500 draws of next-period profitability in the experiment like in the forecasting analysis reported in table 3. Then perform a statistical test to see if the mean FI (median FI) is positive at the 0.01 significance level using the t test (Wilcoxon signed rank test). Count the results over the 500 experiments of a given set of distribution type and parameter combination to obtain the measure. |
| *pct.OLS.Prevail* | Percentage of the times where OLS prevails under MSFE | Similar to the above but the FIs are redefined as the difference from the SFE of the QR forecast minus that of the OLS |
| *IncrAccur* | Incremental forecasting accuracy (simulated-data version) | = *pct.QR.Prevail* − *pct.OLS.Prevail* |
| *RelAccur* | Relative forecasting accuracy (simulated-data version) | = log(*pct.QR.Prevail*) – log(*pct.OLS.Prevail*), where *pct.QR.Prevail* and *pct.OLS.Prevail* are set to 0.001 whenever they have a zero value |
| Archival-data analysis: | | |
| *fir.QR.Prevail* | Forecast improvement ratio of QR under MAFE | $= \text{mean}(AFE_{OLS})/\text{mean}(AFE_{QR})$ |
| *fir.OLS.Prevail* | Forecast improvement ratio of OLS under RMSFE | $= [\text{mean}(SFE_{QR})/\text{mean}(SFE_{OLS})]^{½}$ |
| *IncrAccur* | Incremental forecasting accuracy (archival-data version) | = *fir.QR.Prevail* – *fir.OLS.Prevail* |
| *RelAccur* | Relative forecasting accuracy (archival-data version) | = log(*fir.QR.Prevail*) – log(*fir.OLS.Prevail*) |

† In log value when used in regression analysis; ‡ In cube-root value when used in regression analysis.

**TABLE 2**
Sample selection and descriptive statistics

| | |
|---|---|
| **Panel A:** Sample selection | |
| Observations with identifiable SIC codes and data available for computing the profitability measures | 288,318 |
| Less financial and utility firms, U.S. postal service, and public administration | 62,787 |
| Less observations with profitability larger than 1 in absolute value | 3,792 |
| Less observations with small denominators | 18,024 |
| Less observations with growth exceeding 100% | 8,621 |
| Observations available for the in-sample estimation step of the forecasting analysis | 195,094 |
| Observations available for the in-sample estimation step for each profitability measure: | |
| *GP* | 163,704 |
| *OP* | 171,528 |
| *CbOP_BS* | 171,493 |
| *CbOP_CF* | 137,026 |
| *RNOA* | 144,829 |
| *ROE* | 169,832 |

This panel summarizes the procedure for selecting the firm-year observations available for use in the in-sample estimation step where the estimated coefficients are obtained to construct the forecast improvements for the period from 1989 to 2018. The in-sample estimation step is done for each year in the period on a rolling basis using data available in the previous ten years. The step requires the use of the predictor variable *PREDGSL* (i.e., the forecast of growth in sales), which needs another ten earlier years of data to construct. Thus, the data used in the in-sample estimation step can go as far back as from 1969. Depending on the data availability, the actual number of observations used in each round of in-sample estimation can vary. A firm-year observation's SIC code is identifiable if its value is not missing or otherwise may be imputed based on the non-missing SIC code of the firm in the nearest future year. See table 1 for the definitions of the profitability measures.

**TABLE 2** (continued)
Sample selection and descriptive statistics

**Panel B:** Descriptive statistics

| Variable | Obs. | Mean | Std. Dev. | Min. | Median | Max. | Kurtosis | Skewness Coefficient |
|---|---|---|---|---|---|---|---|---|
| *Gross profit* | 163,704 | 833.6 | 3,785.7 | -21,536 | 66.2 | 137,106 | 217.33 | 12.01 |
| *Operating profit* | 171,528 | 472.6 | 2,391.6 | -21,913 | 26.4 | 95,801 | 228.94 | 12.61 |
| *Cash-based operating profit* (balance-sheet approach) | 171,493 | 468.6 | 2,471.5 | -40,099 | 23.8 | 177,172 | 415.10 | 14.89 |
| *Cash-based operating profit* (cash-flow approach) | 137,026 | 534.1 | 2,582.8 | -21,874 | 28.6 | 92,472 | 198.80 | 11.71 |
| *OPINC* | 144,829 | 293.7 | 1,518.5 | -19,095 | 18.3 | 71,230 | 369.10 | 14.92 |
| *NI* | 169,832 | 134.6 | 1,016.6 | -44,574 | 3.3 | 59,531 | 564.51 | 16.11 |
| *TA* (lagged) | 171,744 | 2,941.2 | 14,721.7 | 10.0 | 193.0 | 507,560 | 259.84 | 13.64 |
| *NOA* (average) | 144,829 | 2,000.1 | 9,575.2 | 10.0 | 165.9 | 314,139 | 265.07 | 13.78 |
| *BV* (average) | 169,832 | 1,109.9 | 6,067.6 | 1.0 | 75.1 | 280,051 | 389.91 | 16.50 |
| *SALES* (lagged) | 168,846 | 2,501.5 | 12,352.4 | 10.0 | 207.6 | 496,785 | 424.29 | 16.65 |
| *GP* | 163,704 | 35.6% | 25.7% | -100.0% | 33.3% | 100.0% | 4.53 | -0.21 |
| *OP* | 171,528 | 14.7% | 16.2% | -99.9% | 14.6% | 100.0% | 7.83 | -0.41 |
| *CbOP_BS* | 171,493 | 13.6% | 16.5% | -99.8% | 13.9% | 100.0% | 7.68 | -0.46 |
| *CbOP_CF* | 137,026 | 12.4% | 16.8% | -99.8% | 12.9% | 100.0% | 7.74 | -0.57 |
| *RNOA* | 144,829 | 12.6% | 22.0% | -99.9% | 12.7% | 100.0% | 7.54 | -0.62 |
| *ROE* | 169,832 | 2.9% | 25.5% | -100.0% | 8.6% | 99.8% | 6.10 | -1.37 |
| *GSL* | 168,846 | 9.2% | 24.6% | -100.0% | 7.9% | 100.0% | 5.48 | 0.08 |

This panel gives an overview of the full sample of firm-year observations available for use in the in-sample estimation step where the estimated coefficients are obtained to construct the forecast improvements for the period from 1989 to 2018. The observations actually used in the in-sample estimation regression for each rolling 10-year window are subject to a further top and bottom 1% trimming. Except for the profitability and growth in sales measures, the descriptive statistics reported are in USD million. See table 1 for the variable definitions. The Kurtosis column reports the sample measure of the moment coefficient of kurtosis, which is nonnegative and has a value of 3 for the Gaussian distribution. The Skewness Coefficient column reports the sample measure of the adjusted Fisher-Pearson standardized moment coefficient of skewness, with negative and positive values representing negative and positive skewness, respectively.

**TABLE 3**
Profitability forecast improvements of economy-wide quantile regression over economy-wide OLS regression

| | Value | | *p-Value* |
|---|---|---|---|
| *GP* | | | |
| Mean | 0.138% | *** | 0.000 |
| Median | 0.121% | *** | 0.000 |
| *OP* | | | |
| Mean | 0.063% | *** | 0.000 |
| Median | 0.096% | *** | 0.000 |
| *CbOP_BS* | | | |
| Mean | 0.068% | *** | 0.000 |
| Median | 0.061% | *** | 0.000 |
| *CbOP_CF* | | | |
| Mean | 0.071% | *** | 0.000 |
| Median | 0.070% | *** | 0.000 |
| *RNOA* | | | |
| Mean | 0.120% | *** | 0.000 |
| Median | 0.193% | *** | 0.000 |
| *ROE* | | | |
| Mean | 0.415% | *** | 0.000 |
| Median | 1.492% | *** | 0.000 |

This table reports the profitability forecast improvements of economy-wide quantile regression (the alternative approach) over economy-wide OLS regression (the benchmark approach). The forecast improvement (FI) is measured through a matched-pair comparison of the absolute forecast errors (AFE) from the two competing approaches. A positive FI means the AFE from the benchmark approach is larger than that from the alternative approach. Both forecasting approaches use the same set of predictor variables like those in Fairfield et al. (2009). Regardless of the forecasting approaches, the underlying predictor variable *PREDGSL* (i.e., the predicted growth in sales) is constructed in the same way by industry-specific OLS regression. Industries are defined using the first-digit Standard Industry Classification (SIC). Firm-specific forecasts are obtained in two steps. First, the coefficients of a forecasting model are estimated for each year from 1989 to 2018 on a rolling basis using data available in the previous ten years. Next, the estimated coefficients are applied on a firm's data of the previous year to obtain a firm-specific forecast for the current year. The mean and median FIs of all firm-years in the sample are reported for different profitability measures (see table 1 for the definitions of the measures). The test on the mean FI is a regression-based t-test using robust standard errors controlling for two-way clustering by firm and year. The test on the median FI is the Wilcoxon signed rank test. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

**TABLE 4**
Descriptive statistics of the simulated and archival data for the distributional shape analysis

**Panel A:** Simulated data

| Variable | Mean | Std. Dev. | Min. | Median | Max. |
|---|---|---|---|---|---|
| Forecasting accuracy (Wilcoxon-test based): | | | | | |
| *pct.QR.Prevail* | 0.319 | 0.313 | 0.012 | 0.185 | 0.972 |
| *pct.OLS.Prevail* | 0.033 | 0.026 | 0.000 | 0.026 | 0.102 |
| *IncrAccur* | 0.286 | 0.334 | -0.074 | 0.154 | 0.972 |
| *RelAccur* | 2.148 | 2.333 | -1.792 | 2.001 | 6.879 |
| Forecasting accuracy (t-test based): | | | | | |
| *pct.QR.Prevail* | 0.338 | 0.323 | 0.014 | 0.198 | 0.982 |
| *pct.OLS.Prevail* | 0.175 | 0.139 | 0.000 | 0.124 | 0.612 |
| *IncrAccur* | 0.164 | 0.251 | -0.106 | 0.057 | 0.924 |
| *RelAccur* | 0.518 | 1.566 | -1.792 | 0.342 | 6.820 |
| Distributional properties (mean-aggregated): | | | | | |
| Mean%Extremes | 0.136 | 0.102 | 0.000 | 0.137 | 0.319 |
| Kurtosis† | 3.884 | 1.897 | 1.104 | 4.294 | 7.247 |
| Tails Asymmetry‡ | -0.002 | 0.193 | -0.279 | -0.046 | 0.278 |
| Mean-less-median‡ | -0.006 | 0.464 | -0.684 | -0.114 | 0.683 |
| Skewness Coeff.‡ | -0.097 | 1.253 | -2.451 | -0.315 | 2.275 |
| sd(*Profit.*)† | 0.798 | 1.325 | 0.224 | 0.264 | 8.127 |
| Distributional properties (median-aggregated): | | | | | |
| Mean%Extremes | 0.135 | 0.104 | 0.000 | 0.140 | 0.320 |
| Kurtosis† | 3.092 | 1.635 | 1.102 | 3.142 | 7.204 |
| Tails Asymmetry‡ | -0.003 | 0.194 | -0.279 | 0.000 | 0.278 |
| Mean-less-median‡ | -0.009 | 0.467 | -0.685 | -0.143 | 0.686 |
| Skewness Coeff.‡ | -0.110 | 1.107 | -2.320 | -0.313 | 2.162 |
| sd(*Profit.*)† | 0.530 | 0.719 | 0.198 | 0.242 | 4.702 |

This panel gives an overview of the 1,024 observations used in the simulated-data distributional shape analysis based on data from 512,000 simulated experiments (500 experiments for each set of the distribution type and parameter combination over 4 distribution types and 256 parameter combinations). The forecasting accuracy measures are computed based on the Wilcoxon-test or t-test based forecasting performance of the quantile regression and OLS approaches in each 500 simulated experiments of the 4 × 256 sets of the distribution type and parameter combination. The measures of the distributional properties are computed based on the 2,500 draws of the simulated next-period firm profitability to be forecast in each simulated experiement. Presented in this panel are these measures mean- or median-aggregrated to the distribution type-parameter combination level. See panel B of table 1 for the definitions of the forecasting accuracy and distributional property measures. † indicates measures in log value and ‡ in cube-root value.

**TABLE 4** (continued)
Descriptive statistics of the simulated and archival data for the distributional shape analysis

**Panel B:** Archival data

| Variable | Mean | Std. Dev. | Min. | Median | Max. |
|---|---|---|---|---|---|
| Size of indusry-year | 82.2 | 82.7 | 20 | 50 | 631 |
| Forecasting accuracy: | | | | | |
| *fir.QR.Prevail* | 1.027 | 0.067 | 0.817 | 1.016 | 2.130 |
| *fir.OLS.Prevail* | 0.996 | 0.043 | 0.571 | 1.000 | 1.246 |
| *IncrAccur* | 0.031 | 0.104 | -0.422 | 0.018 | 1.559 |
| *RelAccur* | 0.298 | 1.003 | -4.137 | 0.181 | 13.167 |
| Distributional properties: | | | | | |
| Mean%Extremes | 0.076 | 0.236 | 0.000 | 0.000 | 2.174 |
| Kurtosis† | 1.552 | 0.475 | 0.274 | 1.521 | 3.583 |
| Tails Asymmetry‡ | 0.011 | 0.302 | -0.523 | 0.000 | 0.497 |
| Mean-less-median‡ | 0.064 | 0.671 | -1.142 | 0.378 | 1.129 |
| Skewness Coeff.‡ | -0.034 | 0.896 | -1.741 | -0.126 | 1.568 |
| sd(*Profit.*)† | -1.978 | 0.386 | -3.238 | -1.964 | -0.824 |

This panel gives an overview of the 6,751 observations of profitability-industry-years used in the archival-data distributional shape analysis. The sample is constructed from the firm-year observations used in the out-of-sample tests reported in table 3. A minimum of 20 firms in each industry-year is required to avoid unreliable estimates of the profitability distributional properties. The industry classification is based on two-digit SIC. The forecasting accuracy measures are computed for each profitability measure using the forecasting performance of the quantile regression and OLS approaches for each firm aggregated across all firms in an industry-year based on the mean absolute forecast error (MAFE) and root mean squared forecast error (RMSFE) criteria, respectively. The measures of the distributional properties are computed for each profitability measure based on all firms in an industry-year. See panel B of table 1 for details of the variable definitions. † indicates variables in log value and ‡ in cube-root value.

**TABLE 5**
Incremental forecasting accuracy and profitability distributional shape: simulated-data analysis at the mean-aggregrated level (pooled sample of both stable and IHS distributions)

| *IncrAccur* = | Wilcoxon-test based | | | | | | t-test based | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Asymmetric* = | Taleb's Tails Asym.‡ | | Mean-less-median‡ | | Skewness Coeff.‡ | | Taleb's Tails Asym.‡ | | Mean-less-median‡ | | Skewness Coeff.‡ | |
| *Heavy* = | Mean%Extrem | Kurtosis† | Mean%Extrem | Kurtosis† | Mean%Extrem | Kurtosis† | Mean%Extrem | Kurtosis† | Mean%Extrem | Kurtosis† | Mean%Extrem | Kurtosis† |
| *Heavy* | 1.814*** | 0.170*** | 1.233*** | 0.114*** | 1.554*** | 0.143*** | 1.676*** | 0.159*** | 1.521*** | 0.142*** | 1.566*** | 0.148*** |
| | (0.038) | (0.004) | (0.035) | (0.003) | (0.045) | (0.005) | (0.024) | (0.002) | (0.026) | (0.003) | (0.025) | (0.003) |
| *Asymmetric* | -0.071 | -0.049 | -0.013 | -0.006 | -0.003 | 0.001 | -0.053 | -0.033 | -0.003 | 0.006 | 0.004 | 0.009** |
| | (0.058) | (0.060) | (0.016) | (0.017) | (0.007) | (0.007) | (0.036) | (0.038) | (0.012) | (0.013) | (0.004) | (0.004) |
| *Asymmetric*$^2$ | 7.348*** | 7.682*** | 1.449*** | 1.497*** | 0.145*** | 0.151*** | 1.225*** | 1.507*** | 0.309*** | 0.359*** | 0.034*** | 0.037*** |
| | (0.206) | (0.212) | (0.028) | (0.028) | (0.004) | (0.005) | (0.127) | (0.132) | (0.021) | (0.021) | (0.003) | (0.003) |
| sd(*Profit.*)† | 0.143*** | 0.089*** | 0.137*** | 0.101*** | 0.072*** | 0.025*** | 0.128*** | 0.077*** | 0.128*** | 0.082*** | 0.114*** | 0.066*** |
| | (0.003) | (0.004) | (0.002) | (0.003) | (0.004) | (0.004) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Intercept | -0.453*** | -1.047*** | -0.416*** | -0.811*** | -0.437*** | -0.929*** | -0.303*** | -0.856*** | -0.298*** | -0.793*** | -0.301*** | -0.812*** |
| | (0.015) | (0.021) | (0.010) | (0.016) | (0.014) | (0.022) | (0.009) | (0.013) | (0.008) | (0.012) | (0.008) | (0.012) |
| Profitability FE? | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1,024 | 1,024 | 1,024 | 1,024 | 1,024 | 1,024 | 1,024 | 1,024 | 1,024 | 1,024 | 1,024 | 1,024 |
| Adjusted $R^2$ | 0.893 | 0.885 | 0.935 | 0.931 | 0.883 | 0.870 | 0.928 | 0.920 | 0.936 | 0.930 | 0.934 | 0.925 |

This table is based on observations from 512,000 simulated experiments mean-aggregated to the distribution type-parameter combination level. In each experiment, 2,500 draws of next-period firm profitability are simulated by applying the intercept and slope parameters and 2,500 independent draws of the error term of a first-order autoregressive model on 2,500 draws of current-period firm profitability, which were simulated from iterative applications of the model on a simulated firm profitability seed. The draws of the error term at different stages and the draw of the seed are independent draws from a stable or IHS distribution with their tail and skewness parameters set to different values. 500 experiments are run for each of the 256 parameter combinations and 4 distribution types (i.e., a positively or negatively skewed stable or IHS distribution). Sample distributional properties of profitability are measured using the 2,500 draws of the simulated next-period firm profitability to be forecast in each experiment. See appendix B in the online appendix for further details of the simulated experiments. The regression model in this table is $IncrAccur = \alpha_0 + \alpha_1\ Heavy + \alpha_2\ Asymmetric + \alpha_3\ Asymmetric^2 + \alpha_4$ sd(*Profit.*) + Distribution type fixed effects + $\varepsilon$, where the following experiment-level explanatory variables are mean-aggregated to the distribution type-parameter combination level: *Heavy* = Mean%Extremes or Kurtosis†; *Asymmetric* = Tails asymmetry‡, Mean-less-median‡, or Skewness coefficient‡; sd(*Profit.*)† = Standard deviation of the sample distribution of profitability. See panel B of table 1 for further details of the variable definitions. For brevity, the coefficient of the distribution type fixed effect is omitted from all the panels and the coefficients of the intercept and sd(*Profit.*) are omitted from the panels for individual distributions. Standard errors are reported in parentheses. † indicates variables in log value and ‡ in cube-root value; ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

**TABLE 6**
Relative forecasting accuracy and profitability distributional shape: simulated-data analysis at the mean-aggregrated level (pooled sample of both stable and IHS distributions)

| *RelAccur* = | Wilcoxon-test based | | | | | | t-test based | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Asymmetric* = | Taleb's Tails Asym.‡ | | Mean-less-median‡ | | Skewness Coeff.‡ | | Taleb's Tails Asym.‡ | | Mean-less-median‡ | | Skewness Coeff.‡ | |
| *Heavy* = | Mean%Extrem | Kurtosis† | Mean%Extrem | Kurtosis† | Mean%Extrem | Kurtosis† | Mean%Extrem | Kurtosis† | Mean%Extrem | Kurtosis† | Mean%Extrem | Kurtosis† |
| *Heavy* | 13.615*** | 1.296*** | 10.253*** | 0.967*** | 12.035*** | 1.128*** | 9.193*** | 0.873*** | 11.151*** | 1.042*** | 10.649*** | 1.024*** |
| | (0.166) | (0.016) | (0.158) | (0.015) | (0.227) | (0.023) | (0.205) | (0.020) | (0.213) | (0.021) | (0.206) | (0.020) |
| *Asymmetric* | -0.988*** | -0.826*** | -0.357*** | -0.296*** | -0.117*** | -0.083** | -0.092 | 0.019 | -0.068 | -0.003 | -0.002 | 0.030 |
| | (0.251) | (0.260) | (0.074) | (0.075) | (0.034) | (0.037) | (0.310) | (0.315) | (0.099) | (0.103) | (0.031) | (0.032) |
| *Asymmetric*$^2$ | 51.131*** | 53.219*** | 9.269*** | 9.560*** | 0.974*** | 1.002*** | -17.614*** | -16.148*** | -4.149*** | -3.781*** | -0.482*** | -0.473*** |
| | (0.891) | (0.911) | (0.124) | (0.124) | (0.023) | (0.024) | (1.100) | (1.104) | (0.167) | (0.170) | (0.020) | (0.020) |
| sd(*Profit.*)† | 1.002*** | 0.588*** | 0.941*** | 0.631*** | 0.493*** | 0.127*** | 0.859*** | 0.581*** | 0.861*** | 0.529*** | 1.064*** | 0.735*** |
| | (0.013) | (0.015) | (0.010) | (0.012) | (0.019) | (0.021) | (0.016) | (0.019) | (0.014) | (0.017) | (0.017) | (0.017) |
| Intercept | -2.913*** | -7.439*** | -2.582*** | -5.949*** | -2.779*** | -6.671*** | -1.203*** | -4.250*** | -1.209*** | -4.836*** | -1.030*** | -4.561*** |
| | (0.064) | (0.092) | (0.047) | (0.073) | (0.072) | (0.111) | (0.079) | (0.112) | (0.063) | (0.100) | (0.065) | (0.095) |
| Profitability FE? | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1,024 | 1,024 | 1,024 | 1,024 | 1,024 | 1,024 | 1,024 | 1,024 | 1,024 | 1,024 | 1,024 | 1,024 |
| Adjusted $R^2$ | 0.959 | 0.956 | 0.973 | 0.972 | 0.939 | 0.930 | 0.862 | 0.857 | 0.892 | 0.884 | 0.889 | 0.887 |

This table is based on observations from 512,000 simulated experiments mean-aggregated to the distribution type-parameter combination level. In each experiment, 2,500 draws of next-period firm profitability are simulated by applying the intercept and slope parameters and 2,500 independent draws of the error term of a first-order autoregressive model on 2,500 draws of current-period firm profitability, which were simulated from iterative applications of the model on a simulated firm profitability seed. The draws of the error term at different stages and the draw of the seed are independent draws from a stable or IHS distribution with their tail and skewness parameters set to different values. 500 experiments are run for each of the 256 parameter combinations and 4 distribution types (i.e., a positively or negatively skewed stable or IHS distribution). Sample distributional properties of profitability are measured using the 2,500 draws of the simulated next-period firm profitability to be forecast in each experiment. See appendix B in the online appendix for further details of the simulated experiments. The regression model in this table is $RelAccur = \alpha_0 + \alpha_1\ Heavy + \alpha_2\ Asymmetric + \alpha_3\ Asymmetric^2 + \alpha_4$ sd(*Profit.*) + Distribution type fixed effects + $\varepsilon$, where the following experiment-level explanatory variables are mean-aggregated to the distribution type-parameter combination level: Heavy = Mean%Extremes or Kurtosis†; Asymmetric = Tails asymmetry‡, Mean-less-median‡, or Skewness coefficient‡; sd(*Profit.*)† = Standard deviation of the sample distribution of profitability. See panel B of table 1 for further details of the variable definitions. For brevity, the coefficient of the distribution type fixed effect is omitted from all the panels and the coefficients of the intercept and sd(*Profit.*) are omitted from the panels for individual distributions. Standard errors are reported in parentheses. † indicates variables in log value and ‡ in cube-root value; ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

**TABLE 7**
Incremental forecasting accuracy and profitability distributional shape: Achival-data analysis at the mean-aggregrated industry-year level with industry-year distributional properties

**Panel A:** Pooled sample of all profitability measures

| | Unweighted | | | | | | Size-weighted | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Asymmetric* = | Taleb's Tails Asym.‡ | | Mean-less-median‡ | | Skewness Coeff.‡ | | Taleb's Tails Asym.‡ | | Mean-less-median‡ | | Skewness Coeff.‡ | |
| *Heavy* = | Mean%Extrem | Kurtosis† | Mean%Extrem | Kurtosis† | Mean%Extrem | Kurtosis† | Mean%Extrem | Kurtosis† | Mean%Extrem | Kurtosis† | Mean%Extrem | Kurtosis† |
| *Heavy* | 0.025*** | 0.021*** | 0.026*** | 0.021*** | 0.022*** | 0.028*** | 0.026*** | 0.021*** | 0.028*** | 0.021*** | 0.027*** | 0.028*** |
| | (0.01) | (0.00) | (0.01) | (0.00) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.01) | (0.00) |
| *Asymmetric* | 0.019*** | 0.019*** | 0.008*** | 0.008*** | 0.003** | 0.004*** | 0.017*** | 0.017*** | 0.008*** | 0.008*** | 0.002* | 0.003*** |
| | (0.01) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| *Asymmetric*$^2$ | -0.063*** | -0.062*** | -0.019*** | -0.016*** | 0.005* | -0.008** | -0.094*** | -0.087*** | -0.023*** | -0.020*** | 0.001 | -0.008*** |
| | (0.02) | (0.02) | (0.01) | (0.01) | (0.00) | (0.00) | (0.02) | (0.02) | (0.00) | (0.00) | (0.00) | (0.00) |
| sd(*Profit.*)† | -0.013*** | -0.019*** | -0.014*** | -0.020*** | -0.015*** | -0.020*** | 0.006* | 0.002 | 0.005 | 0.001 | 0.005 | 0.000 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Intercept | -0.069*** | -0.112*** | -0.069*** | -0.112*** | -0.082*** | -0.125*** | -0.024** | -0.065*** | -0.024** | -0.065*** | -0.034*** | -0.082*** |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| Profitability FE? | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 6,751 | 6,751 | 6,751 | 6,751 | 6,751 | 6,751 | 6,751 | 6,751 | 6,751 | 6,751 | 6,751 | 6,751 |
| Adjusted $R^2$ | 0.136 | 0.141 | 0.136 | 0.140 | 0.134 | 0.139 | 0.169 | 0.173 | 0.170 | 0.174 | 0.164 | 0.170 |

The industry-year observations used in this table are constructed from the firm-year observations used in the out-of-sample tests reported in table 3. A minimum of 20 firms in each industry-year is required to avoid unreliable estimates of the profitability distributional properties. The industry classification is based two-digit SIC. The regression model is IncrAccur = α0 + α1 Heavy + α2 Asymmetric + α3 Asymmetric2 + α4 sd(Profit.) + Profitability fixed effects (only for the pooled all-profitability regression) + First-digit SIC Industry fixed effects + Year fixed effects + ε, where IncrAccur is redefined as the forecast improvement ratio of quantile regression (QR) under the mean absolute forecast error (MAFE) criterion minus the forecast improvement ratio of OLS under the root mean squared forecast error (RMSFE); Heavy = Mean%Extrem or Kurtosis†; Asymmetric = Tails Asymmetry‡, Mean-less-median‡, or Skewness coefficient‡; sd(Profit.)† = Standard deviation of the profitability distribution in an industry-year. See table 1 for the details of the variable definitions. For brevity, the coefficients of the profitability, industry, and year fixed effects are omitted from all the panels and the coefficients of the intercept and sd(Profit.) are omitted from the panels for individual profitability measures. Robust standard errors adjusted for clustering by profitability-industry-year are reported in parentheses. The industry classification for the robust standard errors is based on the first-digit SIC. The Size-weighted columns are the results of weighted regressions with the size of each industry-year as the weight. The number of observations in the individual-profitability regressions ranges from 1,081 to 1,153. † indicates variables in log value and ‡ in cube-root value; ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

**TABLE 7** (continued)
Incremental forecasting accuracy and profitability distributional shape: Achival-data analysis at the mean-aggregrated industry-year level with industry-year distributional properties

| | Unweighted | | | | | | Size-weighted | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Asymmetric* = | Taleb's Tails Asym.‡ | | Mean-less-median‡ | | Skewness Coeff.‡ | | Taleb's Tails Asym.‡ | | Mean-less-median‡ | | Skewness Coeff.‡ | |
| *Heavy* = | Mean%Extrem | Kurtosis† | Mean%Extrem | Kurtosis† | Mean%Extrem | Kurtosis† | Mean%Extrem | Kurtosis† | Mean%Extrem | Kurtosis† | Mean%Extrem | Kurtosis† |
| **Panel B:** *GP* | | | | | | | | | | | | |
| *Heavy* | 0.040 | 0.012 | 0.045* | 0.015 | -0.015 | -0.047*** | 0.033 | 0.012 | 0.042* | 0.020** | -0.023 | -0.043*** |
| | (0.03) | (0.01) | (0.03) | (0.01) | (0.03) | (0.02) | (0.02) | (0.01) | (0.02) | (0.01) | (0.02) | (0.01) |
| *Asymmetric* | -0.065*** | -0.065*** | -0.017** | -0.019** | -0.032*** | -0.037*** | -0.089*** | -0.087*** | -0.027*** | -0.027*** | -0.036*** | -0.042*** |
| | (0.02) | (0.02) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| *Asymmetric*$^2$ | 0.136* | 0.112 | 0.037** | 0.037** | 0.049*** | 0.087*** | 0.142** | 0.117* | 0.027* | 0.027* | 0.050*** | 0.079*** |
| | (0.07) | (0.08) | (0.02) | (0.02) | (0.01) | (0.02) | (0.07) | (0.07) | (0.01) | (0.01) | (0.01) | (0.01) |
| | No | No | No | No | No | No | No | No | No | No | No | No |
| Adjusted R$^2$ | 0.201 | 0.201 | 0.196 | 0.195 | 0.214 | 0.220 | 0.242 | 0.242 | 0.223 | 0.224 | 0.257 | 0.264 |
| **Panel C:** *OP* | | | | | | | | | | | | |
| *Heavy* | 0.018* | 0.012** | 0.014 | 0.012** | -0.004 | -0.002 | 0.014 | 0.010** | 0.012 | 0.010** | -0.003 | 0.000 |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| *Asymmetric* | -0.006 | -0.007 | -0.013*** | -0.013*** | -0.006** | -0.006** | -0.003 | -0.003 | -0.008** | -0.008** | -0.004 | -0.004 |
| | (0.01) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) | (0.01) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) |
| *Asymmetric*$^2$ | 0.045 | 0.044 | 0.019* | 0.020* | 0.018*** | 0.018** | 0.001 | 0.006 | 0.014 | 0.015 | 0.013** | 0.012** |
| | (0.05) | (0.05) | (0.01) | (0.01) | (0.01) | (0.01) | (0.04) | (0.04) | (0.01) | (0.01) | (0.01) | (0.01) |
| FE? | No | No | No | No | No | No | No | No | No | No | No | No |
| Adjusted R$^2$ | 0.148 | 0.150 | 0.156 | 0.159 | 0.156 | 0.156 | 0.249 | 0.250 | 0.253 | 0.255 | 0.254 | 0.254 |
| **Panel D:** *CbOP_BS* | | | | | | | | | | | | |
| *Heavy* | 0.016** | 0.003 | 0.015** | 0.003 | 0.021** | 0.006 | 0.014** | 0.006 | 0.014** | 0.005 | 0.021*** | 0.010** |
| | (0.01) | (0.00) | (0.01) | (0.00) | (0.01) | (0.01) | (0.01) | (0.00) | (0.01) | (0.00) | (0.01) | (0.00) |
| *Asymmetric* | 0.003 | 0.003 | -0.004 | -0.004 | 0.001 | 0.001 | 0.005 | 0.005 | -0.001 | -0.001 | 0.002 | 0.002 |
| | (0.01) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) | (0.01) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) |
| *Asymmetric*$^2$ | -0.001 | -0.001 | 0.003 | 0.004 | -0.005 | -0.003 | -0.022 | -0.020 | -0.001 | 0.000 | -0.005 | -0.005 |
| | (0.03) | (0.03) | (0.01) | (0.01) | (0.00) | (0.01) | (0.03) | (0.03) | (0.01) | (0.01) | (0.00) | (0.00) |
| FE? | No | No | No | No | No | No | No | No | No | No | No | No |
| Adjusted R$^2$ | 0.137 | 0.134 | 0.139 | 0.136 | 0.139 | 0.134 | 0.263 | 0.261 | 0.262 | 0.260 | 0.264 | 0.262 |

See the note under panel A for variable descriptions and other details.

**TABLE 7** (continued)
Incremental forecasting accuracy and profitability distributional shape: Achival-data analysis at the mean-aggregrated industry-year level with industry-year distributional properties

| | Unweighted | | | | | | Size-weighted | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Asymmetric* = | Taleb's Tails Asym.‡ | | Mean-less-median‡ | | Skewness Coeff.‡ | | Taleb's Tails Asym.‡ | | Mean-less-median‡ | | Skewness Coeff.‡ | |
| *Heavy* = | Mean%Extrem | Kurtosis† | Mean%Extrem | Kurtosis† | Mean%Extrem | Kurtosis† | Mean%Extrem | Kurtosis† | Mean%Extrem | Kurtosis† | Mean%Extrem | Kurtosis† |
| **Panel E:** *CbOP_CF* | | | | | | | | | | | | |
| *Heavy* | 0.017** | 0.014*** | 0.016* | 0.015*** | 0.009 | 0.013** | 0.019** | 0.013*** | 0.019** | 0.013*** | 0.020** | 0.016*** |
| | (0.01) | (0.00) | (0.01) | (0.00) | (0.01) | (0.01) | (0.01) | (0.00) | (0.01) | (0.00) | (0.01) | (0.01) |
| *Asymmetric* | 0.003 | 0.003 | -0.001 | -0.001 | -0.001 | -0.001 | 0.006 | 0.006 | -0.001 | -0.001 | 0.000 | 0.001 |
| | (0.01) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) | (0.01) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) |
| *Asymmetric*$^2$ | -0.004 | -0.004 | 0.009 | 0.012 | 0.007 | 0.001 | -0.026 | -0.021 | 0.002 | 0.004 | -0.001 | -0.005 |
| | (0.04) | (0.04) | (0.01) | (0.01) | (0.01) | (0.01) | (0.03) | (0.03) | (0.01) | (0.01) | (0.00) | (0.01) |
| Adjusted $R^2$ | 0.156 | 0.161 | 0.157 | 0.162 | 0.158 | 0.161 | 0.265 | 0.268 | 0.264 | 0.267 | 0.264 | 0.268 |
| **Panel F:** *RNOA* | | | | | | | | | | | | |
| *Heavy* | 0.005 | 0.016*** | 0.001 | 0.014** | -0.018 | 0.003 | 0.015* | 0.017*** | 0.012 | 0.015*** | -0.004 | 0.004 |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| *Asymmetric* | 0.017* | 0.018** | 0.002 | 0.002 | 0.005 | 0.005* | 0.020*** | 0.022*** | 0.007** | 0.008** | 0.004 | 0.004* |
| | (0.01) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) | (0.01) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) |
| *Asymmetric*$^2$ | 0.149*** | 0.170*** | 0.031*** | 0.035*** | 0.020*** | 0.013* | 0.120*** | 0.140*** | 0.017* | 0.021** | 0.018*** | 0.014** |
| | (0.05) | (0.05) | (0.01) | (0.01) | (0.01) | (0.01) | (0.04) | (0.04) | (0.01) | (0.01) | (0.01) | (0.01) |
| Adjusted $R^2$ | 0.200 | 0.206 | 0.195 | 0.199 | 0.198 | 0.196 | 0.270 | 0.275 | 0.265 | 0.269 | 0.267 | 0.267 |
| **Panel G:** *ROE* | | | | | | | | | | | | |
| *Heavy* | 0.015 | 0.021** | 0.018 | 0.020** | 0.024* | 0.047*** | 0.016 | 0.029*** | 0.021* | 0.028*** | 0.026** | 0.059*** |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| *Asymmetric* | 0.118*** | 0.120*** | 0.047*** | 0.048*** | 0.041*** | 0.039*** | 0.112*** | 0.118*** | 0.048*** | 0.049*** | 0.038*** | 0.037*** |
| | (0.02) | (0.02) | (0.01) | (0.01) | (0.01) | (0.01) | (0.02) | (0.02) | (0.01) | (0.01) | (0.01) | (0.01) |
| *Asymmetric*$^2$ | -0.041 | -0.014 | -0.048*** | -0.044** | 0.010 | -0.014 | -0.111 | -0.053 | -0.053*** | -0.043*** | 0.011 | -0.016 |
| | (0.08) | (0.08) | (0.02) | (0.02) | (0.01) | (0.01) | (0.08) | (0.08) | (0.02) | (0.02) | (0.01) | (0.01) |
| Adjusted $R^2$ | 0.375 | 0.377 | 0.382 | 0.383 | 0.370 | 0.376 | 0.412 | 0.416 | 0.421 | 0.424 | 0.399 | 0.411 |

See the note under panel A for variable descriptions and other details.

**Table 8**
Incremental forecasting accuracy and cash flows distributional shape: Quantile regression forecasting versus OLS

**Panel A:** Lagged cash flows or lagged earnings as the predictor variable, with short to long in-sample estimation windows

| Window (years) = | 2 | | | 4 | | | 7 | | 10 | |
|---|---|---|---|---|---|---|---|---|---|---|
| Predictor = | $CF_{t-1}$ | $CF_{t-1}$ | $EARN_{t-1}$ | $CF_{t-1}$ | $CF_{t-1}$ | $EARN_{t-1}$ | $CF_{t-1}$ | $CF_{t-1}$ | $CF_{t-1}$ | $CF_{t-1}$ |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Intercept | 0.009** | -0.088** | -0.164*** | 0.011* | -0.100* | -0.161*** | 0.014** | -0.066 | 0.016*** | -0.053 |
| | (0.004) | (0.038) | (0.041) | (0.006) | (0.049) | (0.048) | (0.006) | (0.048) | (0.005) | (0.041) |
| *Heavy* | | 0.016** | 0.007** | | 0.022*** | 0.011** | | 0.011*** | | 0.006* |
| | | (0.006) | (0.003) | | (0.005) | (0.004) | | (0.003) | | (0.003) |
| *Asymmetric* | | -0.001 | 0.008*** | | -0.006 | 0.002 | | -0.005 | | -0.004 |
| | | (0.006) | (0.002) | | (0.006) | (0.004) | | (0.005) | | (0.005) |
| $Asymmetric^2$ | | -0.027** | -0.013** | | -0.026*** | -0.013** | | -0.011** | | -0.003 |
| | | (0.011) | (0.006) | | (0.006) | (0.005) | | (0.005) | | (0.006) |
| sd(*CF*) | | 0.677** | 1.715*** | | 0.62 | 1.618*** | | 0.465 | | 0.444 |
| | | (0.297) | (0.418) | | (0.407) | (0.479) | | (0.422) | | (0.357) |
| sd($EARN_{t-1}$) | | | -0.315*** | | | -0.343*** | | | | |
| | | | (0.028) | | | (0.030) | | | | |
| Observations | 26 | 26 | 26 | 26 | 26 | 26 | 26 | 26 | 26 | 26 |
| Adjusted $R^2$ | 0 | 0.232 | 0.743 | 0 | 0.23 | 0.821 | 0 | 0.063 | 0 | 0.076 |

This panel presents the results of the cash flows distributional shape analysis for the full sample of US firms based on out-of-sample forecasts from 1990 to 2015 (with in-sample estimation data as far back as in 1987). The yearly observations used in this table are constructed from the firm-year observations used for forecasting cash flows out-of-sample with a rolling window of in-sample estimation. Each yearly observation is based on the distributional properties of cash flows, or lagged earnings, for the cross section of firms in a given year and the incremental forecasting accuracy of the quantile regression approach (versus OLS) to forecasting cash flows for this cross section. The forecasting model used for comparing the quantile regression approach to OLS has the lagged cash flows or the lagged earnings as the only predictor variable (see Nallareddy et al. 2020). The dependent variable of the distributional shape analysis in this table is the incremental forecasting accuracy *IncrAccur* computed yearly for a given forecasting model. *IncrAccur* is defined as the forecast improvement ratio of quantile regression under the mean absolute forecast error (MAFE) criterion minus the forecast improvement ratio of OLS under the root mean squared forecast error (RMSFE) criterion. The independent variables in this table are: *Heavy* = Kurtosis† of the cash flows distribution of a year; *Asymmetric* = Skewness coefficient‡ of the cash flows distribution of a year; sd(*CF*) = Standard deviation of the cash flows distribution of a year; sd($EARN_{t-1}$) = Standard deviation of the lagged earnings distribution of a year. Cash flows (*CF*) are defined as net cash flow from operating activities less cash flow from extraordinary items and discontinued operations (Compustat: OANCF – XIDOC). Earnings (*EARN*) are defined as income before extraordinary items and discontinued operations (Compustat: IB). Both variables are deflated by total assets (Compustat: AT) averaged over the current and the prior year. See table 1 for the details of the definitions of *IncrAccur*, kurtosis, and skewness coefficient. Newey-West robust standard errors are reported in parentheses (Newey and West 1994). † indicates variable in log value and ‡ in cube-root value; ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table 8** (continued)

Incremental forecasting accuracy and cash flows distributional shape: Quantile regression forecasting versus OLS

**Panel B:** Subsamples for various exclusion criteria (lagged cash flows as the predictor variable and two-year in-sample estimation window)

| Subsample excluding | Intangible-intensive firms | | Loss firms | | Smaller firms | | Size-tails firms | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Intercept | 0.005** | -0.055 | 0.001 | -0.196*** | 0.008** | -0.098*** | 0.009*** | -0.047* |
| | (0.002) | (0.040) | (0.002) | (0.055) | (0.003) | (0.031) | (0.003) | (0.023) |
| *Heavy* | | 0.018 | | 0.004 | | 0.010** | | 0.011*** |
| | | (0.012) | | (0.014) | | (0.004) | | (0.003) |
| *Asymmetric* | | 0.003 | | 0.012** | | 0.008* | | 0.0002 |
| | | (0.007) | | (0.005) | | (0.004) | | (0.005) |
| *Asymmetric*$^2$ | | -0.0005 | | -0.002 | | -0.020* | | -0.017*** |
| | | (0.010) | | (0.020) | | (0.011) | | (0.005) |
| sd(*CF*) | | 0.162 | | 1.906*** | | 0.908*** | | 0.345* |
| | | (0.395) | | (0.604) | | (0.267) | | (0.191) |
| Observations | 26 | 26 | 26 | 26 | 26 | 26 | 26 | 26 |
| Adjusted $R^2$ | 0 | 0.036 | 0 | 0.114 | 0 | 0.429 | 0 | 0.117 |

This panel presents the results of the cash flows distributional shape analysis for the subsamples excluding the following firms one at a time: *intangible-intensive firms* defined as the firms in the Health, Business Equipment, Telecommunication, and Chemical sectors of the Fama-French 12-industry classification, *loss firms* defined as those with negative earnings (*EARN* < 0), *smaller firms* defined as those below the first quartile of the firm size distribution (where firm size is measured by total assets), and *size-tails firms* defined as those outside the 12.5$^{th}$ and the 87.5$^{th}$ percentile of the firm size distribution. The dependent variable in this table is the incremental forecasting accuracy *IncrAccur* computed yearly for the forecasting model with the lagged cash flows as the only predictor variable. See the note below panel A for other details.