Earnings Volatility Forecast: a Quantile Regression Approach

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Abstract

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Earnings volatility is a key dimension of firm risk, with important implications for equity valuation and credit risk assessment. This thesis develops a forward-looking measure of one-year-ahead earnings volatility based on accounting fundamentals by modeling the conditional distribution of future earnings. The empirical analysis uses annual Compustat North America data for U.S. publicly listed non-financial firms over 1987–2023. Earnings are measured as income before extraordinary items scaled by total assets, ensuring comparability across firms of different sizes.

The methodological framework is based on quantile regression. A grid of quantiles is estimated to approximate the full conditional distribution of future earnings, and the Composite Quantile Regression (CQR) approach is applied to stabilize the tails. The shape of the predicted distribution is also examined through measures of asymmetry. Volatility is then constructed from the dispersion of predicted quantiles, providing a forward-looking measure of earnings uncertainty that captures both downside and upside risk.

The results indicate a negatively skewed implied earnings distribution, suggesting that downside earnings risk is more pronounced than upside outcomes. The volatility measure varies over time and rises during major macroeconomic events, including the early-2000s dot-com period, the Global Financial Crisis, and the COVID-19 pandemic. A comparison with a benchmark volatility measure derived from OLS residuals shows a Pearson correlation of 0.74 between yearly averages. Overall, the findings show that accounting fundamentals contain meaningful information about the distribution and volatility of future earnings, offering a useful framework for measuring firm-level risk beyond traditional market-based indicators.

A volatilidade dos resultados constitui uma dimensão fundamental do risco empresarial, refletindo a incerteza quanto à rentabilidade futura e tendo implicações relevantes para a valorização das ações e a avaliação do risco de crédito. Esta dissertação desenvolve uma medida prospetiva da volatilidade dos resultados a um ano, derivada de fundamentos contabilísticos através da modelação da distribuição condicional dos resultados futuros. A análise empírica baseia-se em dados anuais da Compustat North America relativos a empresas não financeiras cotadas nos Estados Unidos, no período de 1987 a 2023. Os resultados são definidos como o *income before extraordinary items* escalado pelo ativo total.

O enquadramento metodológico assenta em técnicas de regressão quantílica. É estimada uma grelha densa de regressões quantílicas para aproximar a distribuição condicional completa dos resultados futuros, sendo a abordagem de *Composite Quantile Regression* (CQR) aplicada para estabilizar as caudas extremas da distribuição. A volatilidade é depois construída a partir da dispersão dos quantis previstos, originando uma estimativa prospetiva da incerteza dos resultados, capaz de captar o risco em baixa e o potencial em alta. Adicionalmente, a forma da distribuição prevista é analisada através de medidas de assimetria.

Os resultados indicam uma clara assimetria negativa na distribuição dos resultados e um aumento da volatilidade em períodos de maior tensão macroeconómica. A comparação com uma medida derivada dos resíduos de OLS revela uma correlação de 0,74 entre as médias anuais. Globalmente, os resultados demonstram a relevância informativa dos fundamentos contabilísticos.

1. Introduction

Forecasting volatility of firm earnings can be crucial in financial analysis, as it provides valuable insights into future investment profitability, financial stability, and overall risk exposure. From both a credit and equity perspective, earnings volatility is particularly relevant for assessing default probabilities and expected returns.

The relationship between accounting and market information is established in the literature. One important example is provided by Goldstein, Ju, and Leland (2001), who extend Merton's framework by deriving firm asset value from earnings before interest and taxes (EBIT)[1].

Other existing studies rely on market-based indicators, such as realized stock return or option-implied volatility. Although these measures are widely used, recent literature emphasized the relevance of firms' accounting-based measures of volatility. These types of measures can provide additional predictive power for firm performance and credit risk, since they may not be fully incorporated into market prices.

A contribution in this direction is provided by Correia (2025), who shows how accounting-based measures of volatility are able to explain cross-sectional variation in credit spreads beyond what is captured by market-based volatility measures. Their results suggest that markets may underestimate fundamental information as sources of risk and fail to fully incorporate accounting-based volatility into prices. For this reason, a more detailed analysis of firm fundamentals can improve forecasts of credit-risk outcomes.

Following this path of research, this study uses quantile regression methodology to forecast earnings volatility using a set of fundamental accounting variables. Quantile regression, introduced by Koenker and Bassett (1978), models different points of the conditional distribution of a dependent variable, not focusing exclusively on its conditional mean. This approach is particularly well suited to accounting data, which often exhibits non-normal, skewed, and heavy-tailed distributions. By estimating conditional quantiles of future profitability, quantile regression can capture cross-sectional heterogeneity in earnings risk and provides a detailed measure of volatility

[1] In their model, the firm's capital structure and credit risk depend on the stochastic behavior of operating earnings, making volatility in EBIT a fundamental driver of default probability. This refinement emphasizes the direct link between the firm's real economic performance and its financial risk, reinforcing the idea that earnings variability, rather than market noise, captures the true underlying risk of default. This connection has consequently motivated extensive research into how volatility can be measured and predicted.

dynamics. The quantile regression is estimated on pooled firm-year observations, so that the conditional distribution evolves over time through changes in firm fundamentals rather than through time-varying coefficients.

Under this approach, earnings forecasted volatility is obtained from the dispersion implied by the estimated conditional quantiles. This methodology yields a forward-looking measure of risk that does not rely on firm-level time-series variance, but instead on the shape of the conditional earnings distribution, estimated using both time-series and cross-sectional information from a panel of firms.

This framework provides a robust, cross-sectional approach to forecasting earnings volatility based on firm fundamentals. By connecting insights from corporate finance and econometrics, it implements the understanding of how accounting information can be used to explain and forecast risk, presenting results that are statistically rigorous and economically relevant for credit and equity valuation.

2. Literature Review

As mentioned above, there are two main paths along which empirical research on corporate risk has evolved: market-based measures, which infer firms' risk from asset prices, and accounting-based measures, built upon firm fundamentals. Early research focused on market-based indicators which represent more investors' perspectives and expectations regarding risk, such as realized stock return volatility and option-implied volatility. The latter is typically viewed as forward-looking and so it incorporates market perceptions about future uncertainty. These metrics are mainly used in asset pricing and risk management models and are based on the assumption that markets are efficient and instantly reflect all relevant information. However, in practice, markets may fail to fully capture economic and firm-specific risks, especially when information asymmetries, behavioral biases, or financial frictions affect price determinants.

This limitation motivated a second path of research, which studies fundamental sources of volatility obtained directly from financial statements and accounting numbers. A relevant contribution in this direction, as briefly mentioned before, is provided by Correia (2025), who tests whether accounting-based measures of volatility can improve the prediction of credit risk of traditional market-based proxies. The study concludes that the enduring value of accounting information, which has consistently demonstrated strong predictive utility, often compensates for declines in the predictive power of equity market data. Moreover, the author finds that credit markets often underestimate these fundamental indicators, leading to potential mispricing in credit instruments.

Quantile regression, developed by Koenker and Bassett (1978), provides a robust alternative to ordinary least squares (OLS) by modeling different points of the conditional distribution without assuming homoscedasticity or normality of the error term. Since earnings data typically show non-normal, skewed, and heavy-tailed distributions, quantile regression's robustness to outliers and its ability to capture heterogeneous relationships across the conditional distribution become particularly suitable.

Building on this foundation, Taylor (2005) proposed a method to generate volatility forecasts directly from quantile estimates. His study demonstrates that the interval between symmetric quantiles, such as the 0.025 and 0.975 quantiles, can be used to approximate the conditional standard deviation of returns, thereby linking Value-at-Risk estimates to volatility forecasting. Empirical comparisons across stock indices show that this quantile-based volatility measure outperforms traditional GARCH-type models, particularly in capturing asymmetric and nonlinear volatility patterns. This quantile-based volatility framework provides a forward-looking perspective that is especially interesting in settings characterized by non-Gaussian distributions.

Konstantinidi and Pope (2016) presented a methodology that employs quantile regression to infer firms' risk directly from accounting fundamentals. Using a panel of firm-level data, they estimate multiple conditional quantiles of one-year-ahead earnings as a function of a set of established accounting variables that capture different dimensions of profitability and risk. Specifically, their model includes accruals, cash flow, special items and a loss indicator. By allowing the effects of these variables to vary across quantiles of the future earnings distribution, their approach captures heterogeneous effects of earnings risk that cannot be observed in mean-based models.

The choice of the predictors is well established in the accounting and corporate finance literature. Sloan (1996) decomposes earnings into accrual and cash flow components, showing that high accrual levels reduce earnings persistence and increase volatility. Richardson et al. (2006) further confirm this decomposition, emphasizing that the quality and composition of accruals have predictive implications for the stability of future earnings. Penman (2010) documents that leverage amplifies the effects of operational shocks, while firm size is negatively associated with earnings volatility due to diversification and greater information transparency. Loss indicators have also been widely used in the literature to capture the asymmetric dynamics of firms experiencing temporary or structural distress, which often exhibit more volatile earnings patterns.

From the estimated conditional quantiles, Konstantinidi and Pope (2016) derive forward-looking measures of earnings risk such as the interquartile range (IQR) or conditional variance, which serve as representations of earnings dispersion and volatility. Their findings show that these quantile-based forecasts significantly explain variation in analysts' risk assessments, bond yield spreads, and stock return volatility. Similar to the conclusions of Correia et al. (2018), they demonstrate the potential of accounting-based quantile models to measure uncertainty and risk without relying on market data. The econometric foundation of their approach, rooted in the work of Koenker and Bassett (1978), allows for flexible estimation of risk measures under distributional heterogeneity, offering a valuable extension of traditional risk modeling techniques.

Beyond these studies, other researchers have extended the quantile regression approach to different contexts of volatility forecasting and risk measurement. Chang et al. (2021) extend the approach of Konstantinidi and Pope by modeling not only the variance of future earnings but also higher moments such as skewness and kurtosis. Using a dense grid of quantiles and rearrangement techniques to prevent quantile crossing, they aim to forecast the full conditional distribution of future profitability. Their results show that accounting information offers strong signals about the asymmetry and tail behavior of future earnings. Moreover, they find that markets price these higher-moment characteristics differently: equity investors tend to reward upside risk, while credit markets penalize higher kurtosis, which captures extreme downside events. This study reinforces the idea that accounting-based quantile models provide a rich representation of firm-level risk.

While quantile regression and its extensions form the methodological foundation of this research, literature has also proposed alternative methods to compute or forecast earnings volatility. Early approaches rely on GARCH-type models (Bollerslev & Engle, 1986), which estimate time-varying conditional variances based on past squared residuals. Although widely used, these models assume a fixed conditional distribution and are primarily applied to high-frequency market data.

A major contribution in this field has been proposed with the Conditional Autoregressive Value-at-Risk (CAViaR) model, developed by Engle and Manganelli (2004). Their work models conditional quantiles of financial returns directly in an autoregressive framework, avoiding distributional assumptions. The CAViaR model represents an important step in the evolution of quantile-based methods, as it introduces a dynamic approach to capturing time-varying risk in the tails of the return distribution.

In the accounting and corporate finance literature, other studies have analyzed volatility from both fundamental and macroeconomic perspectives. De Veirman and Levin (2018), for instance, investigate cyclical changes in firm-level volatility. They find that firm-specific volatility of sales and earnings is only moderately counter-cyclical, rising during recessions but not sufficiently to drive aggregate fluctuations. Their analysis emphasizes that firm-level volatility contains different information about business risk that is not necessarily aligned with macroeconomic cycles.

Collectively, these studies demonstrate that fundamental accounting variables convey valuable information about firm-level risk and that quantile regression provides a robust framework for transforming such insights into forward-looking measures of volatility. The approach developed in this thesis builds on the predictive structure of Konstantinidi and Pope (2016) and the conceptual foundation of Correia et al. (2018), while incorporating methodological insights from Engle and Manganelli (2004), Taylor (2005), and Chang et al. (2021). By applying quantile regression to forecast one-year-ahead earnings based exclusively on fundamental data, and by deriving volatility from the distribution of these predicted earnings, this research contributes to the literature by emphasizing the role of accounting information in capturing cross-sectional differences in earnings risk without relying on market-based expectations.

3. Data

3.1 Data Sources and Sample Construction

The empirical analysis relies on annual accounting data obtained from WRDS Compustat North America Fundamentals Annual database. The sample consists of U.S. publicly listed firms over the period 1987–2023. Financial firms are excluded due to their difference in balance sheet structure and accounting practices, which make their financial statements not directly comparable to those of non-financial firms. Utilities firms are included in the sample.

A minimum size filter (AT ≥ 100) is imposed to remove very small firms and reduce noise from extreme ratios driven by low denominators.

The dataset obtained forms an unbalanced panel every year, accepting firm entry and exit over time due to IPOs, delisting, mergers, and bankruptcies. On average, the sample includes around 3500 firm-year observations per year, with coverage increasing rapidly after the late 1980s and remaining relatively stable thereafter.

Table 1

Industry	SIC codes	N	% of Obs
Manufacturing	2000–3999	50374	42,74
Transportation/Utilities	4000–4999	22618	19,19
Services	7000–8999	20616	17,49
Retail	5200–5999	9159	7,77
Mining	1000–1499	7634	6,48
Wholesale	5000–5199	4356	3,7
Construction	1500–1799	1672	1,42
Other/Missing SIC	Outside ranges	982	0,83
Agriculture/Forestry/Fishing	0100–0999	458	0,39
Total		117869	100

All accounting variables are denominated in U.S. dollars, as reported in Compustat, and so no currency conversions are performed. Observations with zero total assets are removed to ensure meaningful scaling of financial variables. Firm-year observations with missing values for any of the variables used in the empirical analysis are excluded.

3.2 Dependent Variable: Future Earnings

The dependent variable captures one-year-ahead firm profitability and is constructed to be comparable across firms of different sizes. The variable Earnings is defined as income before extraordinary items in year $t + 1$scaled by total assets in year t:

$$\text{Earnings}_{i,t+1} = \frac{\text{Income Before Extraordinary Items}_{i,t+1}}{\text{Total Assets}_{i,t}}.$$

This definition is consistent with a large set of accounting research that scales earnings by assets to control firm size and to focus on operating performance rather than absolute levels. Importantly, scaling future earnings by contemporaneous assets avoids linking the dependent variable to balance sheet realizations at $t + 1$and maintains the forward-looking perspective of the forecasting framework.

All continuous variables are annually winsorized at the 1st and 99th percentiles, to mitigate the influence of extreme accounting inputs.

3.3 Accounting-Based Predictors

The selection of explanatory variables is guided by prior literature on earnings persistence, earnings quality, and firm-level risk. In particular, the set of predictors follows the variables employed by Konstantinidi and Pope (2016) and Correia et al. (2018). All predictors are measured at fiscal year t and are scaled by total assets where appropriate.

-Accruals (ACC).

Accruals are defined as the difference between accounting earnings and operating cash flows, scaled by total assets:

$$\mathrm{ACC}_{i,t} = \frac{\text{Income Before Extraordinary Items}_{i,t} - \text{Net Cash Flow}_{i,t}}{\text{Total Assets}_{i,t}}.$$

This variable captures the non-cash component of earnings. Prior research shows that accruals are generally less persistent than cash flows and are associated with lower earnings quality and greater uncertainty in future profitability (Sloan, 1996; Richardson et al., 2006). High accrual intensity is therefore expected to be related to higher dispersion and downside risk in future earnings.

-Operating Cash Flow (OCF).

Operating cash flow is measured as cash flow from operations scaled by total assets:

$$\mathrm{OCF}_{i,t} = \frac{\text{Cash Flow from Operations}_{i,t}}{\text{Total Assets}_{i,t}}.$$

Cash flows are typically more persistent and less subject to accounting discretion than accruals. As such, operating cash flow provides information about the sustainability of earnings and is expected to be negatively related to earnings volatility and tail risk (Dechow, 1994; Konstantinidi and Pope, 2016).

-Leverage (LEV).

Financial leverage is defined as the ratio of total debt to total assets, where total debt is the sum of short-term and long-term debt:

$$\mathrm{LEV}_{i,t} = \frac{\text{Debt in Current Liabilities}_{i,t} + \text{Long-Term Debt}_{i,t}}{\text{Total Assets}_{i,t}}.$$

Leverage amplifies the effect of operating shocks on residual earnings and equity returns. Firms with higher leverage are therefore expected to exhibit greater earnings volatility, particularly in the lower tail of the earnings distribution (Penman, 2010; Correia et al., 2018).

-Firm Size (SIZE).

Firm size is measured as the natural logarithm of total assets:

$$\mathrm{SIZE}_{i,t} = \log\left(\mathrm{Total\ Assets}_{i,t}\right).$$

Larger firms tend to be more diversified across products and markets and are subject to greater disclosure requirements. These characteristics are generally associated with more stable earnings and lower uncertainty, implying a negative relation between firm size and earnings volatility (Fama and French, 2001; Konstantinidi and Pope, 2016).

-Loss Indicator (LOSS).

The loss indicator is a binary variable equal to one if income before extraordinary items is negative in year t, and zero otherwise:

$$\mathrm{LOSS}_{i,t} = \mathbb{1}\left(\mathrm{Income\ Before\ Extraordinary\ Items}_{i,t} < 0\right).$$

Loss-making firms are known to exhibit asymmetric earnings dynamics and substantially higher earnings volatility, particularly in the lower tail of the distribution. The loss indicator captures this nonlinearity and is expected to be strongly associated with downside risk in future earnings (Hayn, 1995; Correia et al., 2018).

3.4 Timing, Information Set, and Data Cleaning

The analysis assumes that accounting information for year t is publicly available before the realization of earnings in year $t+1$, ensuring that the forecasting practice is based on an economically reasonable information set. The quantile regression coefficients are estimated using the full sample and are therefore interpreted as structural conditional relationships rather than real-time forecasting parameters.

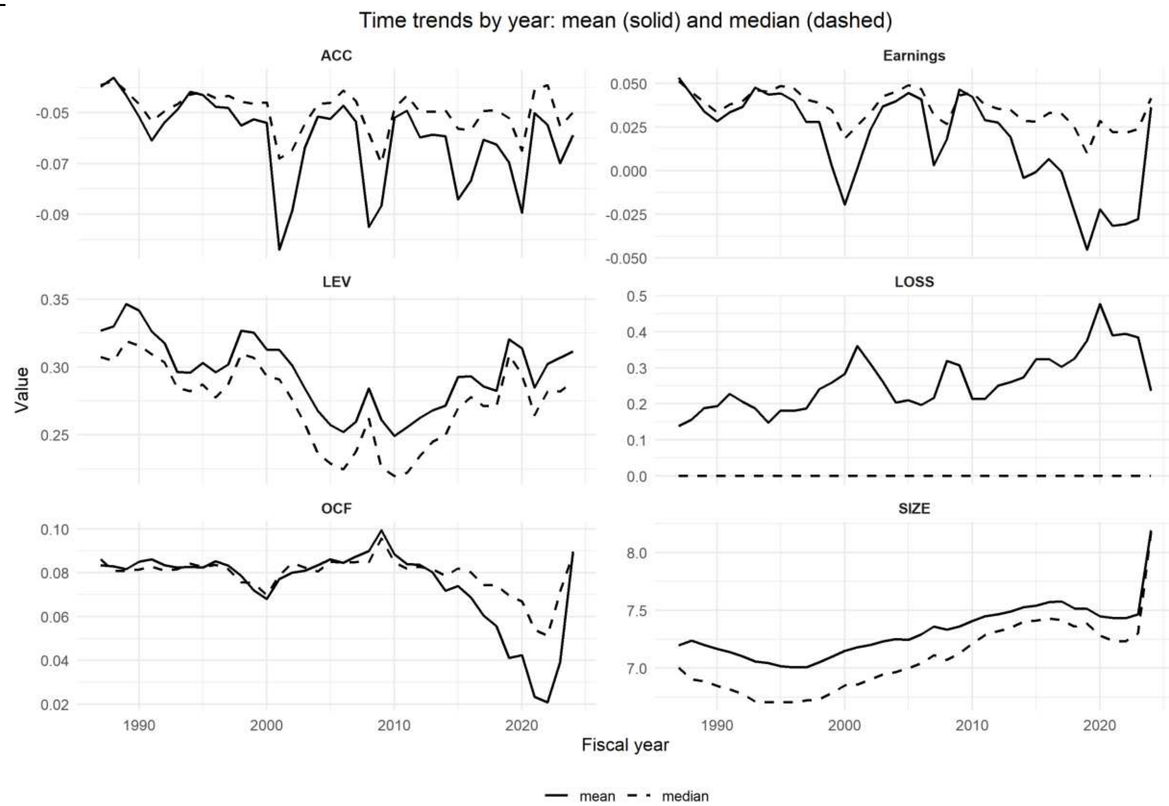
To ensure that firm size is measured in real rather than nominal terms, total assets were adjusted for inflation using the U.S. Consumer Price Index (CPIAUCSL) obtained from the Federal Reserve Economic Data (FRED) database. For each fiscal year, nominal assets were deflated by dividing by the corresponding CPI value and rescaled to a common base period. This adjustment removes the effect of general price level changes over time and ensures that the size variable reflects real economic magnitude rather than inflation-driven growth in accounting values. The deflated measure is then used to construct the size variable in the empirical analysis, defined as the logarithm of real total assets.

Table 2 reports descriptive statistics for the full sample of firm-year observations used in the empirical analysis. The table summarizes the distribution of the accounting-based predictors and the Earnings variable after data cleaning and winsorization. The statistics confirm substantial heterogeneity across firms, as well as asymmetry and dispersion in the Earnings variable, further motivating the use of a distributional forecasting approach. Figure 1 instead models the time evolution of the yearly means and median of the variables over the sample period.

Table 2

	Earnings	ACC	OCF	LEV	SIZE	LOSS
N	117869	117869	117869	117869	117869	117869
Mean	0,02	-0,06	0,07	0,29	7,31	0,27
SD	0,14	0,09	0,11	0,23	1,66	0,44
Min	-1,06	-1,08	-0,6	0	4,36	0
P25	-0,01	-0,09	0,04	0,1	5,96	0
Median	0,04	-0,05	0,08	0,27	7,05	0
P75	0,08	-0,02	0,13	0,42	8,39	1
Max	0,45	0,24	0,38	1,27	13,76	1

Figure 1



4. Model

This chapter presents the econometric framework used to forecast the conditional distribution of firm earnings and derive a forward-looking measure of earnings volatility. The empirical methodology is centered on CQR and the model built on the structure of the quantile regression framework introduced by Koenker and Bassett (1978) and follows the accounting-based forecasting methodology presented by Konstantinidi and Pope (2016).

The quantile-based approach employed in this study exploits cross-sectional variation in accounting fundamentals to infer forward-looking dispersion in future earnings, even for firms with relatively short histories.

While the main focus of the chapter is on the CQR specification, standard Quantile Regression (QR), is useful for illustrating the behavior of the estimated conditional distribution in the absence of tail stabilization.

4.1 Quantile regression framework

Let $Earnings_{i,t+1}$ denote earnings of firm i in fiscal year $t+1$, measured as income before extraordinary items and scaled by total assets in year t. Let $X_{i,t}$ be a vector of accounting-based characteristics observed at fiscal year t, including the accounting variables described in Chapter 3, namely accruals (ACC), operating cash flow (OCF), leverage (LEV), firm size (SIZE), and loss indicator (LOSS). The model does not include firm and industry fixed effects, as these tend to capture past behavior and often do not work well for forecasting. For a given quantile level $\tau \in (0,1)$, the conditional τ-quantile of future earnings is modeled as:

$$Q_\tau(Earnings_{i,t+1} \mid X_{i,t}) = \alpha_\tau + X'_{i,t}\beta_\tau.$$

I wanted to obtain a detailed approximation of the conditional distribution of future earnings, and so I estimated the model over a grid composed of 99 equally spaced quantiles.

The model is estimated using pooled firm-year observations over the entire sample period, so that for each quantile level a single set of coefficients is obtained and applied uniformly across years. This estimation procedure is robust to outliers and heteroskedasticity and does not rely on parametric assumptions regarding the distribution of the error term.

Since estimating extreme conditional quantiles can be sometimes challenging in finite samples, I estimated the quantiles between 0.01 and 0.1 and between 0.9 and 0.99 using CQR. This methodology pools information across multiple quantiles by imposing a common slope coefficient vector while allowing intercepts to vary by quantile.

Formally, for a set of quantiles $\mathcal{T} = \{\tau_1, \dots, \tau_m\}$, the composite model can be written as:

$$Q_\tau(Earnings_{i,t+1} \mid X_{i,t}) = b_\tau + X'_{i,t}\beta, \tau \in \mathcal{T},$$

where the slope vector β is common across the quantiles in $\mathcal{T}$, while the intercept b_τ remains quantile specific. By constraining slope coefficients to be fixed across extreme quantiles, CQR improves estimation efficiency and robustness precisely in those areas of the distribution where data can be more unstable.

In the context of earnings forecasting, the objective of the CQR extension is not to replace the baseline dense-grid quantile regression, but to stabilize the extreme tails of the predicted conditional distribution. The procedure is implemented in two steps.

First, I estimate two composite quantile regression (CQR) models, one for the lower tail and one for the upper tail, using sets of tail quantile levels (e.g., $\mathcal{T}_L = \{0.01,0.02 \dots 0.10\}$ and $\mathcal{T}_U = \{0.90, 0.91 \dots 0.99\}$), with the same information set used throughout the thesis (ACC, OCF, LEV, SIZE, LOSS). In each tail, CQR pools information across the selected quantiles by estimating a common slope vector for the covariates, while allowing the intercept to vary with the quantile level. Second, the CQR-implied tail quantile forecasts are used to replace the corresponding tail quantiles from the baseline grid of QR, leaving thereby the central part of the distribution unchanged. As a result, the final predictive distribution preserves the flexibility of standard QR in the center, but features more stable behavior in the tails, which is particularly relevant for tail-risk and volatility measures derived from the full set of predicted quantiles.

4.2 Determinants of future earnings across quantiles

This section examines how accounting fundamentals affect different parts of the conditional distribution of one-year-ahead earnings by analyzing how the quantile regression coefficients vary across quantiles of the earnings distribution. The analysis presents the pooled quantile regression estimates obtained over the grid of quantiles following the standard QR approach (τ = 0.01–0.99), presenting also the values at the extremes, to then follow the analysis using at the tails the CQR coefficients estimates.

Table 3 presents the estimated coefficients at selected quantiles (τ = 0.05, 0.20, 0.40, 0.50, 0.60, 0.80, 0.95) for each explanatory variable, while Figure 2 illustrates the full coefficient paths as a function of τ for all 99 quantiles with the flat curves in the extreme quantiles following the CQR approach.

Together, these results allow for a detailed assessment of cross-quantile heterogeneity in the forecasting process of earnings.

-Accruals (ACC)

Accruals are positively associated with future earnings across most of the conditional distribution, with the strongest effects observed at low and central quantiles. The coefficient profile exhibits a clear negative slope as τ increases, declining smoothly toward zero in the upper tail. This pattern indicates that accruals should have a negative impact on earnings volatility because downside and typical earnings outcomes are pushed upwards as accruals increase, while the very strong future outcomes stay almost unchanged.

-*Operating Cash Flow (OCF)*

Operating cash flow exhibits a positive relationship with future earnings across the entire distribution. Similar to accruals, the coefficient profile shows a negative slope, with larger effects at low and central quantiles and a gradual attenuation toward the upper tail. Again, this implies a negative relation between operating cash flow and volatility because the two sides of the distribution become closer.

-Leverage (LEV)

The leverage coefficient starts positive in the very low quantiles and then declines steadily as τ increases, crossing around zero and becoming negative across most of the upper part of the distribution (with only a small uptick at the extreme top tail). Overall, LEV displays a downward-sloping profile: leverage is associated with higher predicted outcomes in the lower tail, but it compresses the upper tail. More leveraged firms appear less likely to realize exceptionally high future earnings. This pattern is consistent with a debt overhang constrained-upside mechanism, where the presence of debt limits the firm's ability (or incentives) to capture high future payoffs.

-Loss Indicator (LOSS)

The loss dummy is strongly negative in the lower tail and remains negative through low and mid quantiles, then moves upward toward zero and turns slightly positive in the upper tail, with a more visible increase close to the highest quantiles. This sign reversal suggests that, for most of the distribution, loss-making firms have worse expected earnings outcomes, but among the upper-tail realizations there is evidence of turnaround potential (a subset of loss firms can still generate very strong future earnings). The upward slope across quantiles indicates increasing marginal impact of LOSS as we move toward the right tail.

-Firm Size (SIZE)

Firm size exhibits a monotonically declining coefficient profile across quantiles. The effect is weakly positive at low quantiles, becomes negligible around the center, and turns negative in the upper tail. This negative slope suggests that larger firms experience a compression of earnings outcomes, with reduced exposure to both downside risk and extreme upside realizations.

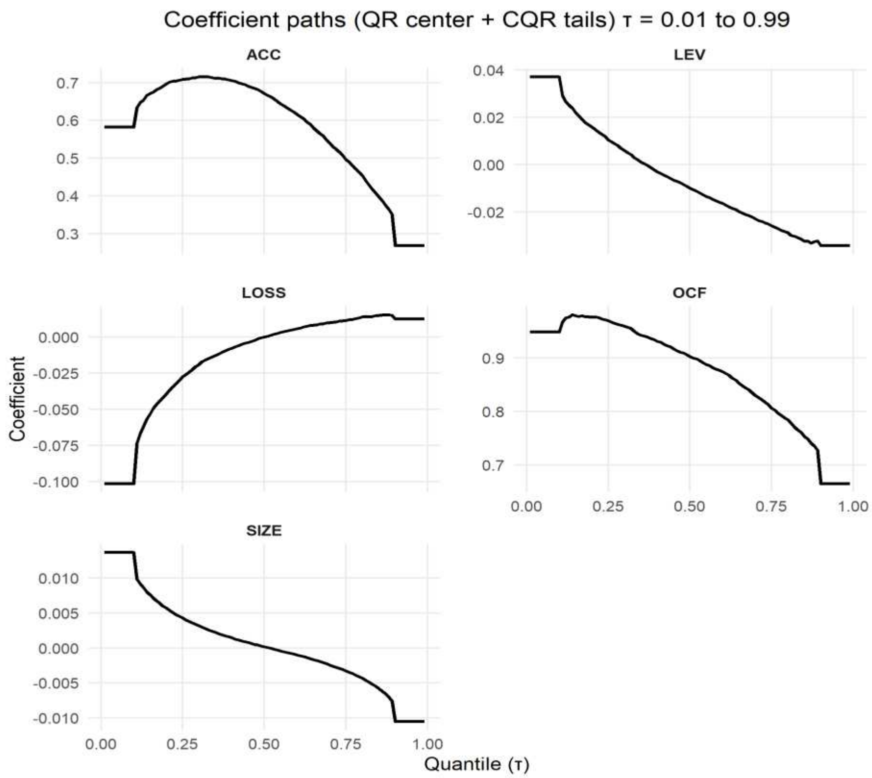
Across variables, most accounting fundamentals display negative slopes across quantiles, indicating stronger associations with downside and central earnings outcomes than with the upper tail. Leverage stands out as the only variable with an upward-sloping profile, suggesting a distinct role in shaping upper-tail earnings risk. Overall, the coefficient paths confirm substantial cross-quantile heterogeneity, consistent with the accounting-based quantile regression literature.

Consistent with Konstantinidi and Pope (2016), accruals and operating cash flows exhibit stronger effects at lower quantiles, with coefficients declining toward the upper tail, indicating that these fundamentals primarily load on downside risk and earnings dispersion rather than extreme upside outcomes. While variables related to firms' financial structure display more pronounced distributional asymmetries relative to operating fundamentals.

Table 3

	τ 0.05	τ 0.2	τ 0.4	τ 0.5	τ 0.6	τ 0.8	τ 0.95
Intercept	-0.263***	-0.09***	-0.021***	-0.001***	0.017***	0.069***	0.198***
Acc	0.543***	0.696***	0.705***	0.67***	0.616***	0.453***	0.257***
OCF	0.928***	0.976***	0.931***	0.903***	0.874***	0.785***	0.664***
LEV	0.042***	0.016***	-0.003***	-0.01***	-0.016***	-0.029***	-0.033***
SIZE	0.016***	0.006***	0.001***	0***	-0.001***	-0.004***	-0.013***
LOSS	-0.116***	-0.039***	-0.008***	0	0.006***	0.014***	0.015***

Figure 2[2]



4.3 Distribution-Implied Earnings Volatility

Once the conditional distribution of future earnings for each firm i and for each year t , has been estimated, firm-level earnings volatility is constructed from the predicted quantiles. Let $\hat{Q}_{q,i,t}$denote the predicted value of the q-th conditional quantile of $E_{i,t+1}$, for $q = 1, \dots, Q$, where $Q = 99$.

Earnings volatility is defined as the square root of the conditional variance implied by the estimated distribution:

[2] Notes: Slope coefficients associated with those quantiles in the tails (i.e. between 0.01 and 0.10 and between 0.9 and 0.99) were estimated using composite quantile regressions.

$$\mathrm{Vol}_{i,t}^{\mathrm{Quant}} = \sqrt{\frac{1}{Q}\sum_{q=1}^{Q} \hat{Q}_{q,i,t}^{2} - \left(\frac{1}{Q}\sum_{q=1}^{Q} \hat{Q}_{q,i,t}\right)^{2}}.$$

This measure represents the standard deviation of the conditional distribution of future earnings and provides a forward-looking estimate of firm-level earnings volatility. Volatility is inferred from the shape of the predicted earnings distribution, which is itself determined by current accounting fundamentals. It captures both downside and upside risk and reflects the full distribution of potential future earnings outcomes.

5. Results

In this chapter I present the empirical results from the quantile-based forecasting framework previously described. Section 5.1 reports the overall distributional forecasts of future earnings ($Earnings_{t+1}$) and then focuses on their estimates across years. Section 5.2 presents the quantile-implied volatility estimates obtained from the predicted distribution of earnings. Section 5.3 compares the quantile-based estimates with a volatility measure weighted by assets and finally section 5.4 analyses the impact of high-tech firms in the volatility estimation.

5.1 Distributional forecasts of one-year-ahead earnings ($\mathrm{Earnings}_{i,t+1}$)

One-year-ahead earnings are forecast using cross-sectional quantile regressions of $\mathrm{Earnings}_{i,t+1}$on accounting fundamentals observed at t (ACC, OCF, LEV, SIZE, and LOSS), estimated on pooled firm-year observations.

Since quantile regressions are estimated independently at each quantile level, the predicted quantiles may fail to satisfy the monotonicity condition required for a distribution function, leading to quantile crossing. To address this issue, monotonicity is enforced on the estimated conditional quantiles. This ensures that, for each firm-year observation, the fitted quantile function is non-decreasing in τ and that the estimated distribution is internally consistent.

Section 5.1.1 presents the overall shape of the forecasted earnings distribution in the full sample by analyzing the quantile-implied density and the associated asymmetry (Kelley skewness). Section 5.1.2 focuses on the time-series evolution of the distribution's central tendency by reporting the yearly patterns in the forecasted mean and median.

5.1.1 Shape and Asymmetry of the Predicted Earnings Distribution

The quantile regression framework delivers the entire conditional distribution of one-year-ahead earnings for each firm-year observation. This allows a direct examination of the distributional shape without relying on moment-based measures such as the conditional mean.

To get a visual idea of the underlying distribution, I standardized the fitted quantiles at the firm-year level. For each observation (i, t), the standardized quantiles are defined as:

$$Z_{\tau,i,t} = \frac{\hat{Q}_{\tau,i,t} - \hat{Q}_{0.50,i,t}}{\widehat{VolCQR}_{\;i,t}},$$

where $\hat{Q}_{\tau,i,t}$denotes the predicted τ-th conditional quantile and $\widehat{Vol}\;CQR_{i,t}$is the quantile-implied volatility constructed from the full predicted distribution. For each quantile level τ, the standardized values are averaged across all firm-year observations:

$$\bar{Z}_{\tau} = \frac{1}{N}\sum_{i,t} Z_{\tau,i,t}.$$

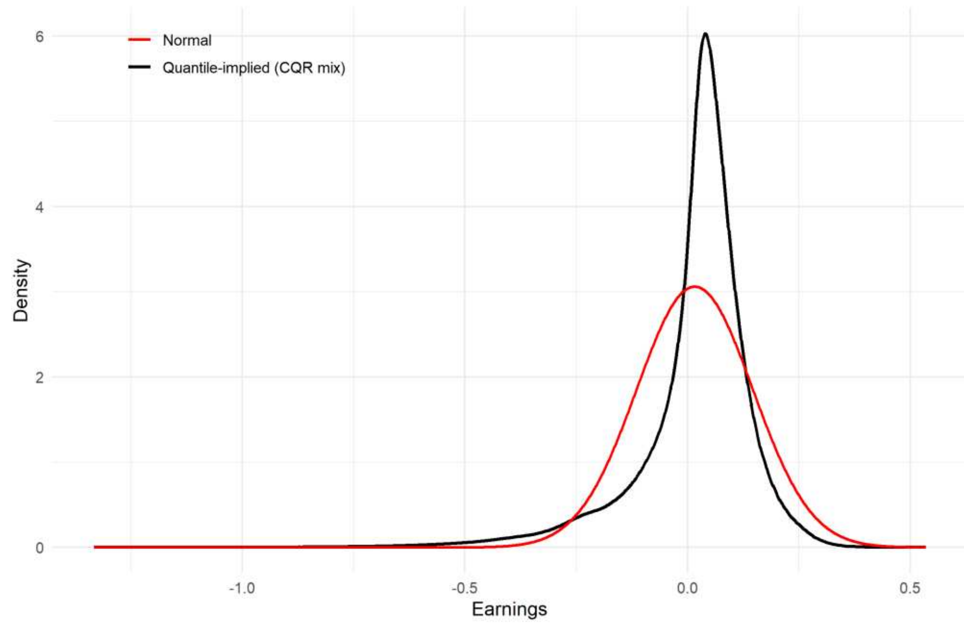
The resulting curve $\{\bar{Z}_{\tau}\}$ represents a standardized proxy for the typical conditional earnings distribution across firms. To express this representative distribution in earnings units, the standardized quantiles are rescaled using the median predicted median earnings $\tilde{Q}_{0.50}$ and the median quantile-implied volatility $\tilde{\sigma}$:

$$\tilde{Q}_{\tau} = \tilde{Q}_{0.50} + \tilde{\sigma} \cdot \bar{Z}_{\tau}.$$

This reconstruction yields a representative predicted earnings distribution consistent with cross-sectional dispersion.

Figure 3 plots the quantile-implied density (black line) of forecasted earnings obtained from the CQR predictive distribution. Pooling these fitted quantiles across firm-years yields a large set of predicted earnings values that approximates the model-implied cross-sectional distribution of one-year-ahead profitability. A density estimator is then applied to these predicted values to obtain a smooth estimate of the implied density.

Figure 3



The red curve ("Normal") is a reference normal density calibrated to have the same location and dispersion as the quantile-implied distribution. The black curve results in being more peaked around the center and showing heavier tails than the benchmark. This indicates that the model-implied distribution concentrates substantial probability mass near typical earnings outcomes while still assigning significant probability to extreme realizations especially in downside observations. In addition, the distribution exhibits asymmetry. This left skew is then confirmed with Kelley Skewness estimation.

It is computed through the formula:

$$KS = \frac{(Q_{0.90} - Q_{0.50}) - (Q_{0.50} - Q_{0.10})}{Q_{0.90} - Q_{0.10}}.$$

The estimated Kelley skewness equals -0.139, indicating a left-skewed predicted earnings distribution. This implies that the expected magnitude of adverse earnings realizations exceeds that of positive outcomes of comparable probability mass. In other words, conditional downside risk dominates upside potential.

5.1.2 Time-Series Behavior of Central Tendency

This subsection focuses on the evolution of the central tendency of the earnings distribution across years.

Table 4 reports yearly cross-sectional summaries of the expected and median one-year-ahead earnings. The forecasted mean is estimated by integrating the fitted quantile function over τ; this is implemented as the average of fitted quantiles across τ. The forecasted median is the fitted 0.50 quantile, $\hat{Q}_{0.50,i,t}$. Then, for each fiscal year t , I aggregate across firms by taking the cross-sectional average. This produces a time series of yearly forecasted mean and median earnings that summarizes how the center of the predicted distribution evolves over time.

Table 4

Year	N	Earnings Mean	Earnings Median	Skewness
1987	462	3,89%	4,62%	-0,99
1988	2102	4,01%	4,68%	-0,86
1989	2277	3,45%	4,31%	-0,94
1990	2315	3,25%	4,17%	-1,03
1991	2394	2,76%	3,85%	-1,1
1992	2548	2,98%	3,96%	-1,09
1993	2697	3,20%	4,10%	-1,04
1994	2874	3,70%	4,49%	-1,05
1995	3166	3,54%	4,51%	-1,07
1996	3380	3,53%	4,57%	-1,17
1997	3475	3,31%	4,43%	-1,19
1998	3577	2,41%	3,81%	-1,17
1999	3712	1,96%	3,62%	-1,31
2000	3780	1,51%	3,42%	-1,38
2001	3650	-0,68%	2,88%	-2,49
2002	3562	0,54%	3,40%	-1,95
2003	3537	2,12%	3,82%	-1,35
2004	3492	3,15%	4,45%	-1,34
2005	3474	3,32%	4,66%	-1,3
2006	3410	3,51%	4,81%	-1,4
2007	3411	3,37%	4,70%	-1,31
2008	3381	1,03%	3,71%	-1,47
2009	3323	2,38%	3,97%	-1,21
2010	3298	3,57%	4,62%	-1,24

2011	3328	3,34%	4,53%	-1,21
2012	3344	2,65%	4,20%	-1,44
2013	3384	2,39%	4,04%	-1,43
2014	3328	1,59%	3,79%	-1,65
2015	3238	0,26%	3,43%	-1,8
2016	3169	0,23%	3,31%	-1,79
2017	3148	0,49%	3,58%	-1,96
2018	3226	-0,07%	3,41%	-1,81
2019	3303	-1,84%	2,63%	-1,57
2020	3514	-3,02%	1,64%	-1,55
2021	3658	-2,27%	2,42%	-2
2022	3532	-2,79%	2,32%	-1,54
2023	3398	-2,05%	2,79%	-1,74

Across some years, a divergence emerges between the mean and the median. The median predicted earnings remain generally close to 5%, whereas the mean varies between -2% and 4%. For example, in 1988 the mean equals 4,01% while the median is 4,68%; similarly, in 2014 the median is approximately 3,79% whereas the mean reaches 1,59%.

This divergence is consistent with quantile-based evidence of left-skewness.

Time variation is also pronounced. The mean predicted earnings deteriorate during periods associated with macroeconomic stress, including the early 2000s, the Global Financial Crisis, and the COVID-19 period. By contrast, the median remains relatively stable even during crisis episodes, suggesting that fluctuations in expected earnings are driven primarily by shifts in the lower tail of the distribution rather than by symmetric changes in profitability.

Taken together, the quantile-based skewness analysis and the divergence between mean and median confirm that expected earnings risk is dominated by downside outcomes and exhibits time variation concentrated in the lower tail.

5.2 Volatility analysis. Quantile-implied earnings volatility

In this section I present the forward-looking measure of earnings volatility derived from the predicted conditional distribution of one-year-ahead earnings.

5.2.1 Construction of quantile-implied volatility

For each firm-year observation, volatility is computed as the cross-quantile dispersion of the predicted conditional quantiles of Earnings_{t+1}.

The measure captures how widely the predicted quantiles are around their center: a wider separation between lower and upper quantiles results in higher volatility, while a more concentrated distribution implies lower volatility.

Descriptive statistics for CQR volatility are reported below:

5.2.2 Time-series behavior of quantile-implied volatility

Table 5 reports yearly summaries of the CQR-based quantile-implied volatility, including the cross-

Mean	N	SD	Min	Max	P25	P75	Median
0,077	117869	0,027	0,030	0,264	0,058	0,088	0,069

sectional mean, median, standard deviation and Skewness. It gives a direct view of how forward-looking earnings uncertainty evolves over time under the main empirical specification.

From the analysis of the results, we can infer that CQR-based quantile-implied volatility is able to show time variation, indicating changes in aggregate earnings uncertainty across the sample period. During the late 1980s and early 1990s, average volatility remains relatively moderate, with mean values between approximately 0.07 and 0.074. Volatility then fluctuates through the mid-1990s before rising more sharply toward the end of the decade and into the early 2000s. In particular, mean volatility increases from around 0.075 in 1998 to 0.077 in 2000 and reaches a peak of approximately 0.084 in 2001. This pattern reflects a marked widening of the predicted earnings distribution during that period.

Following the peak, volatility declines but remains elevated in the early 2000s, with mean values around 0.08 in 2002 before gradually decreasing thereafter. A further increase in volatility is observed around the global financial crisis, with mean volatility rising from 0.073 in 2006 and then to approximately 0.080 in 2008. More recently, volatility increases again in 2020–2021, reaching 0.082 in 2019 and 0.087 in 2020, before moderating slightly in the following years. Overall, these dynamics suggest that the proposed measure captures economically meaningful fluctuations in aggregate earnings uncertainty across different macroeconomic environments.

Second, the mean of the volatility distribution consistently exceeds the median, highlighting the presence of substantial cross-sectional heterogeneity. In every year, median volatility is lower than the mean. For example, in 1999 the mean volatility equals approximately 0.076, while the median is 0.07; similarly, in 2020 the mean is about 0.087 compared to a median of 0.079. This persistent gap indicates that increases in aggregate volatility are driven by a subset of firms whose predicted earnings distributions become particularly wide, while the typical firm faces more moderate uncertainty. As a result, mean volatility alone overstates the level of earnings risk experienced by the median firm.

Third, the yearly summaries suggest that cross-sectional dispersion becomes more pronounced during periods of heightened uncertainty. High-volatility episodes, such as the early 2000s and the 2020–2021 period, are characterized not only by an upward shift in the center of the volatility distribution, but also by a wider gap between the mean and the median. In terms of the quantile-based construction, this implies that the separation between lower and upper predicted quantiles increases more strongly for a subset of firms, leading to a broader predicted earnings distribution. This confirms that the CQR-based volatility measure captures not only aggregate movements in expected earnings risk, but also substantial heterogeneity in how uncertainty is distributed across firms.

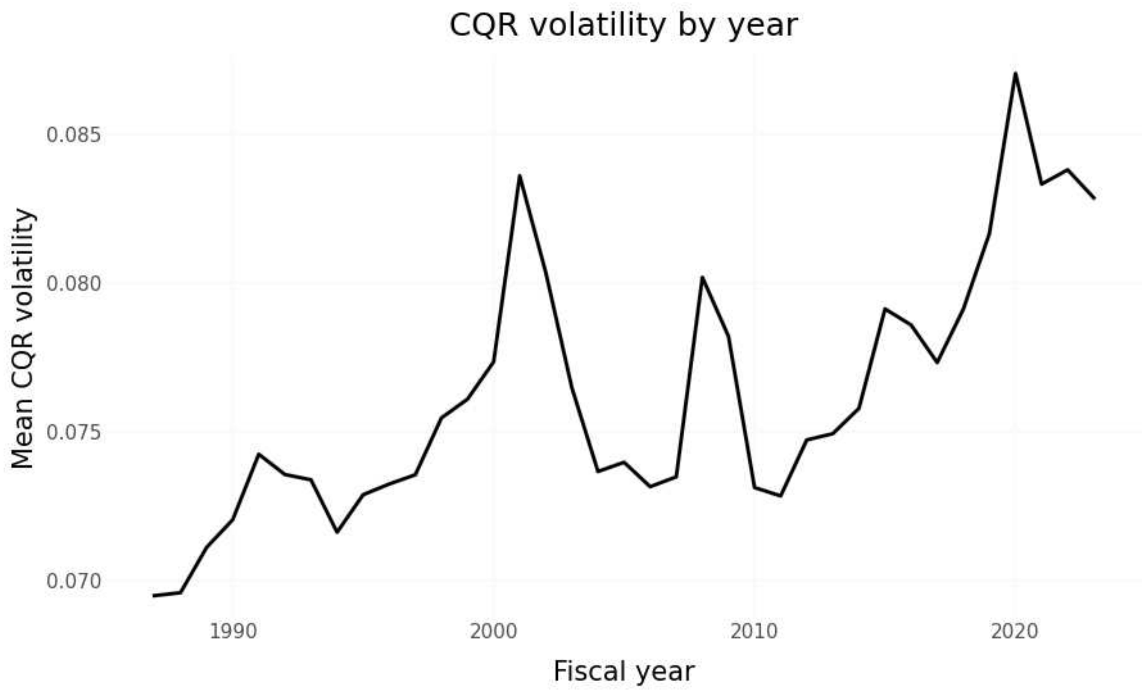
Figure 4 reports the full cross-sectional distribution of quantile-implied volatility cumulating all years and illustrates the substantial heterogeneity underlying the summary statistics.

Table 5

Year	N	CQR Vol Mean	CQR Vol Median	SD	Skewness
1987	462	0,07	0,066	0,016	1,408
1988	2102	0,07	0,067	0,017	1,161
1989	2277	0,071	0,068	0,018	1,104
1990	2315	0,072	0,068	0,019	1,132
1991	2394	0,074	0,07	0,02	1,049
1992	2548	0,074	0,07	0,019	1,133
1993	2697	0,073	0,07	0,019	1,178

1994	2874	0,072	0,069	0,018	1,313
1995	3166	0,073	0,069	0,019	1,153
1996	3380	0,073	0,069	0,02	1,202
1997	3475	0,074	0,069	0,02	1,253
1998	3577	0,075	0,07	0,022	1,048
1999	3712	0,076	0,07	0,023	1,053
2000	3780	0,077	0,07	0,025	1,06
2001	3650	0,084	0,073	0,033	1,816
2002	3562	0,08	0,071	0,029	1,427
2003	3537	0,076	0,07	0,024	1,029
2004	3492	0,074	0,068	0,023	1,212
2005	3474	0,074	0,068	0,023	1,145
2006	3410	0,073	0,068	0,023	1,247
2007	3411	0,073	0,068	0,024	1,121
2008	3381	0,08	0,071	0,03	1,163
2009	3323	0,078	0,071	0,026	0,819
2010	3298	0,073	0,068	0,023	1,114
2011	3328	0,073	0,067	0,023	1,168
2012	3344	0,075	0,068	0,025	1,129
2013	3384	0,075	0,068	0,026	1,049
2014	3328	0,076	0,067	0,028	1,106
2015	3238	0,079	0,069	0,031	1,144
2016	3169	0,079	0,068	0,03	1,056
2017	3148	0,077	0,067	0,031	1,092
2018	3226	0,079	0,068	0,032	1,037
2019	3303	0,082	0,07	0,034	0,964
2020	3514	0,087	0,079	0,034	0,663
2021	3658	0,083	0,07	0,035	0,813
2022	3532	0,084	0,069	0,036	0,796
2023	3398	0,083	0,07	0,035	0,859

Figure 4



5.3 Asset-weighted quantile-implied volatility

As an additional robustness exercise, I computed an asset-weighted version of the quantile-implied volatility measure. The baseline time-series aggregates firm-year volatilities using an equal-weighted mean, so that each firm-year observation contributes equally to the yearly average. While this approach summarizes the volatility of the "average firm", it may over-represent smaller firms.

To ensure comparability over time, total assets are first expressed in real terms by deflating nominal assets. As explained in Section 3.4, this adjustment removes the effect of general price level changes over the sample period and prevents mechanical growth in firm size driven by inflation. The deflated asset measure is then used both in the construction of the SIZE variable and as the weighting variable in the asset-weighted aggregation.

For each firm-year (i, t), the CQR procedure delivers a firm-level quantile-implied volatility estimate $\sigma_{i,t}$, computed from the cross-quantile dispersion of predicted earnings. I then form year-specific weights proportional to firm size:

$$w_{i,t} = \frac{AT_{i,t}}{\sum_{j \in t} AT_{j,t}},$$

and compute the asset-weighted mean volatility in year $t$as

$$\bar{\sigma}_t^{AW} = \sum_{i \in t} w_{i,t} \, \sigma_{i,t}.$$

To remain consistent with the forecast interpretation of the model, the resulting time series is indexed by the forecast year $(t+1)$, since volatility is derived from the distribution of predicted $Earnings_{t+1}$conditional on information available at time t.

Empirically, as shown in Figure 6, the asset-weighted series lies systematically below the equal-weighted average and displays a smoother evolution over time, while still reproducing the main episodes of elevated volatility, most notably the early-2000s spike and the increase observed after 2020. However, it can be observed how the general trend of Volatility tends to decrease over time.

This can be explained by the fact that the average real assets of firms, as shown in Figure 5, increase substantially over the sample period, rising by approximately 100% between 1990 and 2020. This trend reflects the growing scale and concentration of economic activity among large firms. Since firm size enters the forecasting model through the logarithm of assets and is estimated to have a negative effect on earnings volatility, the increase in average firm size mechanically contributes to a lower aggregate volatility when asset weights are applied. In other words, as larger firms represent a greater share of total assets over time, and these firms tend to exhibit more stable earnings dynamics, the asset-weighted volatility measure places increasing weight on relatively stable firms, generating a gradual downward trend relative to the equal-weighted series.

Figure 5

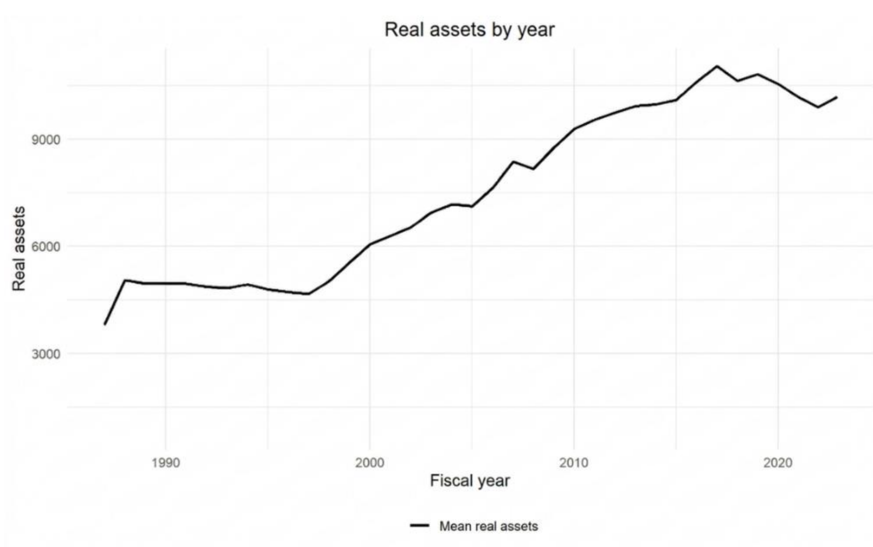
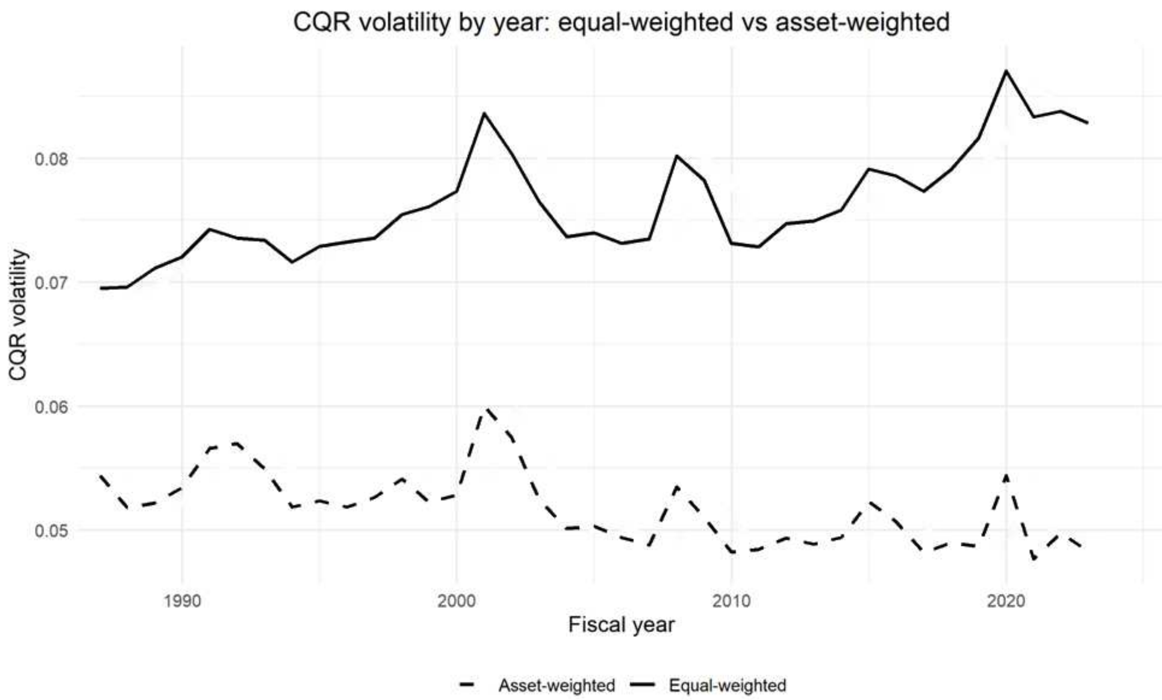


Figure 6



5.4 Impact of High-Tech Firms

By observing in detail the yearly trend of CQR Volatility, it is notable how, the 2001 Dot-com bubble shows a greater spike than 2008 Global financial crises. The time-series pattern of quantile-implied volatility is in fact influenced by the changing composition of the sample, most notably by the exclusion of financial firms from the dataset (the most affected by Global Financial Crisis) and the rising weight of high-tech firms (most affected by dot-com bubble).

As the high-tech share increases over time, as shown in Figure 7 their contribution to aggregate volatility becomes more important, and this is particularly evident around the dot-com episode. As presented then in Figure 8, mean volatility for high-tech firms rises sharply and peaks in the early 2000s, while non-high-tech firms exhibit a much flatter evolution, implying that the prominent spike in the overall CQR volatility series is driven by sector-specific widening of the predicted earnings distribution among high-tech firms during the bubble and its collapse. By contrast, the increase around the Global Financial Crisis is more contained. This spike is consistent with two features of the empirical setting: first, the crisis shock was initially concentrated in the financial sector, which is excluded from the sample; second, for non-financial firms the downturn is reflected more in a broad deterioration of earnings levels than in an equally strong increase in cross-quantile dispersion. Overall, these patterns support the interpretation that large volatility spikes in the constructed measure primarily emerge when a major macro/market episode simultaneously affects a large and increasingly represented segment of the dataset.

Figure 7

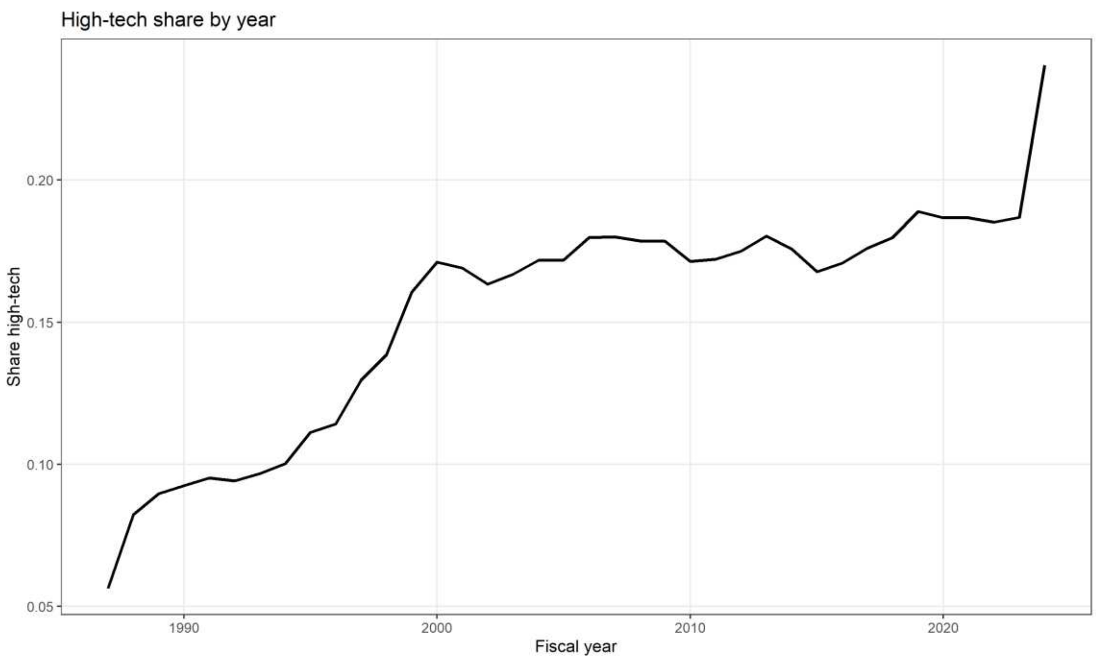
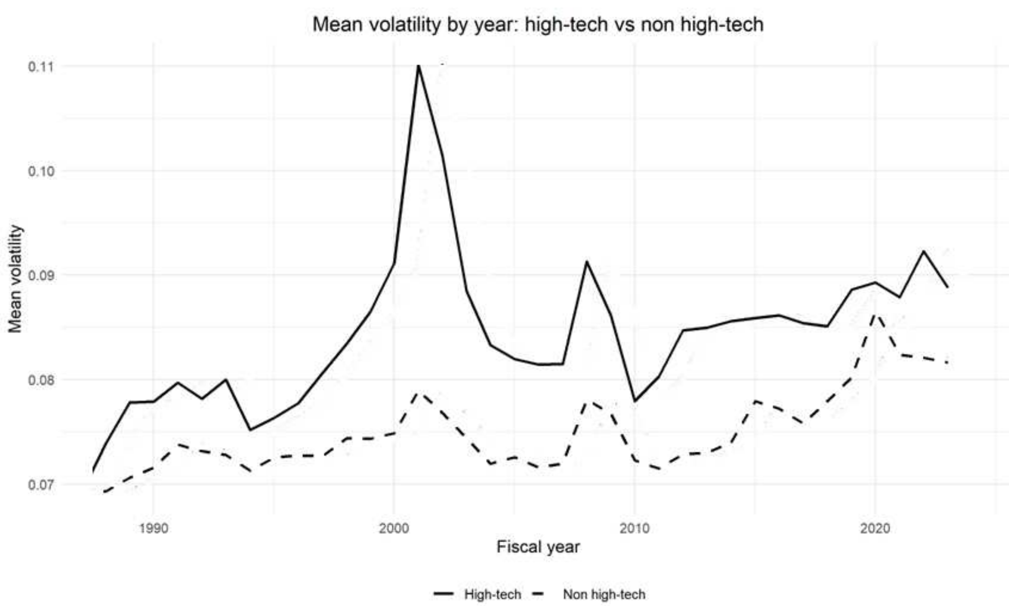


Figure 8



6. OLS residual-based earnings dispersion as a benchmark proxy

To provide a benchmark comparison to the quantile-based approach, volatility of earnings is also estimated using the residuals from an Ordinary Least Squares (OLS) regression.

The OLS benchmark is based on a linear conditional mean specification and provides an asymptotic estimator of earnings variance under the assumption that the regression residuals are Normally distributed. In this sense, the measure is intended to recover the true volatility on average when observed across many realizations. However, the OLS-based estimate is highly noisy at the individual observation level and may remain unreliable even after aggregation when the underlying distribution of earnings is substantially non-Normal. By contrast, the quantile regression approach does not impose a parametric distribution ex ante, allowing the conditional distribution of future earnings to be modeled more flexibly, particularly in the presence of asymmetry and tail risk.

For each fiscal year, a cross-sectional OLS regression is estimated where one-year-ahead earnings $Y_{t+1}$are regressed on the same set of firm-level predictors used in the quantile framework: accruals (ACC), operating cash flow (OCF), leverage (LEV), firm size (SIZE), and the loss indicator (LOSS). The specification can be written as:

$$Y_{i,t+1} = \alpha_t + \beta_{1,t}ACC_{i,t} + \beta_{2,t}OCF_{i,t} + \beta_{3,t}LEV_{i,t} + \beta_{4,t}SIZE_{i,t} + \beta_{5,t}LOSS_{i,t} + \varepsilon_{i,t+1}$$

where the regression is estimated separately for each year t. This cross-sectional approach ensures that the model captures the contemporaneous relationship between firm characteristics and future earnings.

Following the estimation of the yearly regressions, firm-level residuals are obtained as the difference between realized earnings and fitted values:

$$\varepsilon_{i,t+1} = Y_{i,t+1} - \hat{Y}_{i,t+1}$$

These residuals measure the forecast error of the linear model and for this reason capture the unexpected component of future earnings. This measure is based on realized earnings at time $t + 1$, on the other hand, quantile approach uses only information up to t. To construct a volatility proxy comparable across firms and time, the absolute value of the residuals is used. Under the assumption of Normal Epsilon, the following estimator converges asymptotically to the true volatility:

$$Vol_{i,t}^{Asymptotic} = \sqrt{\frac{\pi}{2}} \mid \hat{\varepsilon}_{i,t} \mid$$

The above measure provides however very noisy volatility estimates. To obtain a yearly measure of earnings uncertainty, firm-level volatility estimates are aggregated across firms for each year.

Here are presented descriptive statistics for OLS Volatility estimates:

Mean	N	SD	Min	Max	P25	P75	Median
0,069	117869	0,095	0,000	1,472	0,016	0,083	0,038

The analysis focuses on the cross-sectional annual means of my OLS-based volatility estimates. These results are presented in Figure 9. The pattern reveals several periods of elevated earnings volatility that correspond to major macroeconomic events.

In particular, a pronounced increase in volatility can be observed around the early 2000s, consistent with the economic uncertainty following the dot-com crash. A second spike occurs during the 2008–2009 global financial crisis, reflecting the substantial deterioration in corporate earnings stability during that period. More recently, volatility rises again around the COVID-19 shock, indicating the significant disruption experienced by firms during the pandemic.

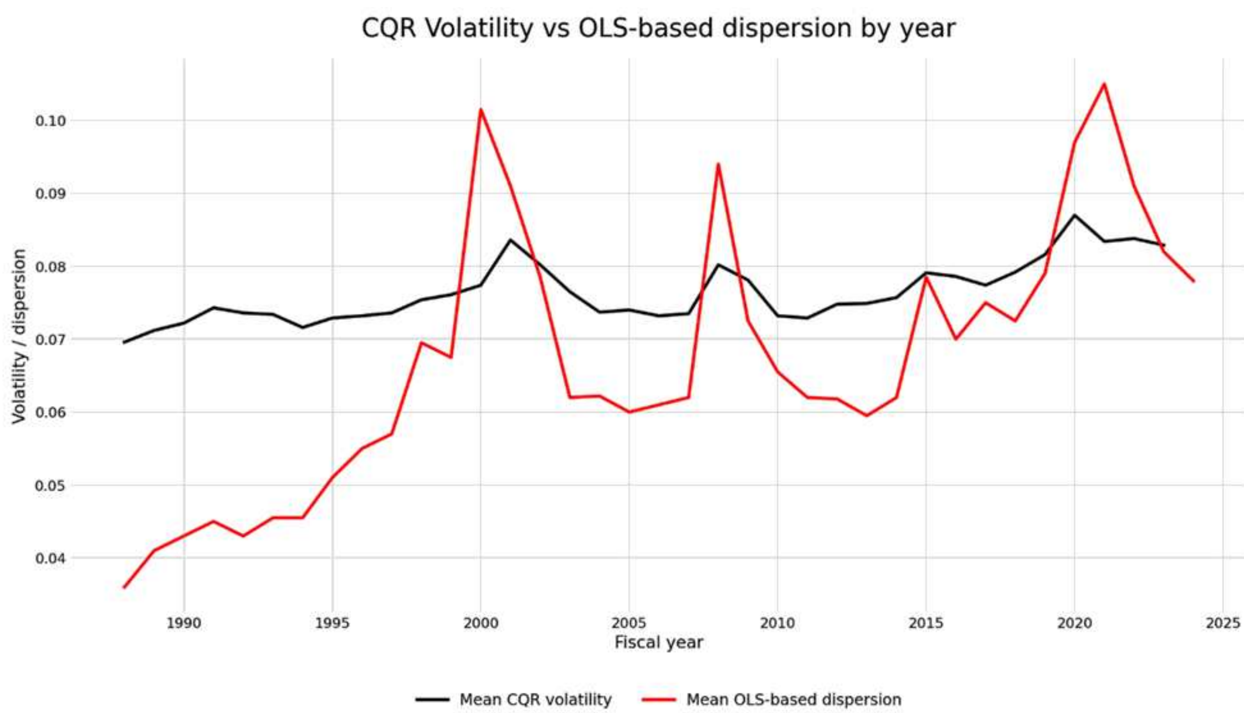
The OLS benchmark captures these broad macroeconomic fluctuations in earnings uncertainty; however, its estimation differs fundamentally from the quantile-based measure presented in the previous chapter. The OLS volatility is obtained from realized forecast errors and thus cannot be seen as a forecasting measure.

While both series capture periods of heightened earnings uncertainty, such as the early-2000s and the post-2020 period, the OLS measure shows a substantially more volatile pattern over time. To evaluate the relationship between the two approaches, the yearly OLS volatility series is compared with the CQR Volatility.

The correlation between the two series is positive and statistically meaningful, with a Pearson correlation of 0.74 and a Spearman correlation of 0.78. These results indicate that the two measures broadly track similar macroeconomic movements in earnings uncertainty.

At the same time, the correlations are not perfect, suggesting that the two methodologies capture earnings risk in different ways. The OLS-based measure can be interpreted as an asymptotic estimator of conditional variance under the assumption that the regression residuals are Normally distributed. However, it is highly noisy at the individual observation level and may remain unreliable even after aggregation when the underlying earnings distribution deviates substantially from Normality. By contrast, the quantile-based approach does not impose a parametric distribution ex ante but instead estimates the conditional distribution of future earnings more flexibly. This makes it better suited to capturing asymmetry, heterogeneity across firms, and variation in tail behavior. While the OLS benchmark provides a useful reference measure, the quantile-based volatility offers a representation of earnings risk that is more robust when the conditional distribution is non-Normal.

Figure 9



7. Conclusion

This dissertation studies the extent to which accounting fundamentals contain information about the distribution of future earnings, with particular attention to the measurement of forward-looking earnings volatility. Using quantile regression methods to estimate the conditional distribution of one-year-ahead earnings, it develops a volatility measure based on the spread of predicted quantiles rather than on realized deviations from the mean alone. The evidence shows that earnings uncertainty is heterogeneous across firms, evolves over time with macroeconomic conditions, and is characterized by substantial downside asymmetry and that companies are more exposed to negative shocks than to positive events of equal magnitude. Indeed, the distribution of earnings shows a significant skewness, showing a more pronounced tendency toward downside risk.

In terms of time, it is shown that the volatility of earnings increases substantially during periods of economic stress. This is the case of the first years of 2000, the years of the Global Financial crisis and the post-2020 Covid-19 period. This pattern is consistent with the idea that firm-level uncertainty increases when macroeconomic conditions deteriorate.

On the cross-section, it is shown evidence, however, that uncertainty is not uniformly distributed among firms. In particular, the differences between CQR Volatility Mean and Median suggest that aggregate risk is largely driven by a subset of firms, particularly exposed to high levels of uncertainty.

The thesis also highlights that firm characteristics matter in determining how earnings uncertainty is distributed. Larger firms appear, on average, to exhibit more stable earnings trends, while specific groups of firms, particularly high-tech firms in the early 2000s, play a disproportionate role in determining the dynamics of aggregate volatility. This suggests that the evolution of earnings risk reflects not only general macroeconomic shocks, but also structural differences across firms and sectors.

The quantile approach implemented in this dissertation is an alternative to the more traditional methods, which are based on observed residuals from conditional mean regressions. As a robustness check, I compare my quantile-based measure with an estimator of volatility based on OLS residuals. While both approaches identify similar periods of elevated uncertainty, the quantile-based measure provides a smoother pattern suggesting that risk is not present only when extreme realizations are observed. This suggests that focusing on the entire distribution of future earnings allows for a richer understanding of firm risk than relying solely on realized deviations from the mean.

Overall, this dissertation supports the idea that accounting fundamentals contain relevant information not only about expected future earnings but also about the uncertainty surrounding them. This makes the analysis relevant to a wide range of financial applications, including equity valuation, credit risk measurement, and business analysis, contexts in which understanding downside risk exposure and the dispersion of future profitability is crucial.

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