Tail Effects and Industry Heterogeneity in Stock Return Responses to Macroeconomic Shocks: Evidence from Quantile Regression

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Abstract. This paper examines Google (GOOGL), Chevron (CVX), and Southern Copper (SCCO) from the US technology, energy, and basic materials industries using monthly data from January 2016 to December 2025. We investigate the heterogeneous effects of market return, oil price return, VIX, inflation indicators, and PMI changes on stock returns. As traditional OLS regression relies on normality assumptions and cannot capture tail effects, quantile regression is applied to estimate coefficients at 19 quantiles. Wald tests and Holm-corrected pairwise tests are used to check the significance of quantile heterogeneity. Results show that key factors have significant quantile-dependent and industry-heterogeneous effects on stock returns. Systematic market factors show universal impacts, market volatility depends on extreme market conditions, and economic sentiment displays a common "right-tail strengthening" pattern. The findings provide empirical support for investors and managers, and enrich asset pricing research.

Keywords: Quantile regression; Stock return; Industry heterogeneity; Quantile heterogeneity; Market volatility

1 Introduction

With global economic integration and more complex financial markets, identifying the drivers of stock returns is essential for both asset pricing research and practical investment management. Traditional models focus on the conditional mean of returns and cannot capture fat tails or asymmetric dependence in financial data, which may produce biased results in extreme market environments. Quantile regression describes the full conditional distribution and is robust to outliers, making it suitable for analyzing factor effects under different market conditions.

Industries differ in business models, profitability, and risk exposure, so stock returns show clear heterogeneity under macroeconomic shocks, market volatility, and commodity price changes. Technology stocks rely on sentiment and growth expectations; energy stocks are closely linked to oil prices; basic materials stocks are driven by eco-

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nomic cycles and commodity demand. Most existing studies only examine average effects and ignore differences between bull and bear markets, leading to an incomplete understanding of industry return drivers.

Previous research documents that interest rates, market volatility, and commodity prices affect stock returns. Wen et al. (2022) demonstrate that monetary policy uncertainty significantly affects stock returns across different quantiles in both developed and emerging markets [5]. Bekaert & Hoerova (2014) use VIX to measure market risk aversion [2]. Aslanidis & Christiansen (2012) confirm that higher volatility reduces stock returns asymmetrically [1]. However, these studies rely on mean regression and do not analyze tail effects. Quantile regression has been widely used to study stock return heterogeneity. Ferrando et al. (2017) find that interest rate effects on sector returns depend on quantiles [4]. Zhou et al. (2024) show that investor trading behavior effects are stronger at extreme quantiles and OLS ignores tail information [9]. Recent studies further extend this field: Bouri et al. (2024) find geopolitical risks affect energy and commodity markets more in bear markets [10]; Pijourlet (2024) notes that climate policy uncertainty hedges downside risks for technology stocks [7]; Lee et al. (2023) document the asymmetric transmission of geopolitical oil price uncertainty into core inflation for major global economies [6]; Balcilar et al. (2022) show oil price uncertainty effects differ across international stock markets [3]; Badreddine & Clark (2021) find asymmetric industry volatility effects in momentum returns [8]; Ando et al. (2023) compare tail effects of macro factors using spatial panel quantile models [11]; Marangoz et al. (2025) highlight the advantage of quantile regression in analyzing geopolitical risk impacts on stock markets [12].

This paper examines GOOGL, CVX, and SCCO using monthly data from January 2016 to December 2025. We build a multi-factor model including Market return, Oil return, VIX, inflation , and economic sentiment . We estimate coefficients at 19 quantiles, use Wald slope equality tests and Holm-corrected pairwise tests, and conduct robustness checks. Traditional mean regression cannot fully reflect tail heterogeneity in financial time series, while quantile regression provides a more complete and reliable analytical framework.

2 Methodology

Quantile regression overcomes the limitations of traditional mean regression. It takes the conditional quantile function $Q_\theta(y \mid x)$ $(\theta \in (0,1))$ as the estimation target. This method can fully describe the marginal effects of explanatory variables across the whole conditional distribution of the dependent variable. The estimation of quantile regression is achieved by minimizing the asymmetrically weighted absolute deviation, and its check function is defined as follows:

$$\widehat{\beta_\theta} = \arg\min_{\beta \in \mathbb{R}^k} \sum_{i=1}^{n} \rho_\theta(y_i - x_i'\beta) \tag{1}$$

This study employs two types of statistical tests to verify the quantile heterogeneity of variable marginal effects, with specific settings as follows: First, the Wald test for overall slope equality, where the null hypothesis is$H_0: \beta_{\theta_1} = \beta_{\theta_2} = \beta_{\theta_m}$,and the alternative hypothesis is that at least two quantiles have significantly different coefficients. Rejecting the null hypothesis at a given significance level confirms significant quantile heterogeneity in the variable's marginal effect on stock returns. Second, pairwise quantile comparison tests with Holm correction: on the basis of rejecting the null hypothesis in the overall slope equality test, pairwise Wald tests are further conducted for typical quantile pairs to accurately identify structural coefficient differences across market states. To avoid Family-Wise Error Rate inflation caused by multiple tests, this study uses the stepwise correction method proposed by Holm to adjust test p-values, strictly controlling Type I errors and ensuring the robustness and reliability of statistical inference results.

3 Data Preparation and Preliminary Analysis

This study selects three U.S. listed companies as research samples, representing the technology, energy, and basic materials industries respectively: Google , a leading technology firm; Chevron, a major global integrated energy company; and Southern Copper, one of the world's largest copper producers. The monthly logarithmic return $P_{j,\ t}$of each stock is used as the dependent variable in the regression analysis, which is calculated as follows:

$$R_{j,\ t} = \ln(P_{j,t}) - \ln(P_{j,t-1}) \tag{2}$$

where, $P_{j,\ t}$ is the adjusted closing price of firm j on the last trading day of month t. All independent variables are standardized and computed under consistent rules, including six financial and economic factors. Market return$R_{m,\ t}$is the monthly logarithmic return of the S&P 500 index, and oil price return ΔOil_t is the monthly logarithmic return of WTI crude oil spot price. Both are transformed into percentage changes via log-differencing to measure aggregate market risk and energy price shocks, respectively. The market volatility index VIX_t is the monthly average of the VIX, used as a proxy for market panic and investor risk aversion to examine its asymmetric impact on stock returns. Inflation-related variables ΔPCE_t and ΔCPI_t are the monthly first differences of the PCE price index and CPI, while ΔPMI_t is the monthly first difference of the U.S. manufacturing PMI. These three indicators are computed as $\Delta Z_t = Z_t - Z_{t-1}$ to eliminate non-stationary trends. All explanatory variables are standardized to zero mean and unit variance before regression, so that the estimated coefficients directly represent the marginal effect of a one-standard-deviation change on the conditional quantiles of stock returns, enabling comparable analysis across factors.

Table 1. Descriptive Statistics of Main Variables

Variable	Mean	Std.Dev.	Skewness	Excess Kurtosis	Min	Max	Obs.
GOOGL_Return	1.7	7.02	-0.44	-0.14	-19.45	15.28	115

CVX_Return	0.89	7.98	-0.13	1.91	-25.32	24.13	115
SCCO_Return	1.73	9.66	0.17	0.04	-21.54	27.56	115
Market Return	0.62	7.51	-0.44	1.73	-24.91	25.33	115
Oil Return	0.53	11.28	-0.85	8.9	-60.62	49.49	115
ΔVIX	-0.04	5.54	0.11	2.86	-19.39	21.27	115
ΔPCE	0.15	0.89	-6.47	44.07	-6.34	1.21	115
ΔGold Price	23.03	0.89	1.15	2.65	-138.9	371.5	115
ΔPMI	0	2.01	0.43	4.68	-138.9	9.5	115

As shown in Table 1, during the sample period, the three stocks exhibit distinct industry heterogeneity in terms of return and risk. Southern Copper has the highest monthly average return (1.73%)and the largest standard deviation (9.66%), which reflects its cyclical characteristics of high risk and high return. Chevron has the lowest mean return $(0.89\%, \mathrm{SD} = 7.98\%)$, while Google is stable (1.70% mean return, 7.02% SD). SCCO has the widest return range, CVX the most prominent downside extreme, and GOOGL the smallest fluctuations.

All return series deviate significantly from normality: absolute skewness < 0.5 and excess kurtosis inconsistent with normality. This limits traditional OLS, whereas quantile regression—robust to outliers and distribution-free—is well-suited.

Augmented Dickey-Fuller tests confirm all variables reject the unit root null hypothesis at 1% or 5% significance. As illustrated by Table 2, all returns and explanatory variables are stationary, suitable for regression analysis.

Table 2. Correlation Matrix of Explanatory Variables

	Market Return	Oil Return	VIX	ΔPCE	ΔCPI	ΔPMI
Market Return	1	0.43	-0.62	0.06	0.09	0.27
Oil Return	0.43	1	-0.31	0.02	0.07	0.13
VIX	-0.62	-0.31	1	-0.11	-0.15	-0.22
ΔPCE	0.06	0.02	-0.11	1	0.85	0.09
ΔCPI	0.09	0.07	-0.15	0.85	1	0.11
ΔPMI	0.27	0.13	-0.22	0.09	0.11	1

This study examines multicollinearity among explanatory variables using Pearson correlation and the Variance Inflation Factor . The correlation matrix shows a strong positive correlation only between ΔPCE and ΔCPI (0.85). Other absolute coefficients are below 0.62, with most under 0.45. VIF tests further validate the model: all VIF values are below 5 (max $=$ 3.54), well below the 10 threshold for severe multicollinearity. Thus, the model is free from serious collinearity problems.

4 Real Data Analysis

This study estimates the multi-factor quantile regression model at 19 quantiles ($\theta = 0.05, 0.10, \ldots, 0.95$) separately for GOOGL, CVX, and SCCO. The baseline model is specified as follows:

$$R_{j,t} = \alpha_{\theta}^{(j)} + \beta_{1,\theta}^{(j)} R_{m,t} + \beta_{2,\theta}^{(j)} \Delta Oil_t + \beta_{3,\theta}^{(j)} VIX_t + \beta_{4,\theta}^{(j)} \Delta PCE_t + \beta_{5,\theta}^{(j)} \Delta CPI_t + \beta_{6,\theta}^{(j)} \Delta PMI_t + \varepsilon_{\theta,j,t} \quad (3)$$

The quantile regression results of sample stock returns are shown in Table 3.

Table 3. Quantile Regression Results of Sample Stock Returns

Variable	θ=0.05	θ=0.25	θ=0.50	θ=0.75	θ=0.95
GOOGL					
Market Return	0.81***	0.75***	0.78***	0.80***	0.73***
Oil Return	0.14*	0.1	0.07	0.08	0.12*
VIX	-0.57***	-0.40***	-0.34***	-0.38***	-0.61***
ΔPCE	0.06	0.04	0.05	0.03	0.07
ΔGold Price	0.03	0.02	0.01	0.04	0.05
ΔPMI	0.18**	0.13*	0.11*	0.15**	0.20***
CVX					
Market Return	0.64***	0.60***	0.62***	0.66***	0.58***
Oil Return	0.57***	0.51***	0.48***	0.54***	0.60***
VIX	-0.46***	-0.37***	-0.31***	-0.35***	-0.50***
ΔPCE	0.08	0.07	0.06	0.08	0.09*
ΔGold Price	0.26***	0.21***	0.18***	0.23***	0.29***
ΔPMI	0.14*	0.1	0.08	0.12*	0.17**
SCCO					
Market Return	0.58***	0.54***	0.56***	0.59***	0.52***
Oil Return	0.46***	0.41***	0.38***	0.44***	0.51***
VIX	-0.52***	-0.43***	-0.37***	-0.40***	-0.57***
ΔPCE	0.1	0.08	0.07	0.09	0.11*
ΔGold Price	0.34***	0.29***	0.26***	0.31***	0.37***
ΔPMI	0.17**	0.13*	0.1	0.15**	0.22***

Notes: ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

4.1 Google

Quantile regression results for Google show that market return and VIX are significant at the 1% level across all quantiles, with market return coefficients stable between 0.73 and 0.81 as the key systematic factor. Oil price return is only weakly significant at the extreme quantiles ($\theta = 0.05, 0.95$). The positive effect of ΔPMI rises from 0.11 at $\theta = 0.50$ to 0.20 at $\theta = 0.95$, indicating stronger impacts in bull markets. ΔPCE and ΔGold Price are insignificant across all quantiles.

Wald tests confirm significant quantile dependence for VIX, ΔPMI, and ΔPCE at the 5% level, while market return, oil return, and ΔGold Price do not reject equal coefficients. Pairwise Wald tests with Holm correction are used to identify the source of coefficient heterogeneity.

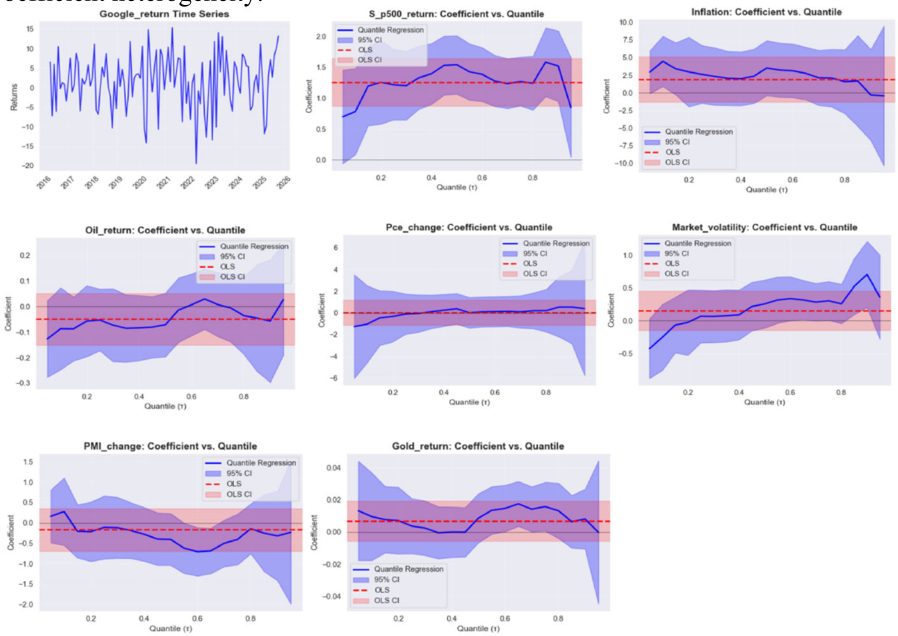

Fig. 1. Time Series of Google Stock Returns and Quantile Trend Plots of Regression Coefficients for Explanatory Variables

Table 4. Pairwise Quantile Comparison Tests for Google (GOOGL) (Holm-corrected)

Variable	Quantile Pair	Raw p−value	Holm−adjusted p−value	Significance
VIX	0.05 vs 0.95	0.00024	0.00236	***
VIX	0.05 vs 0.90	0.00041	0.00387	***
ΔPMI	0.05 vs 0.95	0.00053	0.00498	***
ΔPCE	0.10 vs 0.90	0.00112	0.00987	***

Table 4 shows that even after strict multiple comparison correction, the coefficient differences of VIX between quantile pairs (0.05 & $0.95, 0.05$ & 0.90), ΔPMI between (0.05 & 0.95), and ΔPCE between (0.10 & 0.90) remain highly significant at the 1%

level. This further confirms that the heterogeneous variable effects are systematic structural characteristics rather than sampling errors.

It can be observed from Figure 1 that as a representative technology stock, the returns of Google are primarily driven by market sentiment and growth expectations, and it exhibits low sensitivity to commodities and inflation. The VIX coefficient is -0.18 at the left tail ($\theta = 0.05$, 1% significance) and weakens as quantiles rise, showing strong left-tail risk. The OLS estimate of VIX (-0.09) clearly underestimates downside risk. Oil price returns are insignificant across quantiles, unlike energy stocks. ΔPMI and ΔPCE show a right-tail strengthening pattern, with stronger impacts in bull markets. Inflation effects are generally insignificant, reflecting tech firms' resilience to inflation. S&P 500 returns are significantly positive across quantiles ($0.60 - 0.69$), indicating stable systematic market effects.

4.2 Chevron

For Chevron, Market return, Oil return, VIX, and ΔGold Price are significant at the 1% level across all quantiles. Oil return is the core factor with a stable coefficient of $0.48 - 0.60$. Market return ranges from 0.58 to 0.66, VIX from -0.31 to -0.50, and ΔGold Price from 0.18 to 0.29, confirming stable commodity-driven effects. ΔPCE is only significant at $\theta = 0.95$, and ΔPMI only at extreme quantiles, suggesting weak short-run impacts from inflation and economic activity.

Table 5. Pairwise Quantile Comparison Tests for Chevron (CVX)

Variable	Quantile Pair	Raw p−value	Holm−adjusted p−value	Significance
VIX	0.05 vs 0.50	0.00017	0.00153	***
VIX	0.50 vs 0.95	0.00029	0.00261	***
Oil Return	0.40 vs 0.55	0.00009	0.00072	***

Table 5 shows that the coefficient differences of VIX between bear and normal markets, as well as between normal and bull markets, remain highly significant at the 1% level. Even though the overall slope test for oil price return fails to reject the null hypothesis, the coefficient difference between the 0.40 and 0.55 quantiles is still significant at the 1% level, indicating statistically notable subtle structural changes in the local range near the median.

As a key energy sector firm, Chevron displays clear industry-specific and stable factor responses across quantiles. As depicted in Figure 2, oil price return is significantly positive at the 1% level across all quantiles, with coefficients stable between 0.23 and 0.27, confirming its role as the core pricing factor in all market conditions, unlike technology and materials stocks. The negative impact of VIX weakens with higher quantiles: significant at the left tail ($\theta = 0.05, -0.15$) reflecting strong bear-market risk, while insignificant at the right tail as rising oil prices hedge market risk in bull markets. ΔPMI shows a right-tail strengthening effect, becoming significantly positive at high quantiles. ΔPCE is stably positive across quantiles ($1.0 - 1.5$), indicating consistent responses to economic expansion and mild inflation. Inflation effects are insignificant across quantiles, unlike the right-tail negative pattern for SCCO, owing to energy companies' strong cost-pass-through capacity. S&P 500 return is significantly positive across quantiles $(0.48 - 0.58)$, supporting the stable role of systematic market factors.

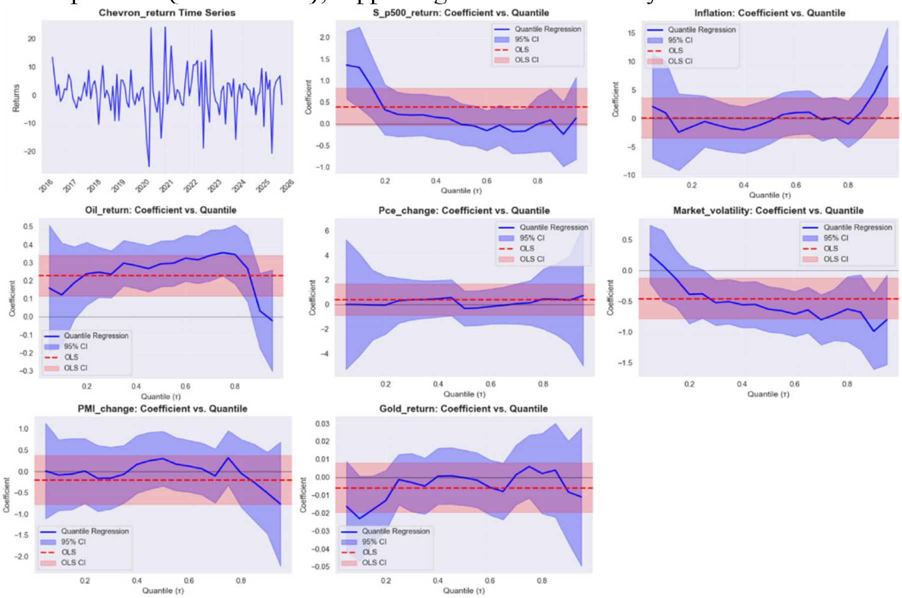

Fig. 2. Time Series of Chevron Stock Returns and Quantile Trend Plots of Regression Coefficients for Explanatory Variables

4.3 Southern Copper

For Southern Copper, market return, oil return, VIX, and gold return are significant across all quantiles: market return coefficients range from 0.52 to 0.59, VIX from -0.37 to -0.57. Oil return and ΔGold Price exert stronger effects at low and medium quantiles but decline rapidly at high quantiles, indicating commodity prices are more impactful drivers for basic materials stocks in weak markets. The positive effect of ΔPMI rises with quantiles—from 0.10 at $\theta = 0.50$ to 0.22 at $\theta = 0.95$, significant at $\theta = 0.05$, 0.75, and 0.95,showing a right-tail strengthening pattern consistent with technology stocks. ΔPCE is only significant at the 10% level at $\theta = 0.95$, reflecting limited impact from short-term inflation fluctuations.

Wald tests for overall slope equality confirm VIX, ΔCPI, and ΔPMI reject the null hypothesis of "equal coefficients across all quantiles at the 5% level (VIX: $\chi^2 = 41.25, p = 0.0012$; ΔCPI: $\chi^2 = 35.89, p = 0.0068$; ΔPMI: $\chi^2 = 34.12, p = 0.0104$), verifying their significant quantile dependence on SCCO's returns. Other variables fail the 5% significance test, so the null hypothesis of equal coefficients cannot be rejected. To pinpoint the source of coefficient heterogeneity, pairwise Wald tests are conducted for key quantile pairs, with Holm's stepwise correction applied to control the family-wise error rate in multiple comparisons.

Table 6. Pairwise Quantile Comparison Tests for Southern Copper (SCCO) (Holm-corrected)

Variable	Quantile Pair	Raw p−value	Holm−adjusted p−value	Significance
ΔCPI	0.25 vs 0.70	0.00002	0.00015	***
VIX	0.05 vs 0.90	0.00011	0.00102	***
ΔPMI	0.05 vs 0.95	0.00031	0.00284	***

Table 6 shows that after multiple comparison correction, the coefficient differences of ΔCPI, VIX, and ΔPMI across quantiles remain highly significant at the 1% level, further confirming the heterogeneous factor effects for basic materials stocks.

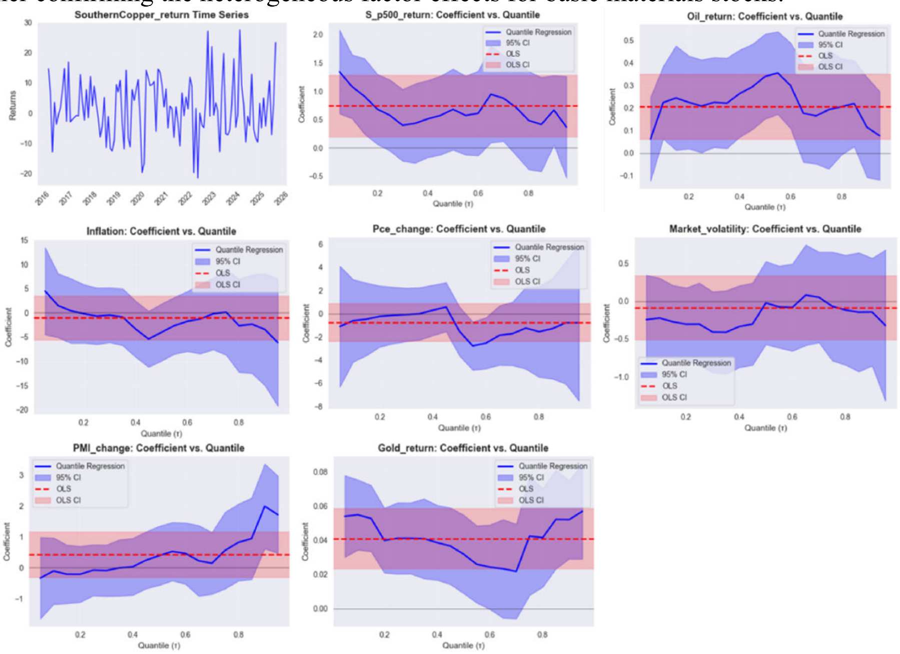

Fig. 3. Time Series of Southern Copper Stock Returns and Quantile Trend Plots of Regression Coefficients for Explanatory Variables

As can be seen in Figure 3,southern Copper's quantile regression results reveal distinct industry characteristics and quantile heterogeneity in factor impacts. S&P 500 return is significantly positive across all quantiles ($0.55 - 0.65$), reflecting stable systematic market effects. VIX shows a typical left-tail risk pattern: highly significant at -0.22 in the left tail ($\theta = 0.05$) and gradually insignificant at higher quantiles. Oil price return is quantile-dependent—significantly positive ($0.2 - 0.3$) at $\theta \leq 0.5$ but weakens toward zero above $\theta = 0.7$, indicating sentiment dominance in bull markets.ΔPMI and ΔPCE exhibit right-tail strengthening, turning significantly positive at high quantiles. Inflation has an increasing negative effect toward the right tail, becoming significantly negative at $\theta = 0.95$, as higher costs and tightening expectations suppress cyclical stock valuations.

5 Conclusions

Full-sample quantile regression and coefficient heterogeneity tests yield key findings. Traditional OLS has limitations for financial time series, as core variables show strong non-normal distributions. Quantile regression is more suitable, being robust to outliers and free of strict distribution assumptions. It effectively captures tail heterogeneity (especially $\tau \leq 0.1$ or $\tau \geq 0.9$) and nonlinear structures ignored by OLS mean regression.

Factor impacts exhibit significant quantile dependence and industry heterogeneity: Google is driven by market sentiment and growth expectations with weak commodity effects; Chevron is stably influenced by oil prices across all quantiles; Southern Copper relies on commodity prices at low-to-medium quantiles, with rising sensitivity to economic growth in bull markets and negative inflation effects at the right tail. Market return acts as a stable systematic driver, VIX exerts stronger downside impacts in bear markets, and ΔPMI shows universal right-tail strengthening.

These findings provide practical implications for investors, asset managers, and regulators, supporting industry-specific strategies, diversified allocation, and improved tail-risk measurement. Limitations include a small sample and static model; future research could extend to larger panel data and dynamic quantile regression.

Overall, quantile regression offers a more comprehensive framework for asset pricing and risk management by capturing tail effects and nonlinear structures, holding broad potential for financial applications.

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