

**Analysing the Impact of China's Crackdown on Stock
Market Performance: A Firm-Level Regression Analysis**

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About the Author

Shikhar Sharma is a student at IIM Indore, as part of its flagship IPM programme. He enjoys academic pursuits, particularly in the areas of finance, geopolitics and development, and research methodologies. Fascinated by China's monumental presence as the world's second-largest economy and its thriving stock market, Shikhar's interests span capital markets, government interventions, policy formulation, and geopolitical dynamics. His active involvement as an associate of the Finance and Investment cell at IIM Indore underscores his commitment to financial literacy and leadership development. Having navigated the nuances of investing in Chinese equities for two years, Shikhar brings a unique blend of theoretical knowledge and practical experience to his role as a research intern at the esteemed Institute of Chinese Studies. With a keen analytical mind and a passion for global economics, Shikhar is committed to making meaningful contributions to the institute's research endeavours.

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Abstract

This study explores the impact of the Chinese government's crackdown on the stock prices of major Chinese technology companies, particularly Alibaba, Tencent, Meituan, Pinduoduo, JD.com, and NetEase. Utilising data from Yahoo Finance, S&P Capital IQ, and FRED, the research analyses financial performance metrics such as net income, R&D expenditure, interest rates, and housing rates. The study employs a linear regression model to evaluate the effect of the regulatory actions, introduced from November 2020 onwards, on the stock prices of these companies. The analysis incorporates dummy variables to represent the tech crackdown period and categorises companies based on growth estimates. Findings indicate a statistically significant negative impact of the tech crackdown on stock prices. This negative impact remains consistent even when companies are segregated into low-, medium-, and high-growth categories and analysed separately. The study also highlights the role of mediating variables like net income rate and housing rate, which significantly influence stock prices.

Keywords: Chinese Technology Companies, Technology, Finance, Stock Prices

Introduction

In recent years, China's regulatory landscape has undergone a dramatic transformation, particularly concerning its powerful and once-unfettered technology sector. Beginning in late 2020, the Chinese Communist Party (CCP) launched an aggressive crackdown on its domestic tech giants—an initiative that wiped out over \$1.1 trillion in market value and reshaped the relationship between the state and private enterprise. At the heart of this regulatory storm was not merely an economic correction but a broader political recalibration aimed at reasserting party dominance over platforms that had grown economically vital and socially influential. Following Jack Ma's public criticism of financial regulators, the blockage of Ant Group's record-setting IPO in 2020 marked a pivotal moment. It ushered in a new era of state intervention that included delistings, licence revocations, content restrictions, and tighter data controls.

However, even as Beijing publicly signals an easing of its two-year-long tech assault, recent developments suggest the state has merely shifted tactics rather than intentions. The introduction of “golden shares”—minority state stakes that offer disproportionate control over corporate decisions—has emerged as a cornerstone of the CCP's new strategy to institutionalise oversight without overt expropriation. These shares allow the government not just economic leverage but the ability to directly influence company boardrooms, platform content, and strategic data flows. As Alex Capri of the Hinrich Foundation notes, this new form of “preemptive” control—favouring embedded influence over brute force—serves to deepen the Party's presence inside China's leading firms. For foreign investors, this evolution presents a dilemma: the rules are more opaque than ever, and the lines between civilian commerce and state-military interests blur under China's policy of civil-military fusion.

Although Beijing has articulated renewed support for the private sector as it attempts to rejuvenate a slowing post-COVID economy, these reassurances ring hollow for many global investors. Regulatory signals remain ambiguous, enforcement inconsistent, and policy reversals—such as the quiet easing of bans on private tutoring and gaming—are executed with minimal transparency to avoid implicating President Xi Jinping. As James Palmer (2024) highlights, Xi's consolidation of power makes it politically untenable for regulators to publicly admit policy missteps. This ambiguity has fuelled widespread investor hesitation, with new business formation in China plummeting from over 51,000 new firms in 2018 to

just 260 in 2024. Even sectors identified as strategic priorities—AI, semiconductors, and EVs—remain constrained by outbound investment controls from Western governments and rising geopolitical tension.

This study examines the financial impact of the tech crackdown, using regression models to assess changes in market valuation and performance since November 2020. Firms are categorised by growth potential—low, medium, and high—to capture the uneven effects of regulation across the sector. The findings are relevant for policymakers balancing reform and stability, investors managing regulatory risk, and scholars studying the evolution of state-capital dynamics in authoritarian economies. The paper proceeds with a literature review, followed by methodology, findings, conclusions, and suggested directions for future research.

Literature Review

The unprecedented expansion of China’s technology sector over the past few decades has positioned it as a pivotal driver of economic growth, fostering the emergence of industry giants like Alibaba, Tencent, Meituan, Pinduoduo, JD.com, and NetEase. However, recent regulatory crackdowns by the Chinese government have introduced significant volatility and uncertainty into this sector, prompting a broad discussion on the impact of such regulatory measures on corporate behaviour and stock market performance.

A. Impact of Regulatory Crackdowns on Firm Performance and Investment

Chen, Jin, and Xu (2021) provide a foundational perspective by analysing the economic repercussions of a corruption crackdown in Heilongjiang province. They found that such crackdowns, while aimed at improving efficiency and transparency, often have immediate negative effects on firm productivity and market entry, particularly for private and foreign firms. This suggests that regulatory crackdowns, though well-intentioned, can disrupt existing operational frameworks and relationships that private firms rely on, leading to short-term economic setbacks.

Wang (2016) extends this understanding by highlighting the negative impact of anti-corruption campaigns on economic growth at the provincial level, primarily through reduced investment activity. This stresses the potential for significant short-term economic disruptions

following regulatory crackdowns, as investment is a crucial driver of growth. The findings indicate that while anti-corruption measures may curb corrupt practices, they also risk dampening economic activity, particularly in investment-driven sectors.

Yu (2015) adds another layer by examining the impact of tariff reductions on firm productivity, highlighting how policy reforms can drive economic efficiency and growth. This suggests that while regulatory interventions can have adverse short-term effects, targeted reforms that improve market conditions and reduce operational expenses can mitigate some of these negative impacts. The tech crackdown's effect on stock prices, therefore, might be understood within this broader context of regulatory changes and their impact on firm performance and market stability.

B. Implications for Innovation and Corporate Governance

In the context of the Chinese technology sector, these insights are particularly relevant. The tech crackdown initiated in November 2020 shares similarities with previous anti-corruption efforts in its potential to disrupt established business practices and investor confidence. The negative impact on stock prices observed in this study aligns with the broader literature's findings on regulatory interventions leading to short-term economic difficulties. This is further supported by Xu and Yano (2017), who found that anti-corruption efforts can enhance innovation by facilitating access to external funds for R&D but primarily benefit firms without political connections and non-state-owned enterprises.

Kong, Wang, and Wang (2020) provide a nuanced view by demonstrating that the effects of anti-corruption campaigns can differ significantly between state-owned and non-state-owned enterprises. Their findings that central SOEs benefit from such campaigns while non-SOEs suffer highlight the dual-edged nature of regulatory interventions. This dual impact is relevant when considering the Chinese tech giants, many of which operate with a degree of independence from direct state control and may therefore experience adverse effects similar to those faced by non-SOEs in the broader anti-corruption literature.

Allen, Qian, and Qian (2005) further elucidate the role of alternative governance mechanisms in supporting economic growth in China. They argue that China's rapid growth, especially in the private sector, has often relied on informal mechanisms such as reputation and relationships rather than formal legal and financial systems. Regulatory crackdowns that

disrupt these mechanisms can therefore have significant economic repercussions, as seen in the immediate negative impact on stock prices in the current study.

C. Summary

In summary, the existing literature provides a comprehensive backdrop against which the effects of the Chinese government's tech crackdown on stock prices can be understood. The findings from Chen, Jin, and Xu (2021), Wang (2016), Xu and Yano (2017), Kong, Wang, and Wang (2020), Allen, Qian, and Qian (2005), and Yu (2015) collectively suggest that while regulatory crackdowns aim to enhance transparency and efficiency, they often result in short-term economic disruptions, particularly for private firms.

Methodology

Sources of Data

The data for this study is collected from several authoritative and widely recognised sources. For stock prices of Alibaba, Tencent, Meituan, Pinduoduo, JD.com, and NetEase, quarterly closing values were obtained from Yahoo Finance, covering the period from the fourth quarter of 2017 to the third quarter of 2023. Financial performance metrics, including quarterly net income and research and development (R&D) expenditures for these companies, were sourced from S&P Capital IQ. Additionally, macroeconomic indicators such as interest rates and housing price indices in China were acquired from the Federal Reserve Economic Data (FRED) system, which provided consistent and reliable data over the same timeframe. These sources collectively offer a robust foundation for the analysis, enabling a thorough examination of the impact of the regulatory crackdown on these prominent tech companies.

Sampling Methodology

The sampling methodology for this research focuses on six major Chinese technology companies—Alibaba, Tencent, Meituan, Pinduoduo (PDD), JD.com, and NetEase—over a detailed timeframe from December 31, 2017, to September 30, 2023. This period encompasses a range of market dynamics and regulatory changes that could significantly impact these firms. The primary objective is to analyse how various factors influence the companies' stock prices (dependent variable or DV) in the context of the Chinese government's technological crackdown (independent variable or IV).

Data was collected quarterly to capture trends and responses to both internal financial performance and external macroeconomic conditions. For firms that had their initial public offerings (IPOs) during the study period, data collection commenced from their first available quarter post-IPO. Pinduoduo, which underwent an Initial Public Offering (IPO) in July 2018, has data starting from the quarter ending September 30, 2018, and Meituan, which went public in September 2018, also has data starting from the same quarter. To ensure comparability and to avoid issues related to differences in currencies and scale, all variables were converted into rates of change, specifically calculated as $(X(t+1) - X(t)) / X(t)$, where X represents the variable of interest at time t.

The dataset includes key financial indicators such as net income and R&D expenditures, market performance metrics like stock prices, and external variables such as the price of the GXC ETF (SPDR S&P China ETF). Additionally, macroeconomic indicators including interest rates and housing prices were considered, along with their lagged values (one and two quarters behind) to capture potential delayed effects on company performance. These interest and housing rates were uniformly applied across all companies for each quarter, ensuring consistent external conditions in the analysis.

Control Variables

To isolate the effect of the primary variables of interest and account for other factors that might influence stock price changes, this analysis incorporates several control variables: interest rates, housing prices, and their respective lagged values. Interest rates are crucial because they represent the cost of borrowing and have significant implications for business operations and investor behaviour. Higher interest rates typically increase borrowing costs for companies, which can lower profits and reduce the attractiveness of stocks. While a conventional inverse relationship is often expected (Shue & Wilmington Trust Corporation 2019) studies like Gu, Zhu, and Wang (2022) have noted that, in China, this correlation can be more complex, sometimes reversing during periods of economic overheating where higher rates don't necessarily suppress rising stock prices. By including both current and lagged interest rates, our analysis aims to capture these time-varying and complex effects, providing a comprehensive understanding of how changes in interest rates impact stock prices over time.

Similarly, housing prices serve as a vital proxy for consumer wealth and broader economic health. Rising housing prices typically increase household wealth, which can encourage stock market participation and investment as individuals feel more financially secure (Lin & Stankov 2025). However, the relationship is multifaceted; Chen and Ji (2017) demonstrated that higher housing prices could also lead to a reallocation of investments away from stocks into real estate or reduce disposable income, thereby negatively affecting stock prices. Including housing prices and their lagged values allows the analysis to account for these complex dynamics and isolate their direct and delayed effects on stock market behaviour.

Mediating Variables

Mediating variables help explain the mechanisms through which the independent variable (the technological crackdown) influences the dependent variable (stock prices). In this study, the mediating variables considered are Net Income Rate, R&D Rate, and GXC Rate.

Net income and R&D expenditures are directly linked to a company's operational efficiency (profitability) and future growth potential. Changes in these metrics often reflect a company's strategic adjustments in response to regulatory pressures or market conditions. For instance, increased regulatory scrutiny, potential fines, or operational restrictions stemming from the crackdown might directly impact a company's ability to generate net income, or could necessitate strategic adjustments to R&D spending to maintain compliance or pivot to less regulated business areas. This connection is supported by research such as Rusdiyanto, R., & Narsa, I. M. (2019), who found a positive and significant effect of net income on stock prices, and Wang, Fu, and Luo (2013), who also noted a significant positive relationship between accounting information and stock prices. By examining these financial indicators, the study aims to understand how internal financial dynamics mediate the impact of regulatory changes on stock prices.

The GXC Rate, representing the performance of the broader Chinese technology sector (SPDR S&P China ETF), serves as a market-wide sentiment indicator. It reflects how the entire sector is perceived and affected under regulatory scrutiny, providing insight into broader market trends that individual companies might also be subject to. This is particularly relevant in understanding how sector-wide regulatory actions can influence individual stock performance, acting as a broad mediation of the crackdown's impact across the industry. As noted in the study by Gu, Zhu, and Wang (2022), the impact of interest rates on stock prices can vary significantly across different economic conditions, indicating that broader market indicators like the GXC Rate can help contextualise company-specific stock movements.

By incorporating these mediators, the study aims to unravel the pathways through which the technological crackdown affects stock prices. This approach facilitates a comprehensive analysis of both the direct and indirect effects of regulatory actions.

Methodology for Analysis

Individual Company Regressions:

Each company is analysed separately to understand how the independent and mediating variables affect their stock price changes. The model specification for each company includes:

$$\text{Price_Rate} = \beta_0 + \beta_1 \text{Net_Income_Rate} + \beta_2 \text{R_D_Rate} + \beta_3 \text{GXC_Rate} + \beta_4 \text{Interest_Rate (or its lag)} + \beta_5 \text{Housing_Rate (or its lag)} + \beta_6 \text{tech_crackdown} + \epsilon$$

**The best results yielding model is considered for individual companies' regression.*

Cumulative Regressions:

To assess the overall impact across all companies, a cumulative regression model is utilised. This approach aggregates data from all six companies to explore the broader effect of the independent variables on stock prices. The model specification is:

$$\text{Price_Rate} = \beta_0 + \beta_1 \text{Net_Income_Rate} + \beta_2 \text{R_D_Rate} + \beta_3 \text{GXC_Rate} + \beta_4 \text{Interest_Rate} + \beta_5 \text{Interest_Lag1_Rate} + \beta_6 \text{Interest_Lag2_Rate} + \beta_7 \text{Housing_Rate} + \beta_8 \text{Housing_Lag1_Rate} + \beta_9 \text{Housing_Lag2_Rate} + \beta_{10} \text{tech_crackdown} + \beta_{11} \text{Company_Tencent} + \beta_{12} \text{Company_Meituan} + \beta_{13} \text{Company_PDD} + \beta_{14} \text{Company_NetEase} + \beta_{15} \text{Company_JD} + \epsilon$$

In this model, we use dummy variables for each company to control for firm-specific effects, with Alibaba serving as the baseline.

Categorised Regressions:

To further refine our analysis, we grouped the companies into high-growth and medium-growth categories based on analysts' growth estimates from Yahoo Finance over the past five years. The categorisation was as follows: Alibaba was placed in the low growth category (0-10%), Tencent and Meituan were classified as medium growth (10%-20%), and JD.com, NetEase, and Pinduoduo were categorised as high growth (above 20%). The low-growth group served as the baseline. We then assessed how the independent variables' effects vary across these growth profiles. The model specification for these categorised regressions is:

$$\text{Price_Rate} = \beta_0 + \beta_1 \text{Net_Income_Rate} + \beta_2 \text{R_D_Rate} + \beta_3 \text{GXC_Rate} + \beta_4 \text{Interest_Rate} + \beta_5 \text{Interest_Lag1_Rate} + \beta_6 \text{Interest_Lag2_Rate} + \beta_7 \text{Housing_Rate} + \beta_8 \text{Housing_Lag1_Rate} + \beta_9 \text{Housing_Lag2_Rate} + \beta_{10} \text{tech_crackdown} + \beta_{11} \text{Group_High_Growth} + \beta_{12} \text{Group_Medium_Growth} + \epsilon$$

This analysis helps in understanding how firms with different growth trajectories respond to regulatory and economic changes.

Outlier Adjustment:

Given Pinduoduo's unique business model and significantly higher growth rate, which may skew the results, we conducted additional models excluding Pinduoduo. These adjusted models, for both individual and categorised regressions, follow the same structure but without Pinduoduo's data. This adjustment helps in evaluating whether the exclusion of a high-

growth outlier affects the overall findings and provides a clearer picture of the crackdown’s impact on the remaining companies.

Findings

This section details the findings from our analysis, structured into three major parts: Individual Company Regression Results, Cumulative Regression Results (both with and without Pinduoduo), and Categorised Regression Results. To provide a concise overview of the most significant outcomes across our models, the following table summarises the key results before we delve into the detailed discussions.

Model Type / Company	Overall Model Significance	Key Significant Predictors (Impact)	R-squared	Notable Insights
Individual Companies				
Alibaba	No (p=0.1635)	Interest_Lag2_Rate (Negative, marginal)	0.4024	Tech crackdown negative but not significant.
Tencent	Yes (p=0.00522)	GXC_Rate, Interest_Rate, Housing_Rate (All Positive)	0.6461	Strong explanatory power.
Meituan	Yes (p=0.02178)	Interest_Rate (Positive); Housing_Lag2_Rate, tech_crackdown (Both Negative)	0.6337	Highly susceptible to tech crackdown.
Pinduoduo	No (insignificant)	None	0.2359	Poor model fit; suggests unique dynamics.
NetEase	No (p=0.1727)	R&D_Rate (Negative); Interest_Rate (Positive)	0.3967	
JD.com	Yes (p=0.0447)	Net_Income_Rate (Positive); Housing_Lag1_Rate (Negative)	0.5153	Tech crackdown negative but not significant.
Cumulative Models				
With Pinduoduo	Yes (in 10 ⁻⁵)	tech_crackdown (Negative); Interest_Rate, Housing_Rate (Positive); Housing_Lag1_Rate	0.3126	Overarching negative impact of crackdown;

		(Negative); Company_PDD (Positive)		PDD an outlier.
Without Pinduoduo	Yes (p = 0.0001)	tech_crackdown (Negative); Interest_Rate, Housing_Rate (Positive); Housing_Lag1_Rate (Negative)	0.3375	Robust confirmation of crackdown impact.
Categorised Models				
With Pinduoduo	Yes (in 10 ⁻⁵)	tech_crackdown (Negative); Interest_Rate, Housing_Rate (Positive); Housing_Lag1_Rate (Negative)	0.2863	Normality issue, interpret cautiously.
Without Pinduoduo	Yes (in 10 ⁻⁵)	tech_crackdown (Negative); Interest_Rate, Housing_Rate (Positive); Housing_Lag1_Rate (Negative)	0.3288	Consistent impacts, growth groups not significant.

1. Individual Company Regression Results

Table 1: Regression Results of Individual companies

Variables	Alibaba	Tencent	Meituan	Pinduoduo	NetEase	JD.com
Constant	+0.20081 (0.28679)	-0.11337 (0.22696)	+0.73451 (0.27915)	+0.43391 (0.44545)	+0.144381 (0.290406)	+0.3664 (0.2793)
tech_crackdown	-0.41987 (0.45100)	+0.23704 (0.36426)	-1.33547** (0.41123)	-0.78893 (0.68655)	-0.301888 (0.459372)	-0.7661 (0.4631)
Net_Income_Rate	-0.04973 (0.21677)	-0.04008 (0.16251)	+0.19848 (0.27933)	-0.04471 (0.28473)	-0.006182 (0.210822)	+0.4496* (0.2041)
R&D_Rate	+0.25644 (0.21039)	+0.08890 (0.17814)	+0.27278 (0.23043)	+0.08625 (0.31967)	-0.438528. (0.219006)	+0.2529 (0.2260)
GXC_Rate	+0.31441 (0.20204)	+0.53576** (0.18167)	+0.03889 (0.19924)	+0.09103 (0.27905)	-0.323492 (0.231998)	-0.0483 (0.1879)
Interest_Rate	-	+0.35720. (0.20392)	+0.50142* (0.19213)	-	+0.781334* (0.267851)	-
Interest_Lag1_Rate	-	-	-	-0.25951 (0.28648)	-	-
Interest_Lag2_Rate	-0.4250 (0.23255)	-	-	-	-	-0.2507 (0.1831)
Housing_Rate	-	+0.49718* (0.18935)	-	-	+0.321092 (0.273607)	-

Housing_Lag1_Rate	-	-	-	-0.18190 (0.34372)	-	-0.4371* (0.2023)
Housing_Lag2_Rate	-0.30264 (0.23291)	-	-0.66626* (0.26409)	-	-	-
R-Square	0.4024	0.6461	0.6337	0.2359	0.3967	0.5153
Adjusted R-Square	0.1783	0.5133	0.4647	-0.1168	0.1704	0.3336

.p<0.1, *p<0.05, **p<0.01, ***p<0.001

Explanation: Number outside bracket is the B coefficient, number inside bracket is the standard error, * sign indicates the level of significance.

Alibaba

The regression model for Alibaba did not show statistical significance overall, with a p-value of 0.1635. This suggests that the variables included in the model do not collectively explain a significant portion of the variation in Alibaba's price rate. Among the individual predictors, none reached statistical significance. However, the second-order lag of the interest rate (Interest_Lag2_Rate) was marginally significant at the 90% confidence level (p-value = 0.103) and showed a negative association with the price rate. This indicates that delayed effects of changes in interest rates may slightly influence Alibaba's stock price in a negative manner. The coefficient for the tech_crackdown variable was also negative, implying that regulatory pressures could be lowering the price rate, although this effect was not statistically significant in this model.

Tencent

Tencent's regression model was statistically significant, with a p-value of 0.00522, suggesting that the included variables collectively explain a substantial portion of the variance in Tencent's price rate. Key significant predictors were the GXC_Rate, Interest_Rate, and Housing_Rate, all of which positively impacted the price rate. This indicates that as the global market exposure (GXC_Rate), interest rates, and housing rates increase, Tencent's price rate also increases. The model had an R-squared value of 64.61%, meaning about 64.61% of the variation in Tencent's price rate is explained by the model, and the adjusted R-squared value of 51.33% reflects a strong explanatory power after adjusting for the number of predictors in the model.

Meituan

The regression model for Meituan was statistically significant, with a p-value of 0.02178. The significant variables in the model included Interest_Rate, Housing_Lag2_Rate, and tech_crackdown. Interest_Rate had a positive effect on the price rate, indicating that higher interest rates are associated with an increase in Meituan's stock price. Conversely, Housing_Lag2_Rate and tech_crackdown had negative associations with the price rate. The tech_crackdown variable was notably significant at the 95% confidence level (p-value = 0.00636), suggesting that regulatory actions have a significant and negative impact on Meituan's stock price. The R-squared was 63.37%, and the adjusted R-squared was 46.47%, showing a substantial portion of the variance in Meituan's price rate is explained by the model.

Pinduoduo

Pinduoduo's regression model performed poorly compared to the other companies, with the overall model being statistically insignificant. None of the predictors showed statistical significance, indicating that the variables in the model do not effectively explain variations in Pinduoduo's price rate. Although the tech_crackdown variable had a negative coefficient, it was not statistically significant. The R-squared value was 23.59%, suggesting that the model explains only a small fraction of the variance in Pinduoduo's price rate. The adjusted R-squared was -0.1168, which is negative, indicating potential overfitting and suggesting that the model does not generalise well to new data. This poor performance led to the consideration of excluding Pinduoduo in subsequent cumulative and categorised analyses.

NetEase

NetEase's regression model was overall statistically insignificant with a p-value of 0.1727. However, two predictors, R&D_Rate and Interest_Rate, were statistically significant. R&D_Rate was negatively associated with the price rate, implying that higher research and development expenditures might be viewed negatively by investors, possibly due to increased costs or uncertain returns. Interest_Rate had a positive association with the price rate. The tech_crackdown variable again showed a negative coefficient but was not statistically significant. The R-squared value was 39.67%, and the adjusted R-squared was 17.04%, indicating that the model explains a moderate portion of the variance in NetEase's price rate.

JD.com

JD.com's regression model was statistically significant with a p-value of 0.0447, which falls under the 95% confidence level. Significant predictors included `Net_Income_Rate` and `Housing_Lag1_Rate`. `Net_Income_Rate` had a positive relationship with the price rate, aligning with expectations that higher net income rates boost stock prices. `Housing_Lag1_Rate` showed a negative association with the price rate, indicating that previous changes in housing rates might have a delayed adverse effect on JD.com's stock price. The `tech_crackdown` variable had a negative coefficient with a p-value of 0.1176, slightly above the 90% confidence level, suggesting a potential but not significant negative impact of regulatory actions on JD.com's stock. The model's R-squared was 51.53%, with an adjusted R-squared of 33.36%.

1.1 Residual Normality Test Results (Shapiro-Wilk)

To assess whether the residuals from the individual company regressions follow a normal distribution, we conducted the Shapiro-Wilk test for each firm. A p-value greater than 0.05 indicates failure to reject the null hypothesis of normality.

Companies	W-Statistic	p-value	Normality Assumption Met?
BABA	0.93833	0.1655	Yes
Tencent	0.93962	0.1764	Yes
Meituan	0.98225	0.9598	Yes
PDD	0.93541	0.1961	Yes
NetEase	0.93033	0.1112	Yes
JD	0.95006	0.2935	Yes

The results show that all companies have residuals that pass the Shapiro-Wilk test at the 5% significance level. Hence, the normality assumption for linear regression residuals is satisfied across all individual company models.

1.2 Multicollinearity Test Results (VIFs)

To assess the presence of multicollinearity in the independent variables used in the individual company regressions, we computed the Variance Inflation Factor (VIF) for each predictor. A VIF exceeding **5** is often considered a sign of moderate multicollinearity, and values exceeding **10** indicate serious multicollinearity concerns.

	Alibaba	Tencent	Meituan	Pinduoduo	NetEase	JD
Net_Income_Rate	1.823709	1.772873	4.558196	2.126116	1.32252	2.297345
R_D_Rate	1.556238	2.323265	4.280635	2.096241	1.34621 7	2.18064
GXC_Rate	1.588591	1.676455	1.70588	1.552049	1.57272 8	1.584094
Interest_Rate	2.875836	2.866777	2.116098	2.41885	2.55257	2.775987
Interest_Lag1_Rate	1.671347	2.211127	2.451442	1.599975	1.54318 9	1.694214
Interest_Lag2_Rate	1.707924	1.823099	1.969521	2.406277	1.76968 5	1.647613
Housing_Rate	2.028568	1.809867	1.74859	1.656229	2.31416 2	2.032031
Housing_Lag1_Rate	1.760765	3.345341	2.465058	2.548953	1.78078 7	1.883689
Housing_Lag2_Rate	1.550736	1.660312	3.327741	2.063889	1.64782 1	2.483153
tech_crackdown	2.402337	1.891076	1.793408	2.220091	1.84020 3	2.306954

All VIF values across companies are well below the commonly used threshold of 10, indicating **no significant multicollinearity issues** in any of the individual company regressions. While Meituan shows moderately high VIFs for Net_Income_Rate and R_D_Rate, they remain within acceptable bounds.

2. Cumulative Regression Results for Both With and Without Pinduoduo

The cumulative regression models aggregate data across all companies to assess broader trends and the collective impact of variables on stock prices. These models were analysed both with and without Pinduoduo to account for its potential outlier effects.

Table 2: Regression Results for Cumulative model

Variables	With Pinduoduo	Without Pinduoduo
Constant	+0.06807 (0.21014)	+0.10626 (0.21202)
tech_crackdown	-0.61578** (0.20711)	-0.59903** (0.22278)
Net_Income_Rate	-0.02228	-0.02002

	(0.08311)	(0.09032)
R&D_Rate	+0.11033 (0.08571)	+0.07612 (0.09068)
GXC_Rate	+0.04149 (0.09361)	+0.03943 (0.10036)
Interest_Rate	+0.40291*** (0.11478)	+0.50919*** (0.12568)
Interest_Lag1_Rate	-0.03443 (0.09587)	+0.03393 (0.10313)
Interest_Lag2_Rate	+0.03904 (0.09911)	+0.06571 (0.10583)
Housing_Rate	+0.23475* (0.10248)	+0.31113** (0.11188)
Housing_Lag1_Rate	-0.18488. (0.09979)	-0.18116. (0.10788)
Housing_Lag2_Rate	-0.08601 (0.09540)	-0.10783 (0.10272)
Company_Tencent	+0.09452 (0.25989)	+0.10728 (0.25685)
Company_Meituan	+0.34956 (0.27117)	+0.40161 (0.26815)
Company_PDD	+0.65821* (0.27337)	N/A
Company_NetEase	+0.22963 (0.26006)	+0.26470 (0.25702)
Company_JD	+0.17589 (0.26049)	+0.19384 (0.25758)
R-Square	0.3126	0.3375
Adjusted R-Square	0.2237	0.2419

.p<0.1, *p<0.05, **p<0.01, ***p<0.001.

Explanation: Number outside bracket is the B coefficient, number inside bracket is the standard error, * sign indicates the level of significance.

With Pinduoduo:

The cumulative regression model, including Pinduoduo, was statistically significant. The R-squared was 31.26%, and the adjusted R-squared was 22.37%, indicating that about a third of the variance in the price rate is explained by the model. Significant variables included Interest_Rate, Housing_rate, Housing_Lag1_Rate, tech_crackdown, and Company_PDD. Interest_Rate and Housing_Rate had positive associations with the price rate, meaning that increases in these rates are linked to higher stock prices. Housing_Lag1_Rate had a negative

coefficient (-0.18488), showing that past increases in housing rates can negatively affect the current price rate. The Company_PDD variable was significantly positive compared to the baseline company, Alibaba, indicating that Pinduoduo generally performs better in terms of price rate. The tech_crackdown variable was statistically significant with a negative association, suggesting a detrimental impact of regulatory crackdowns on stock prices across the firms.

Without Pinduoduo:

Excluding Pinduoduo, the cumulative regression model remained statistically significant with an R-squared of 33.75% and an adjusted R-squared of 24.19%. This model also showed significant effects for Interest_Rate, Housing_rate, Housing_Lag1_Rate, and tech_crackdown. The relationships were consistent with the previous model, where Interest_Rate and Housing_Rate positively impacted the price rate, and Housing_Lag1_Rate negatively affected it. The tech_crackdown variable continued to show a significant negative impact on the price rate, reinforcing the notion that regulatory actions harm the stock performance of these firms. Other company variables, including Company_Tencent, Company_Meituan, Company_NetEase, and Company JD, had positive coefficients compared to Alibaba but were not statistically significant. Company_Meituan was marginally significant (p-value = 0.137).

2.1 Residual Normality Test Results (Shapiro-Wilk Test)

To verify whether the residuals from the cumulative regression models are normally distributed—a key assumption in linear regression—we employed the **Shapiro-Wilk test**. A p-value above 0.05 indicates that the null hypothesis of normality cannot be rejected.

Model	W-Statistic	p-value	Normality Assumption Met?
Cumulative Regression	0.98808	0.3121	Yes
Cumulative Regression w/o PDD	0.9911	0.6833	Yes

Both versions of the cumulative regression models (with and without Pinduoduo) pass the Shapiro-Wilk test for normality at the 5% significance level. This suggests that the residuals

from these models are approximately normally distributed, supporting the validity of statistical inference based on these regressions.

2.2 Multicollinearity Test Results (Variance Inflation Factor – VIF)

To assess the presence of multicollinearity among the independent variables in the cumulative regression models, we employed the **Variance Inflation Factor (VIF)**. A VIF value exceeding 5 typically indicates moderate multicollinearity, while values above 10 suggest serious multicollinearity concerns.

Variable	w/ Pinduoduo	w/o Pinduoduo
Net Income Rate	1.16566	1.194349
R D Rate	1.23974	1.203819
GXC Rate	1.47886	1.474756
Interest Rate	2.22319	2.312483
Interest_Lag1_Rate	1.55097	1.557074
Interest_Lag2_Rate	1.65756	1.639811
Housing Rate	1.77242	1.832554
Housing_Lag1_Rate	1.68056	1.703936
Housing_Lag2_Rate	1.53574	1.544958
tech_crackdown	1.82353	1.83247
Company_Tencent	1.65254	1.590369
Company_Meituan	1.60754	1.558191
Company_PDD	1.6337	-
Company_NetEase	1.65473	1.592566
Company_JD	1.66013	1.599503

All VIF values for both versions of the model (with and without Pinduoduo) are well below the commonly used thresholds of 5 and 10. This indicates **no significant multicollinearity** concerns, and therefore, the estimated coefficients can be interpreted with greater confidence. The consistent VIF values across the two versions of the model further reinforce the robustness of the regression framework.

3. Categorized Regression Results for Both With and Without Pinduoduo

Categorised regression models were used to explore how the impact of variables differed across companies grouped by growth rates. These models were analysed with and without Pinduoduo to evaluate the robustness of the findings across different growth categories.

Table 3: Regression Results for Categorized Regression

Variables	With Pinduoduo	Without Pinduoduo
Constant	0.05996 (0.21135)	0.10671 (0.21123)
tech_crackdown	-0.59552** (0.20804)	-0.59929** (0.22194)
Net_Income_Rate	-0.02297 (0.08297)	-0.02926 (0.08934)
R&D_Rate	0.14457. (0.08418)	0.07756 (0.09010)
GXC_Rate	0.05245 (0.09403)	0.04278 (0.09995)
Interest_Rate	0.39670*** (0.11534)	0.51157*** (0.12513)
Interest_Lag1_Rate	-0.03515 (0.09644)	0.03397 (0.10275)
Interest_Lag2_Rate	0.03793 (0.09970)	0.06575 (0.10544)
Housing_Rate	0.21794* (0.10279)	0.30589** (0.11137)
Housing_Lag1_Rate	-0.19145. (0.10034)	-0.18275. (0.10748)
Housing_Lag2_Rate	-0.09159 (0.09593)	-0.10944 (0.10234)
Group_High_Growth	0.33756 (0.21489)	0.23001 (0.22189)
Group_Low_Growth	(Baseline)	(Baseline)
Group_Medium_Growth	0.21189 (0.22933)	0.24253 (0.22450)
R-Square	0.2863	0.3288
Adjusted R-Square	0.2144	0.2474

.p<0.1, *p<0.05, **p<0.01, ***p<0.001

Explanation: Number outside bracket is the B coefficient, number inside bracket is the standard error, * sign indicates the level of significance.

With Pinduoduo:

The categorised regression model, including Pinduoduo, was statistically significant with an R-squared of 28.63% and an adjusted R-squared of 21.44%. Significant variables included R&D_Rate, Interest_Rate, Housing_rate, Housing_Lag1_Rate, and tech_crackdown. Both Interest_Rate and Housing_Rate positively influenced the price rate, indicating that higher rates in these areas are associated with increased stock prices. Housing_Lag1_Rate had a negative coefficient (-0.19145), suggesting adverse delayed effects of housing rates on stock prices. The tech_crackdown variable was also significantly negative, confirming the negative impact of regulatory actions. Growth group variables, such as Group_High_Growth and Group_Medium_Growth, had positive coefficients compared to the low-growth group baseline, though they were not statistically significant. Group_High_Growth was marginally significant (p-value = 0.118).

Without Pinduoduo:

The categorised regression model excluding Pinduoduo was statistically significant with an R-squared of 32.88% and an adjusted R-squared of 24.74%. Significant variables remained consistent with the previous model, including Interest_Rate, Housing_rate, Housing_Lag1_Rate, and tech_crackdown. Interest_Rate and Housing_Rate continued to show positive associations with the price rate, while Housing_Lag1_Rate had a negative association (-0.18275). The tech_crackdown variable also maintained its significant negative impact, highlighting the detrimental effect of regulatory crackdowns on stock prices. Growth group variables again had positive coefficients compared to the baseline, although they were not statistically significant.

3.1 Residual Normality Test Results (Shapiro-Wilk Test)

To verify the normality of residuals in the categorised regression models, we employed the Shapiro-Wilk test. This test evaluates the null hypothesis that the data is drawn from a normally distributed population. A p-value greater than 0.05 typically suggests that the residuals are approximately normal.

	W-Statistics	p-value	Normality Assumption Met?
Categorised Regression	0.97277	0.009354	No
Categorised Regression w/o PDD	0.98934	0.5294	Yes

For the categorised regression including Pinduoduo, the p-value is below the 0.05 threshold, indicating that the residuals do not follow a normal distribution. This **suggests caution** when interpreting the regression coefficients or making inferential claims, as standard linear regression assumptions are violated.

However, the categorised model excluding Pinduoduo does meet the normality requirement, with a p-value well above 0.05. Therefore, insights drawn from this model can be considered more statistically robust.

Despite the deviation in the full model, useful patterns and directional insights may still be obtained — but should be interpreted carefully and preferably in conjunction with other diagnostic checks or robustness tests.

3.2 Multicollinearity Test Results (Variance Inflation Factor – VIF)

To assess potential multicollinearity in the categorised regression models, the Variance Inflation Factor (VIF) was calculated for all independent variables. A VIF value above 5 (and especially above 10) is often considered indicative of problematic multicollinearity that could distort coefficient estimates.

Variable	w/ Pinduoduo	w/o Pinduoduo
Net Income Rate	1.14783	1.177178
R_D_Rate	1.18169	1.197217
GXC_Rate	1.47426	1.47347
Interest Rate	2.21821	2.309328
Interest_Lag1_Rate	1.55094	1.557052

Interest_Lag2_Rate	1.65743	1.639776
Housing_Rate	1.76165	1.829392
Housing_Lag1_Rate	1.67891	1.703643
Housing_Lag2_Rate	1.53454	1.544658
tech_crackdown	1.81804	1.831988
Group_High_Growth	1.93962	1.773249
Group_Medium_Growth	1.94082	1.774056

The results show that none of the variables exhibit high multicollinearity, with all VIF values comfortably below the conventional threshold of 5. This indicates that the independent variables in both models (with and without Pinduoduo) are not excessively correlated with each other, and thus the regression coefficients can be interpreted with greater confidence.

These VIF scores confirm that multicollinearity is not a concern in the categorised regression models.

Conclusion

This research investigated the profound impact of the Chinese government's regulatory crackdown on the stock prices of major technology companies, specifically Alibaba, Tencent, Meituan, Pinduoduo, JD.com, and NetEase. Our analysis consistently reveals a significant and pervasive negative effect of the tech crackdown on the stock market valuations of these firms. This finding underscores that policy risks are a primary driver of market sentiment and valuation in China's tech sector.

Beyond direct regulation, our study highlights the complex interplay of macroeconomic forces. While current interest rates and housing prices often show a positive association with stock performance, indicating specific market dynamics at play, lagged housing rates reveal a nuanced and sometimes detrimental long-term influence. This suggests that past economic conditions, particularly those impacting consumer wealth and spending through the housing market, can exert a delayed but significant drag on tech company valuations.

We also observed varying degrees of resilience and susceptibility among individual companies. For instance, Tencent's positive association with global market exposure suggests that international diversification or a broader operational footprint can offer a buffer against domestic regulatory pressures. Conversely, Meituan's distinct vulnerability to both the crackdown and lagged housing rates indicates that firms heavily reliant on domestic consumer spending may face compounded challenges. Pinduoduo's unique market dynamics, which were not fully explained by our model, highlight the importance of understanding idiosyncratic company-specific factors alongside broader trends. Furthermore, our categorisation of companies by growth potential indicates that inherent growth trajectories may partially moderate the adverse impacts of regulations, as investors might perceive high-growth firms as better equipped to navigate policy headwinds.

In sum, this research firmly establishes that external factors—regulatory crackdowns and macroeconomic shifts—are dominant drivers of stock price movements for major Chinese tech companies. Internal financial metrics, while important, appear secondary to these powerful external forces during periods of intense scrutiny.

Policy Implications and Investor Strategies

These findings carry significant implications for both Chinese policymakers and global investors. For Chinese regulators, the consistent negative impact of the "tech crackdown" on valuations suggests that unpredictable and stringent regulatory actions carry substantial economic costs, potentially stifling innovation, impacting employment, and deterring both domestic and foreign investment in a crucial growth sector. To foster long-term sustainable growth and maintain market confidence, policymakers should consider adopting a more transparent, predictable, and rule-based regulatory framework. This could involve clearly defined guidelines, phased implementation of new policies, and open dialogue with industry stakeholders to mitigate market shockwaves and encourage compliance rather than reactive withdrawal. A balance between oversight and fostering a vibrant digital economy is essential.

For international investors, our study strongly advises a heightened focus on regulatory risk assessment when evaluating Chinese tech companies. Beyond traditional financial analysis, understanding the nuances of government policy, its potential future trajectories, and the political economy context is paramount. Investors should consider companies' exposure to global markets and their inherent growth potential as key indicators of resilience against domestic policy shifts. The lagged effects of housing rates also suggest that investors should pay close attention to the long-term health of the Chinese consumer economy, as past conditions can have a delayed and significant impact on tech valuations. To navigate this dynamic and politically sensitive market effectively, a strategy that incorporates rigorous regulatory scenario planning, diversification across sectors and geographies, and a long-term perspective will be crucial.

Limitations and Future Directions

Despite the comprehensive scope of our analysis, several limitations should be acknowledged. First, the inclusion of a limited number of major technology companies may restrict the generalisability of our findings. Expanding the dataset to include a broader range of companies across different sectors and growth stages would provide a more diverse perspective and enhance the robustness of our conclusions. This could involve analysing firms from emerging technology sectors or those at varying stages of regulatory scrutiny.

Second, our study primarily utilised linear regression models, which, while effective for identifying relationships, may not fully capture the complex, non-linear dynamics of stock price behaviour. Future research could explore alternative modelling approaches, such as machine learning algorithms or non-linear regression models, to better capture these complexities and provide deeper insights into stock market volatility.

Additionally, our study focused on a specific set of variables, including net income growth, R&D growth, interest rates, housing prices, and regulatory factors. Although these variables are significant, other potential influencers, such as geopolitical events, global market trends, or corporate governance practices, were not considered. Including a broader array of variables in future analyses could provide a more holistic view of the factors driving stock market performance.

Lastly, the temporal scope of our study, constrained to recent years, limits our ability to observe long-term trends and the evolution of regulatory impacts. Expanding the temporal range of our analysis to include historical data could offer valuable insights into how the relationships between economic variables and stock prices evolve over time and under different regulatory regimes.

In conclusion, addressing these limitations in future research will be crucial for a more comprehensive understanding. Expanding the dataset, employing diverse modelling techniques, incorporating additional variables, and extending the temporal scope will collectively contribute to a more thorough analysis of stock market dynamics within the context of a rapidly evolving economic and regulatory landscape.

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Appendix

R code for individual companies: -

```
# Load necessary libraries

library(dplyr)

library(readxl)

# Load the Excel file containing all the data

financial_data <- read_excel("C:/Users/shikh/OneDrive/Desktop/Desktop_New/Left/ICS/Research/CSVs/
BABA_IncomeSt.xls", sheet = "BABA")

# Ensure the 'Date' column is in Date format

financial_data$Date <- as.Date(financial_data$Date, format = "%d-%m-%Y")

# Create the tech_crackdown dummy variable

financial_data$tech_crackdown <- ifelse(financial_data$Date >= as.Date("2020-11-01"), 1, 0)

# Rate of change for all relevant columns

financial_data <- financial_data %>% arrange(Date) %>%

mutate(

  Net_Income_Rate = (lead(`Net Income`) - `Net Income`) / `Net Income`,

  R_D_Rate = (lead(`R&D`) - `R&D`) / `R&D`,

  Price_Rate = (lead(Price) - Price) / Price,

  GXC_Rate = (lead(GXC) - GXC) / GXC,

  Interest_Rate = (lead(Interest) - Interest) / Interest,

  Housing_Rate = (lead(Housing) - Housing) / Housing,

  Interest_Lag1_Rate = (lead(`Interest_lag1`) - `Interest_lag1`) / `Interest_lag1`,

  Interest_Lag2_Rate = (lead(`Interest_lag2`) - `Interest_lag2`) / `Interest_lag2`,

  Housing_Lag1_Rate = (lead(`Housing_lag1`) - `Housing_lag1`) / `Housing_lag1`,
```

```

Housing_Lag2_Rate = (lead(`Housing_lag2`) - `Housing_lag2`) / `Housing_lag2`

) %>%

filter(

  !is.na(Net_Income_Rate) & !is.na(R_D_Rate) & !is.na(Price_Rate) &

  !is.na(GXC_Rate) & !is.na(Interest_Rate) & !is.na(Housing_Rate) &

  !is.na(Interest_Lag1_Rate) & !is.na(Interest_Lag2_Rate) &

  !is.na(Housing_Lag1_Rate) & !is.na(Housing_Lag2_Rate)

)

# Standardise the rate of change columns

financial_data <- financial_data %>%

mutate(

  Net_Income_Rate = scale(Net_Income_Rate),

  R_D_Rate = scale(R_D_Rate),

  Price_Rate = scale(Price_Rate),

  GXC_Rate = scale(GXC_Rate),

  Interest_Rate = scale(Interest_Rate),

  Housing_Rate = scale(Housing_Rate),

  Interest_Lag1_Rate = scale(Interest_Lag1_Rate),

  Interest_Lag2_Rate = scale(Interest_Lag2_Rate),

  Housing_Lag1_Rate = scale(Housing_Lag1_Rate),

  Housing_Lag2_Rate = scale(Housing_Lag2_Rate)

)

# Define the linear regression model

model <- lm(Price_Rate ~ Net_Income_Rate + R_D_Rate + GXC_Rate +

  Interest_Rate + Interest_Lag1_Rate + Interest_Lag2_Rate +

  Housing_Rate + Housing_Lag1_Rate + Housing_Lag2_Rate +

  tech_crackdown, data = financial_data)

```

```

# Summarise the regression results
summary(model)

# --- Normality Checks for Residuals ---

# Extract residuals
residuals_model <- residuals(model)

# Histogram
hist(residuals_model, main = "Histogram of Residuals", xlab = "Residuals", breaks = 20, col =
"lightblue")

# QQ Plot
qqnorm(residuals_model)
qqline(residuals_model, col = "red")

# Shapiro-Wilk test
shapiro_test <- shapiro.test(residuals_model)
print(shapiro_test)

```

R code for cumulative regression: -

```

# Load necessary libraries
library(dplyr)
library(readxl)
library(tidyr)
library(car)      # For VIF
library(stats)    # For Shapiro-Wilk test

# File path
file_path <- "C:/Users/shikh/OneDrive/Desktop/Desktop_New/Left/ICS/Research/CSVs/BABA_IncomeSt.xls"

```

```

# Load the cumulative sheet

df_cumulative <- read_excel(file_path, sheet = "cumulative")

# Convert 'Date' column to Date format

df_cumulative$Date <- as.Date(df_cumulative$Date, format = "%d-%m-%Y")

df_cumulative$Company <- as.factor(df_cumulative$Company)

# Convert relevant columns to numeric (IMPORTANT STEP)

cols_to_numeric <- c("Net Income", "R&D", "Price", "GXC",
                    "Interest", "Housing",
                    "Interest_lag1", "Interest_lag2",
                    "Housing_lag1", "Housing_lag2")

df_cumulative[cols_to_numeric] <- lapply(df_cumulative[cols_to_numeric], function(x)
as.numeric(as.character(x)))

# List of selected companies

companies <- c("BABA", "Tencent", "Meituan", "PDD", "NetEase", "JD")

# Define full date range

full_dates <- as.Date(c(
    "2017-12-31", "2018-03-31", "2018-06-30", "2018-09-30", "2018-12-31",
    "2019-03-31", "2019-06-30", "2019-09-30", "2019-12-31", "2020-03-31",
    "2020-06-30", "2020-09-30", "2020-12-31", "2021-03-31", "2021-06-30",
    "2021-09-30", "2021-12-31", "2022-03-31", "2022-06-30", "2022-09-30",
    "2022-12-31", "2023-03-31", "2023-06-30", "2023-09-30"
))

# Align each company's data

aligned_data_list <- list()

for (company in companies) {

```

```

company_data <- df_cumulative %>%

  filter(Company == company) %>%

  right_join(data.frame(Date = full_dates), by = "Date") %>%

  arrange(Date) %>%

  fill(Company, .direction = "downup")

aligned_data_list[[company]] <- company_data
}

aligned_data <- bind_rows(aligned_data_list)

# Create dummy variables
aligned_data <- aligned_data %>%

  mutate(

    Company_Tencent = ifelse(Company == "Tencent", 1, 0),

    Company_Meituan = ifelse(Company == "Meituan", 1, 0),

    Company_PDD = ifelse(Company == "PDD", 1, 0),

    Company_NetEase = ifelse(Company == "NetEase", 1, 0),

    Company_JD = ifelse(Company == "JD", 1, 0),

    tech_crackdown = ifelse(Date >= as.Date("2020-11-01"), 1, 0)

  )

# Compute rate of change
aligned_data <- aligned_data %>%

  arrange(Company, Date) %>%

  group_by(Company) %>%

  mutate(

    Net_Income_Rate = (lead(`Net Income`) - `Net Income`) / `Net Income`,

    R_D_Rate = (lead(`R&D`) - `R&D`) / `R&D`,

    Price_Rate = (lead(Price) - Price) / Price,

    GXC_Rate = (lead(GXC) - GXC) / GXC,

    Interest_Rate = (lead(Interest) - Interest) / Interest,

```

```

Housing_Rate = (lead(Housing) - Housing) / Housing,

Interest_Lag1_Rate = (lead(Interest_lag1) - Interest_lag1) / Interest_lag1,

Interest_Lag2_Rate = (lead(Interest_lag2) - Interest_lag2) / Interest_lag2,

Housing_Lag1_Rate = (lead(Housing_lag1) - Housing_lag1) / Housing_lag1,

Housing_Lag2_Rate = (lead(Housing_lag2) - Housing_lag2) / Housing_lag2

) %>%

ungroup() %>%

filter(

  !is.na(Net_Income_Rate) & !is.na(R_D_Rate) & !is.na(Price_Rate) &

  !is.na(GXC_Rate) & !is.na(Interest_Rate) & !is.na(Housing_Rate) &

  !is.na(Interest_Lag1_Rate) & !is.na(Interest_Lag2_Rate) &

  !is.na(Housing_Lag1_Rate) & !is.na(Housing_Lag2_Rate)

)

# Standardise the rate of change columns

aligned_data <- aligned_data %>%

mutate(

  Net_Income_Rate = scale(Net_Income_Rate),

  R_D_Rate = scale(R_D_Rate),

  Price_Rate = scale(Price_Rate),

  GXC_Rate = scale(GXC_Rate),

  Interest_Rate = scale(Interest_Rate),

  Housing_Rate = scale(Housing_Rate),

  Interest_Lag1_Rate = scale(Interest_Lag1_Rate),

  Interest_Lag2_Rate = scale(Interest_Lag2_Rate),

  Housing_Lag1_Rate = scale(Housing_Lag1_Rate),

  Housing_Lag2_Rate = scale(Housing_Lag2_Rate)

)

# Run the regression model

```

```

model <- lm(Price_Rate ~ Net_Income_Rate + R_D_Rate + GXC_Rate +

            Interest_Rate + Interest_Lag1_Rate + Interest_Lag2_Rate +

            Housing_Rate + Housing_Lag1_Rate + Housing_Lag2_Rate +

            tech_crackdown + Company_Tencent + Company_Meituan +

            Company_PDD + Company_NetEase + Company_JD,

            data = aligned_data)

# Output summary

summary(model)

# ---- Diagnostics ----

# 1. Normality of Residuals (Shapiro-Wilk Test)

shapiro.test(residuals(model))

# 2. Multicollinearity Check using VIF

vif(model)

```

R code for categorised regression: -

```

# Load necessary libraries

library(dplyr)

library(readxl)

library(tidyr)

library(car)      # For VIF

library(stats)   # For Shapiro-Wilk test

# Define the path to your Excel file

file_path <- "BABA_IncomeSt.xls"

```

```

# Load the "cumulative" sheet

df_cumulative <- read_excel(file_path, sheet = "cumulative")

# Convert 'Date' column to Date format

df_cumulative$Date <- as.Date(df_cumulative$Date, format = "%d-%m-%Y")

# Convert Company to factor

df_cumulative$Company <- as.factor(df_cumulative$Company)

# Ensure all relevant columns are numeric

df_cumulative <- df_cumulative %>%

  mutate(across(c(`Net Income`, `R&D`, Price, GXC, Interest, Housing,

                  Interest_lag1, Interest_lag2, Housing_lag1, Housing_lag2),

                ~as.numeric(.)))

# List of companies

companies <- c("BABA", "Tencent", "Meituan", "PDD", "NetEase", "JD")

# Full list of dates

full_dates <- as.Date(c(

  "2017-12-31", "2018-03-31", "2018-06-30", "2018-09-30", "2018-12-31",

  "2019-03-31", "2019-06-30", "2019-09-30", "2019-12-31", "2020-03-31",

  "2020-06-30", "2020-09-30", "2020-12-31", "2021-03-31", "2021-06-30",

  "2021-09-30", "2021-12-31", "2022-03-31", "2022-06-30", "2022-09-30",

  "2022-12-31", "2023-03-31", "2023-06-30", "2023-09-30"

))

# Align each company's data

aligned_data_list <- list()

for (company in companies) {

```

```

company_data <- df_cumulative %>%

  filter(Company == company) %>%

  right_join(data.frame(Date = full_dates), by = "Date") %>%

  arrange(Date) %>%

  fill(Company, .direction = "downup")

aligned_data_list[[company]] <- company_data
}

aligned_data <- bind_rows(aligned_data_list)

# Define EPS growth groups
high_growth <- c("PDD", "JD", "NetEase")
medium_growth <- c("Meituan", "Tencent")
low_growth <- c("BABA")

# Add dummy variables
aligned_data <- aligned_data %>%

  mutate(

    Group_High_Growth = ifelse(Company %in% high_growth, 1, 0),

    Group_Medium_Growth = ifelse(Company %in% medium_growth, 1, 0),

    Group_Low_Growth = ifelse(Company %in% low_growth, 1, 0),

    tech_crackdown = ifelse(Date >= as.Date("2020-11-01"), 1, 0)

  )

# Compute rate of change for relevant columns
aligned_data <- aligned_data %>%

  arrange(Company, Date) %>%

  group_by(Company) %>%

  mutate(

    Net_Income_Rate = (lead(`Net Income`) - `Net Income`) / `Net Income`,

    R_D_Rate = (lead(`R&D`) - `R&D`) / `R&D`,

```

```

Price_Rate = (lead(Price) - Price) / Price,

GXC_Rate = (lead(GXC) - GXC) / GXC,

Interest_Rate = (lead(Interest) - Interest) / Interest,

Housing_Rate = (lead(Housing) - Housing) / Housing,

Interest_Lag1_Rate = (lead(Interest_lag1) - Interest_lag1) / Interest_lag1,

Interest_Lag2_Rate = (lead(Interest_lag2) - Interest_lag2) / Interest_lag2,

Housing_Lag1_Rate = (lead(Housing_lag1) - Housing_lag1) / Housing_lag1,

Housing_Lag2_Rate = (lead(Housing_lag2) - Housing_lag2) / Housing_lag2

) %>%

ungroup() %>%

filter(

  !is.na(Net_Income_Rate) & !is.na(R_D_Rate) & !is.na(Price_Rate) &

  !is.na(GXC_Rate) & !is.na(Interest_Rate) & !is.na(Housing_Rate) &

  !is.na(Interest_Lag1_Rate) & !is.na(Interest_Lag2_Rate) &

  !is.na(Housing_Lag1_Rate) & !is.na(Housing_Lag2_Rate)

)

# Standardise rate of change columns

aligned_data <- aligned_data %>%

mutate(across(c(Net_Income_Rate, R_D_Rate, Price_Rate, GXC_Rate,

               Interest_Rate, Housing_Rate, Interest_Lag1_Rate,

               Interest_Lag2_Rate, Housing_Lag1_Rate, Housing_Lag2_Rate),

          scale))

# Run the regression model

model <- lm(Price_Rate ~ Net_Income_Rate + R_D_Rate + GXC_Rate +

           Interest_Rate + Interest_Lag1_Rate + Interest_Lag2_Rate +

           Housing_Rate + Housing_Lag1_Rate + Housing_Lag2_Rate +

           tech_crackdown + Group_High_Growth + Group_Medium_Growth,

          data = aligned_data)

```

```
# Print summary of model
summary(model)

# -----

# Normality of Residuals
# -----

shapiro_test <- shapiro.test(residuals(model))

print(shapiro_test)

# -----

# Multicollinearity Test
# -----

vif_values <- vif(model)

print(vif_values)
```

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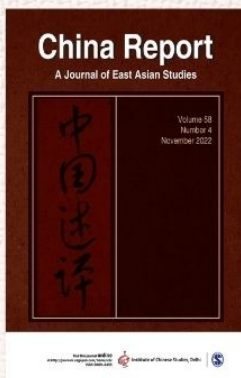


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