

U.S. Technology Stock Market Returns and the Hang Seng TECH Index: Evidence on Cross-Market Spillovers

Tianyi Zhang

*Design School, Xi'an Jiaotong-Liverpool University, Suzhou, China
Tianyi.Zhang23@student.xjtlu.edu.cn*

Abstract. Against the backdrop of growing interconnectedness of global tech asset pricing, this paper investigates cross-market return spillovers from U.S. tech stocks to China's Hong Kong technology sector. Using 733 daily observations spanning January 2023 to December 2025, the study aligns each trading day in China's Hong Kong market with the prior completed U.S. session before China's Hong Kong opens, and adopts OLS and XGBoost to examine linear linkage, out-of-sample performance and feature contributions. After controlling for Hang Seng Index returns, USD/HKD returns, VIX and Sino-U.S. 10-year bond yields, the Nasdaq-100 return coefficient remains significantly positive at the 5% level, revealing the U.S. tech market delivers modest yet robust incremental information for Hang Seng TECH Index returns. Out-of-sample results show OLS marginally outperforms XGBoost, meaning nonlinear tree models fail to boost fitting power within this sample and variable set. SHAP analysis verifies Hang Seng Index returns dominate model explanatory power, while Nasdaq-100 returns carry limited feature importance. By matching non-overlapping trading hours and interpretable machine learning, this paper distinguishes average marginal effects from variable fitting contributions, offering new empirical evidence for tech stock co-movement and risk evaluation of China's Hong Kong tech market.

Keywords: technology stock market, Hang Seng TECH Index, cross-market return spillovers

1. Introduction

In the context of the continuous reshaping of industrial structure and capital allocation by the global digital economy, the technology sector has become an important channel linking innovation expectations, risk appetite, and cross-border capital flows. The Nasdaq-100 Index focuses on the market performance of large technology and growth-oriented firms in the United States, while the Hang Seng TECH Index represents listed companies with strong technology exposure and platform-economy characteristics in China's Hong Kong market. Due to the strong correlation between the two markets in terms of industry exposure, investor structure, and global liquidity environment, as well as obvious differences in trading time zones, the price information formed in the previous trading session of the U.S. market may be repriced when China's Hong Kong market subsequently opens. Existing studies show that the U.S. stock market has long played a leading role in international information transmission, and its return and volatility shocks can spread to the Asia-

Pacific market. Further evidence shows that Nasdaq has a more prominent transmission role in China's technology and growth industries. Accordingly, this paper investigates whether the previous U.S. trading session's Nasdaq-100 Index return significantly affects the contemporaneous Hang Seng TECH Index return.

The existing literature mainly analyzes the relationship between the United States, China's Hong Kong, and China's capital markets from the perspectives of international market linkage, return spillovers, volatility transmission, and state dependence, but evidence remains limited for the specific pairing of the Nasdaq-100 Index and the Hang Seng TECH Index, despite their similar technology-growth exposures. After controlling for the Hang Seng Index return, the USD/HKD return, the VIX return, and Chinese and U.S. long-term government bond yields, this paper uses OLS and XGBoost to estimate these relationships and compares the fitting performance and feature importance of the two models. This paper aims to supplement the empirical evidence of cross-market transmission of technology-stock indices, and to provide evidence for risk identification and data-driven investment decision-making in China's Hong Kong technology sector.

2. Literature review and theoretical analysis

Research on international stock-market information transmission generally finds that the U.S. market plays a strong leading role in information transmission. U.S. market shocks can be quickly transmitted to other markets, while other single markets have relatively limited reverse explanatory power for the U.S. market [1]. Both U.S. and regional factors affect return volatility in markets such as China's Hong Kong, and exchange rates and market openness alter the relative importance of spillovers [2]. The sensitivity of China's Hong Kong market to U.S. stock returns and long-term interest rates varies over time [3]. After accounting for non-overlapping trading hours, return spillovers from the United States to China's Hong Kong are short-lived and state-dependent [4]. U.S. market shocks are often absorbed by Chinese markets on the following trading day, and spillovers from the Nasdaq to technology and growth-oriented sectors are more prominent [5]. Volatility spillovers among Shanghai, China's Hong Kong, and the United States are asymmetric, time-varying, and stronger during high-volatility regimes [6]. The United States is an important source of return and volatility shocks, while China's Hong Kong is a major recipient and transmission node connecting the United States and Mainland China markets [7].

Existing studies also suggest that the cross-market return relationship may not be a stable single linear mapping. The ordinary least squares method can identify the average marginal impact of U.S. technology stock returns after controlling for local market, exchange rate, risk sentiment, and interest rate factors. However, financial returns are affected by market states and interactions among variables, and the potential threshold effect and nonlinear structure may make the linear model miss some predictive information. Machine learning research provides additional evidence. XGBoost performs better in longer-horizon excess-return forecasting, but the traditional model and the machine learning model have their own advantages across different forecast horizons [8]. XGBoost and other tree models can be combined with feature importance to improve predictive interpretability [9]. Models incorporating XGBoost can improve forecasting performance, and lagged VIX and the dollar factor have important explanatory value [10]. Therefore, this paper uses OLS to estimate linear relationships and XGBoost for nonlinear fitting and feature importance comparison, which complement each other.

In theory, the Nasdaq-100 Index may affect the Hang Seng TECH Index through three paths. First, the U.S. market closes before China's Hong Kong market opens. Its closing prices incorporate macroeconomic information, technology-sector expectations, and global risk appetite, which may

subsequently be reflected in China's Hong Kong equity prices. Second, both indices have substantial exposure to technology-oriented firms, and interest rate changes, valuation conditions, and industry earnings expectations may trigger adjustments in the same direction. Third, portfolio rebalancing and sentiment contagion among global institutional investors may strengthen cross-market comovement. After controlling for the Hang Seng Index return, the USD/HKD return, the VIX return, and Chinese and U.S. 10-year government bond yields, the coefficient on the lagged Nasdaq-100 Index return captures its incremental explanatory effect. Accordingly, this paper puts forward the following research hypothesis:

H1: The return of the Nasdaq-100 Index during the most recent completed U.S. trading session before China's Hong Kong market opens has a significant positive effect on the contemporaneous return of the Hang Seng TECH Index.

3. Research design

This paper adopts daily data spanning January 3, 2023 to December 31, 2025. Data of Nasdaq-100, VIX, USD/HKD exchange rate and U.S. 10-year Treasury yield are collected from Nasdaq Indexes, Cboe and Federal Reserve respectively. Hang Seng TECH Index and Hang Seng Index data come from Hang Seng Indexes Company Limited, while China's 10-year government bond yield is sourced from ChinaBond. Given non-overlapping trading hours, each China's Hong Kong trading day is matched with the latest completed U.S. session before China's Hong Kong opens. For holiday-missing exchange rate and bond yield data, the latest available observation is carried forward. All continuous variables are winsorized at the 1st and 99th percentiles before formal regression estimation to mitigate the interference of extreme outliers.

The dependent variable is the daily logarithmic return of the Hang Seng TECH Index, calculated from its closing prices. The core explanatory variable NDX denotes the daily log return of the Nasdaq-100 Index from the latest completed U.S. trading session prior to China's Hong Kong market's opening. A set of control variables are incorporated to isolate cross-market tech spillover effects: HSI is the daily logarithmic return of the broad Hang Seng Index capturing overall equity-market co-movement in China's Hong Kong market. FX stands for the daily log change in the USD/HKD exchange rate to reflect linked exchange rate fluctuations. VIX refers to the logarithmic return of the VIX index observed over the matching U.S. trading session, proxying global market risk sentiment. $CN10Y$ is the raw level of China's 10-year government bond yield, representing domestic long-term interest rate conditions. $US10Y$ is the level of the U.S. 10-year Treasury yield recorded alongside the Nasdaq-100 session, controlling for U.S. valuation and monetary environment shocks. All index and exchange rate metrics are computed as logarithmic returns, while bond yields retain their original level values. All U.S.-originated variables share identical timestamps to ensure all relevant information is fully available before China's Hong Kong market opens. This paper uses the ordinary least squares method to test the average linear association between U.S. technology-stock returns and the Hang Seng TECH Index return. The baseline specification is shown in Equation (1):

$$HSTECH_t = \beta_0 + \beta_1 NDX_{t-1} + \beta_2 HSI_t + \beta_3 FX_t + \beta_4 VIX_{t-1} + \beta_5 CN10Y_t + \beta_6 US10Y_{t-1} + \varepsilon_t \quad (1)$$

4. Empirical results and analysis

4.1. Descriptive statistics

Table 1 reports descriptive statistics for the main variables. The average daily return of the Hang Seng TECH Index is 0.0563%, and the standard deviation is 2.0231%, which is substantially higher than the Hang Seng Index standard deviation of 1.3611%, indicating that China's Hong Kong technology sector has greater return volatility and market sensitivity during the sample period. The average daily return of the Nasdaq-100 Index is 0.1102%, with a standard deviation of 1.1413%, and its average return is higher than that of the Hang Seng TECH Index, but the volatility is relatively low. The sample means of the two technology indices are positive, which initially reflects the strong overall performance of technology assets during the sample period, but descriptive statistics alone do not establish a stable predictive or causal relationship between the two.

Table 1. Rules to format sections

Variable	Observations	Mean	Standard Deviation	Minimum	Median	Maximum
HSTECH_Return	733	0.0563	2.0231	-4.4597	-0.0698	5.6823
NDX_Return	733	0.1102	1.1413	-3.0647	0.1522	2.7393
HSI_Return	733	0.0534	1.3611	-2.8443	-0.0057	3.8916
USDHKD_Return	733	-0.0007	0.0468	-0.1520	0.0000	0.1214
VIX_Return	733	-0.1254	6.5273	-16.0450	-0.5814	20.1645
CN10Y_Level	733	2.2262	0.4205	1.6218	2.2461	2.9169
US10Y_Level	733	4.1584	0.3285	3.3900	4.2200	4.8368

The control variables show different fluctuation characteristics. The standard deviation of the USD/HKD return is only 0.0468%, reflecting the relatively limited short-term variation of the exchange rate under the linked exchange rate system. The standard deviation of the VIX return is 6.5273%, which is substantially higher than the standard deviations of the other return variables, indicating that changes in market risk sentiment have pronounced jumps and asymmetric movements. The sample averages of the Chinese and U.S. 10-year government bond yields are 2.2262% and 4.1584%, respectively, and U.S. long-term interest rates are generally higher. The above differences show that Hang Seng TECH Index returns may be affected not only by information from U.S. technology stocks but also by China's Hong Kong market conditions, risk sentiment, exchange-rate movements, and Chinese and U.S. interest rates. It is therefore necessary to include these variables in the subsequent regressions.

4.2. Baseline regression analysis

Table 2 presents sequential regression results on the linkage between Nasdaq-100 and Hang Seng TECH Index returns. Newey-West standard errors with five lags are adopted to address heteroskedasticity and short-run serial correlation in daily financial data. Model 1 shows the Nasdaq-100 coefficient stands at 0.2362 and is significant at the 1% level, confirming a strong positive raw return spillover without controls. Adding HSI returns in Model 2 cuts the NDX coefficient to an insignificant 0.0050, while HSI reaches 1.3922 at the 1% significance level, and adjusted R^2 rises sharply from 0.0164 to 0.8777. This indicates local China's Hong Kong market

movements dominate contemporaneous Hang Seng TECH fluctuations, and omitting domestic market factors severely overstates the independent predictive power of U.S. technology stock returns.

Table 2. Rules to format sections

Variable	Model 1	Model 2	Model 3
NDX_Return	0.2362*** (4.1408)	0.0050 (0.2064)	0.0843** (2.2755)
HSI_Return	-	1.3922*** (61.5164)	1.4018*** (62.3560)
USDHKD_Return	-	-	-0.8379 (-1.5890)
VIX_Return	-	-	0.0190*** (2.9008)
CN10Y_Level	-	-	0.0920 (1.2442)
US10Y_Level	-	-	0.0744 (0.7196)
Constant	0.0302 (0.4163)	-0.0186 (-0.6621)	-0.5405 (-1.0299)
Observations	733	733	733
Adjusted R ²	0.0164	0.8777	0.8794

Note: Newey-West robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

In Model 3, the coefficient on the Nasdaq-100 Index returns rises to 0.0843 and is significant at the 5% level. The result means that holding the overall market, exchange rate, risk sentiment, and long-term interest rates in China and the United States constant, the Hang Seng TECH Index return is associated with an average increase of approximately 0.084 percentage points for each one-percentage-point increase in the Nasdaq-100 Index return in the previous trading session. The correlation analysis shows a strong negative correlation between the Nasdaq-100 Index return and the VIX return. Adding the risk-sentiment variable may reduce the overlap in the information captured by the two variables and help identify the incremental explanatory power of the U.S. technology sector. Therefore, Hypothesis H1 is supported. Further tests show that the Breusch-Pagan test rejects the null hypothesis of homoskedasticity, while the Breusch-Godfrey test finds no significant residual autocorrelation up to order five, which supports the use of Newey-West standard errors.

4.3. XGBoost model and feature importance analysis

To examine whether nonlinear specifications improve the fitting of Hang Seng TECH Index returns, the full sample is chronologically split into an 80% training set and a remaining 147 out-of-sample test set, with all XGBoost hyperparameters tuned exclusively on training data. Final selected hyperparameters include tree maximum depth of 2, learning rate of 0.05, minimum child weight of 5, subsample and column subsample ratios of 0.8, and 100 boosting rounds. Shallow tree structures mitigate overfitting risks given the limited sample size. Both models explain roughly 85% of test-set return variation, yet OLS delivers slightly superior out-of-sample performance: its test-set R² of 0.8557 exceeds XGBoost's 0.8503, accompanied by lower MAE, MSE and RMSE. This demonstrates complex nonlinear tree models yield no fitting gains under the current predictor set and sample period.

To explain the model output of XGBoost, mean absolute SHAP values were calculated for the test sample, and the relative importance of each explanatory variable was measured accordingly. As shown in Figure 1, the relative importance of the Hang Seng Index return is 81.83%, much higher than that of any other variable, indicating that the overall market volatility in China's Hong Kong is the main source of information for XGBoost to fit the Hang Seng TECH Index return. The USD/HKD return ranks second, but its relative importance is only 6.21%. The corresponding relative importance values for the Chinese 10-year government bond yield, VIX return, Nasdaq-100 Index return, and U.S. 10-year Treasury yield are 3.91%, 3.59%, 2.39%, and 2.08%, respectively.

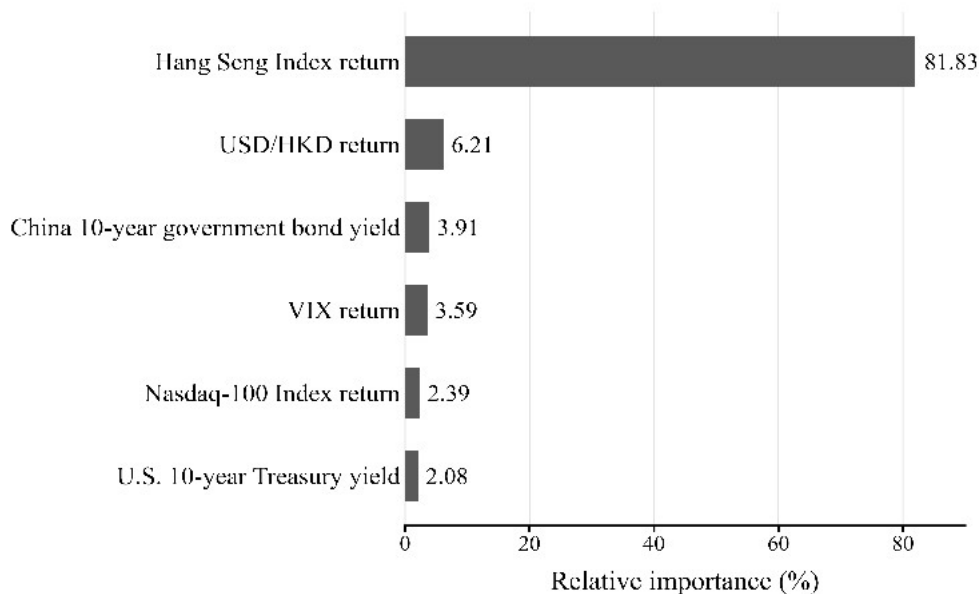


Figure 1. SHAP-based feature importance (picture credit: original)

The fact that the Nasdaq-100 Index return ranks fifth in the SHAP ranking does not mean that it has no association with the Hang Seng TECH Index return. OLS results identify the average incremental association between the Nasdaq-100 Index return and the Hang Seng TECH Index return after controlling for other factors. SHAP values reflect the relative contribution of each variable to XGBoost fitted values across the test sample. Because the Hang Seng Index return can explain most of the contemporaneous fluctuations of the Hang Seng TECH Index, the relative share of other variables in the overall fit of the model is compressed. Therefore, the coefficient on the

Nasdaq-100 Index return is statistically significant in OLS, but accounts for a relatively small share of total SHAP importance. The two results reflect the explanatory effect and the predictive contribution, respectively, and there is no logical conflict.

4.4. Comparison of model fit

Figure 2 compares the actual returns, OLS fitted values, and XGBoost fitted values over the last 60 trading days of the test period. Both models closely track the main movements in Hang Seng TECH Index returns, but there are still some deviations during periods of rapid increases, sharp declines, and short-term reversals. The OLS fitted values align slightly more closely with the actual returns than the XGBoost fitted values, which is consistent with the comparison of the error metrics. On the whole, XGBoost does not outperform the traditional linear model, but SHAP analysis further confirms the dominant role of China's Hong Kong market factors in explaining Hang Seng TECH Index returns, and provides supplementary evidence for identifying the relative contribution of variables such as exchange-rate movements, market sentiment, and interest rates in China and the United States.

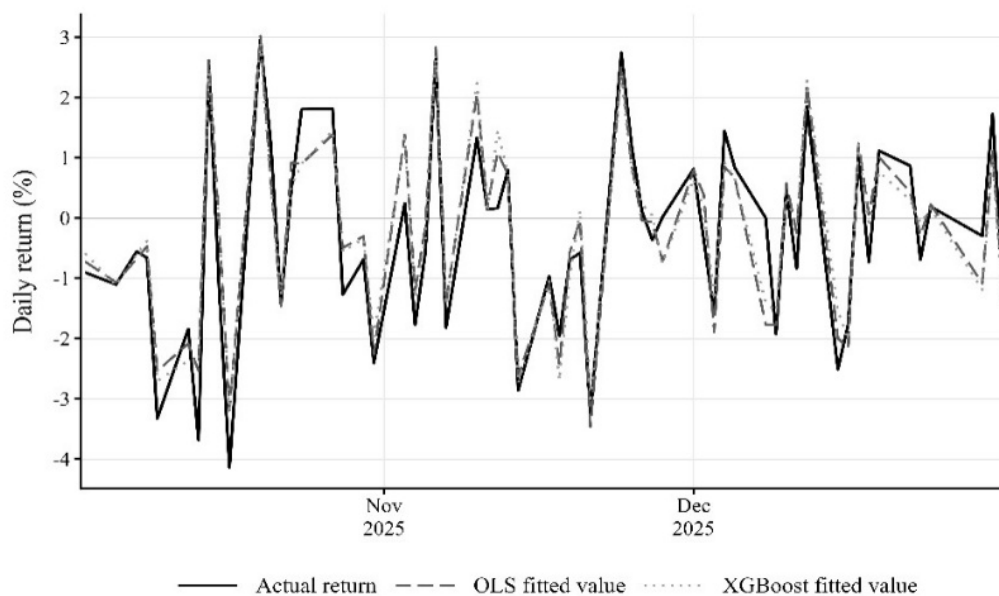


Figure 2. Actual Hang Seng TECH Index returns and fitted values (picture credit: original)

Overall, XGBoost does not show a clear fitting advantage over OLS, but its feature importance analysis further reveals the dominant role of broader China's Hong Kong market factors in Hang Seng TECH Index returns. Because the model includes the contemporaneous Hang Seng Index return, the out-of-sample test in this paper is mainly used to compare the explanatory and fitting performance of the two models, rather than to build a trading forecast model that can be implemented directly before the opening of China's Hong Kong market.

5. Conclusion

This paper employs daily data from January 2023 to December 2025 to investigate cross-market correlations between Nasdaq-100 and Hang Seng TECH Index returns, comparing linear OLS and nonlinear XGBoost fitting characteristics. Without control variables, the two technology indices

exhibit significantly positive co-movement. After controlling for Hang Seng Index returns, USD/HKD returns, VIX, and Chinese and U.S. 10-year bond yields, the Nasdaq-100 coefficient remains significantly positive at the 5% level, proving U.S. tech stocks carry incremental information for China's Hong Kong tech sector. Out-of-sample tests reveal OLS slightly outperforms XGBoost. SHAP results show Hang Seng Index returns dominate model explanatory power, while Nasdaq-100's contribution is limited. Though statistically significant, U.S. market linkage is not the primary driver of daily Hang Seng TECH fluctuations.

This paper's main contribution lies in constructing a cross-market matching framework aligned with non-overlapping trading hours for the two tech indices, and distinguishing average marginal linear associations from variable fitting contributions. The results suggest investors analyzing China's Hong Kong technology stocks should combine overnight U.S. tech signals with local China's Hong Kong market conditions, rather than relying solely on overseas index performance. This study has limitations including a short sample period and daily data's restricted capacity to capture high-frequency transmission. Future research may extend samples, adopt rolling windows, quantile or regime-switching models, and incorporate futures, capital flows and sentiment indicators to test spillover time-variation, asymmetry and predictive value.

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