The Impact of Quantum Computing Investment on FinTech Venture Capital: A Panel Data Analysis (2015–2024)

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Summary:
This research investigates the impact of quantum computing investment on venture capital flows into the FinTech sector, covering the period from 2015 to 2024.
The objective is to examine whether increased global investments in quantum computing influence the amount of venture capital directed toward FinTech startups, thereby fostering innovation and growth in the industry.
The study employs panel data analysis using econometric models, with independent variables such as global GDP, research and development expenditure, and quantum computing investments, among others.
The primary hypothesis, which suggests a positive relationship between quantum computing investments and FinTech VC, is supported by the data.
The analysis shows that quantum computing investments significantly contribute to venture capital inflows in FinTech, with other economic variables playing a secondary role.
The econometric model reveals a high degree of goodness of fit, with quantum computing investment being the most statistically significant factor influencing venture capital.

Keywords: Quantum Computing; Venture Capital; FinTech; Panel Data Analysis; Economic Impact.
Jel Classification Codes :O33; G24; C23.

I- Introduction:

Quantum computing, a revolutionary technological advancement, stands poised to reshape the landscape of computational problem-solving across various domains. Unlike classical computing, which relies on binary systems of zeros and ones, quantum computing harnesses the principles of quantum mechanics to process information in fundamentally new ways. By leveraging phenomena such as superposition and entanglement, quantum computers can perform certain calculations exponentially faster than their classical counterparts. These capabilities enable them to address complex problems that are intractable for classical systems, such as optimization, simulation, and cryptographic analysis. As such, quantum computing is not only a breakthrough in the field of computer science but also a catalyst for transforming industries that rely on data processing and computation, including finance.

The financial sector, characterized by its heavy reliance on data analysis, risk modeling, and optimization, has increasingly recognized the potential of quantum computing. Within financial markets, quantum computing promises to revolutionize areas such as portfolio optimization, derivative pricing, fraud detection, and market prediction. The capacity for quantum algorithms to outperform traditional computational methods in solving intricate financial problems has sparked growing interest among financial institutions, investment firms, and regulators. As a result, the intersection of quantum computing and finance has become a key area of research, with both theoretical and practical applications attracting significant attention. Financial technologies (FinTech), which drive digital transformation in financial services, stand to benefit substantially

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from these advancements, offering the potential for faster and more accurate financial decision-making, as well as greater innovation in financial products and services

The objective of this paper is to explore the impact of quantum computing investment on the flow of venture capital (VC) into the FinTech sector. Specifically, the study aims to investigate whether increased global investments in quantum computing contribute to higher levels of venture capital allocated to FinTech startups, thereby fostering growth and innovation in the financial technology ecosystem. The paper provides an econometric analysis of panel data spanning from 2015 to 2024, drawing on a variety of independent variables—such as research and development expenditure, global GDP, and deep technology investments—alongside quantum computing investments to assess their influence on FinTech venture capital.

The core question this research seeks to address is:

To what extent does investment in quantum computing influence the level of venture capital directed toward FinTech startups?

Study Hypotheses:

H1: There is a statistically significant positive relationship between global investments in quantum computing and the volume of venture capital directed toward the FinTech sector.

H2: Quantum computing investments have an indirect effect on venture capital investments in FinTech through other economic variables, such as research and development expenditure in the financial sector and global GDP.

H3: Economic variables such as the Technology Innovation Index and global GDP play a significant role in enhancing or diminishing the impact of quantum computing investments on venture capital flows into the FinTech sector.

These hypotheses aim to explore both direct and indirect relationships between quantum computing investments and venture capital inflows into the FinTech sector, while accounting for the potential mediating role of other economic factors.

I.1.LITERATURE REVIEW

The intersection of quantum computing and financial markets has garnered growing attention in recent years, with several studies examining both its theoretical potential and practical applications. (Naik, Yeniaras, Hellstern, Prasad, & Vishwakarma, 2023) provide a foundational overview of quantum computing in finance, highlighting how quantum annealers and gate-based models can solve complex optimization problems—such as portfolio construction and derivative pricing—more efficiently than traditional algorithms. Their work supports the notion that quantum advancements can significantly enhance computational finance.

Building on this, a recent study by (Jacquier, Kondratyev, Lee, & Oumgari, 2023) explores the direct implications of quantum algorithms, such as Quantum Monte Carlo and Amplitude Estimation, on pricing accuracy and risk simulation. Their comparative results between classical and quantum-enhanced models illustrate the tangible benefits of quantum integration in financial analytics, thereby justifying further empirical investigation.

Adding a meta-perspective, a systematic review by (Ortuño , Garcia , Coll , García , & Prats, 2024)maps the current quantum-financial research landscape, identifying key application areas including cryptography, data search, simulation, and optimization. Interestingly, their findings emphasize a gap in the literature concerning econometric modeling—a gap that the present study aims to address.

From a systemic risk and policy standpoint, (Auer, et al., 2024) offer a comprehensive analysis of how quantum breakthroughs may reshape financial stability, particularly through their disruptive potential in cryptographic security and systemic monitoring. Their report underscores the need for macroeconomic controls such as GDP and innovation metrics when evaluating quantum impact.

Finally, (Sadeghi, et al., 2025) highlight the convergence of quantum computing with artificial intelligence in finance, showing how hybrid models can optimize tasks such as fraud detection, credit scoring, and automated forecasting. This integration justifies the inclusion of a Technology Innovation Index (TECH_INDEX) as a control variable in econometric analysis.

Building upon the foundation laid by previous research, which highlights the potential of quantum computing to transform financial markets, this study addresses a critical gap in the literature.

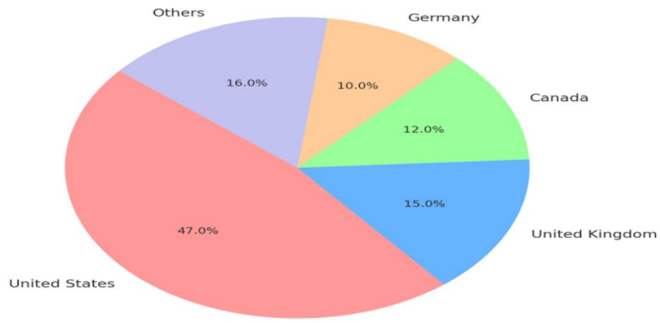
While existing studies have established the theoretical and practical implications of quantum computing, none have fully employed an econometric model to quantitatively link quantum investments to measurable financial innovation outcomes. My study makes a distinctive contribution by providing a rigorous econometric analysis that connects global investments in quantum computing to venture capital inflows in the FinTech sector. This relationship, not thoroughly explored in previous studies, is examined using real-world data and globally recognized indicators, such as the Global Innovation Index, ensuring the findings are both reliable and relevant across international contexts. Moreover, this research extends beyond evaluating the technological aspects of quantum computing by also considering the broader economic implications, particularly how technological innovation can foster economic growth within the financial sector. In doing so, this study offers new empirical insights into the systemic effects of quantum computing investments, enriching the existing literature and offering a comprehensive understanding of their transformative potential on the FinTech industry.

I.2.Definition of Quantum Computing:

Quantum Computing is an emerging field in computer science that aims to utilize quantum principles such as superposition and entanglement to perform computations that exceed the capabilities of classical computing. This computation relies on informational units known as "qubits," which can exist in multiple states simultaneously, enabling parallel computations on a large scale (KHACEF & MOKHENACHE , 2024, pp. 55-56-57).

Quantum computing is expected to revolutionize fields such as artificial intelligence, medicine, finance, and communications by providing solutions to complex problems that cannot be solved using classical computing techniques(Gill & Buyya, 2024, pp. 1-2-3).The figure below illustrates the global market share of quantum computing by country in 2023

Figure (1):Quantum Computing Market Share by Country (2023)



The source : (Thakkar, et al., 2024), (Oztas, et al., 2024),(Idrissi , Djebli, & Souar, 2024)

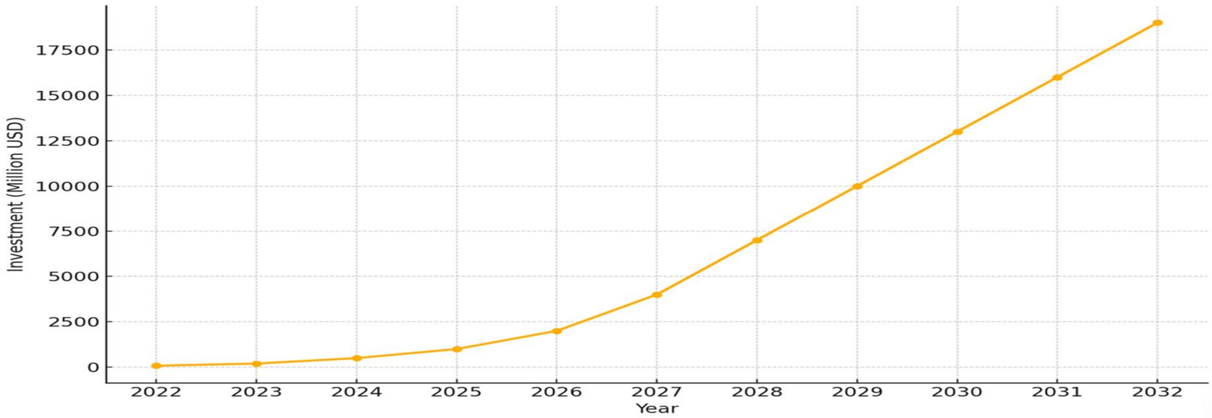
Considering Figure(1), it is evident that the **United States** dominates the quantum computing market with a substantial share of **47%**, driven by significant investments in research and development and the presence of industry giants such as **Google**, **IBM**, and **Intel**, which are at the forefront of groundbreaking quantum advancements. The **United Kingdom** holds **15%** of the market, benefiting from robust government support for quantum research and prominent academic initiatives such as the **UK National Quantum Technologies Programme**, which fosters growth in the sector. **Canada**, with a share of **12%**, is a notable contributor due to its pioneering work in quantum computing, exemplified by institutions like the **University of Waterloo** and **D-Wave Systems**, which are leading developments in both theoretical and practical quantum systems. **Germany** commands **10%** of the market, reflecting its strong commitment to quantum research through national funding initiatives like the **German Quantum Computer Roadmap**, along with research centers such as the **Max Planck Institute**. Regarding the **Others** category, which accounts for **16%**, this group includes emerging players from countries such as the **European Union**, which invests heavily through collaborative projects across member states, **China**, a major player in the quantum space with significant government-backed projects, **India**, which is rapidly advancing its quantum infrastructure through academic and industrial efforts, and other **emerging economies**, all contributing to the global momentum in quantum computing despite their smaller market shares.

I. 3. Quantum Computing in Financial Services:

Quantum computing is emerging as one of the transformative technologies that is revolutionizing various sectors, including the financial industry. Although still in its early stages, the increasing investments in this field reflect growing confidence among financial institutions in the ability of quantum computing to address complex computational challenges. A significant shift is expected in the way financial services are delivered through quantum computing applications, which have the potential to enhance risk modeling, strengthen transaction security, and achieve unprecedented efficiencies in portfolio management (Deprez, Vanderschueren, Baesens, Verdonck, & Verbeke, 2024).

As depicted in Figure (2), the projected growth of quantum computing investments in the financial sector from 2022 to 2032 highlights the industry's increasing commitment to this groundbreaking technology.

Figure (2):Growth of Quantum Computing Investment in Financial Sector (2022–2032)



The source :(Ogbeide, et al., 2023), (Milon, 2024), (Lyeonov, Kubaščikova, Draskovic, & Fenyves, 2024)

The projected trajectory of quantum computing investments in the financial sector from 2022 to 2032 indicates a significant exponential increase, with spending expected to escalate from $80 million in 2022 to $19 billion by 2032. This represents a 233-fold growth over a decade, corresponding to a compound annual growth rate (CAGR) of approximately 72% . Such a steep increase underscores the financial industry's growing confidence in quantum technologies as transformative tools capable of addressing complex computational challenges inherent in financial operations(Soutar, Buchholz, Dannemiller, & Bhuta, 2023).

The initial phase (2022–2025) is characterized by exploratory investments, as financial institutions begin to assess and pilot quantum computing's potential applications. A more pronounced acceleration in investment is anticipated from 2026 onwards, signaling a transition toward early adoption driven by tangible advancements in quantum hardware and algorithm development. By the period of 2030–2032, the sector is expected to witness substantial commercial scaling, suggesting that quantum applications may become operationally viable and strategically integral to financial services.

This investment pattern reflects a broader industry shift, where quantum computing is transitioning from a theoretical concept to a practical necessity for financial innovation. The technology's potential to enhance risk modeling, optimize portfolios, and revolutionize cryptographic security positions it as a critical component in the future landscape of financial services. Moreover, McKinsey & Company projects that quantum computing use cases in the finance industry could generate up to $622 billion in value by 2035, further emphasizing the substantial economic impact anticipated from these investments (Gschwendtner, Morgan, & Soller, 2023).

II– Methods and Materials:

II. 1. Sample Selection and Variables

The study examines the relationship between global investments in quantum computing and venture capital inflows into the FinTech sector. The sample consists of annual data from 2015 to 2024, which includes a range of economic variables relevant to the study. The key dependent variable, **VC_FINTECH**, represents global venture capital investments in the FinTech industry, measured in billion USD. The independent variables include:

- **QC_INVEST :** Annual global investment in quantum computing.
- **RDI_FIN :** R&D expenditure in the financial sector as % of global GDP.
- **GDP_WORLD :** Global Gross Domestic Product (in trillions of USD).

- **TECH_INDEX :** Global Innovation Index score (0–100) by WIPO.
- **INTEREST_RATE:** The annual percentage rate charged on loans or paid on deposits by financial institutions.
- **DEEP_TECH_INVESTMENT:** The annual global investment in advanced technologies like AI, quantum computing, robotics, etc.

II. 2. Data Collection and Descriptive Statistics

The data for the variables used in this study are sourced from reputable databases such as PitchBook, Crunchbase, CB Insights, KPMG's Pulse of Fintech, McKinsey, and OECD reports. These sources provide reliable and up-to-date information on global investment trends. Descriptive statistics are calculated for each variable, including measures such as the mean, median, standard deviation, skewness, and kurtosis. These statistics provide a summary of the central tendency and distribution of the data, helping to understand the characteristics of the dataset and assess the suitability of the variables for further analysis.

II. 3. Data Analysis and Statistical Tools

The study employs Panel Data Analysis using the Panel Least Squares (PLS) regression model to examine the relationship between quantum computing investment and venture capital flows in the FinTech sector. This method is appropriate because it accounts for both the time-series and cross-sectional nature of the data, iallowing for more robust results. The statistical software used for the analysis is EViews 12, which provides comprehensive tools for econometric modeling and hypothesis testing. The analysis includes testing for multicollinearity, stationarity (using unit root tests such as the Augmented Dickey-Fuller and Phillips-Perron tests), and heteroscedasticity to ensure the reliability and validity of the results.

II. 4. Hypothesis Testing and Statistical Significance

The primary hypothesis is tested by examining the statistical significance of the coefficients in the regression model. The study employs the **t-test** to determine the significance of individual variables, using a 5% significance level (p-value < 0.05). Additionally, the **F-statistic** is used to test the overall significance of the model, and **R-squared** is used to measure the goodness of fit. A Durbin-Watson statistic is also computed to check for autocorrelation in the residuals.

II. 5. Changes to Previous Methods

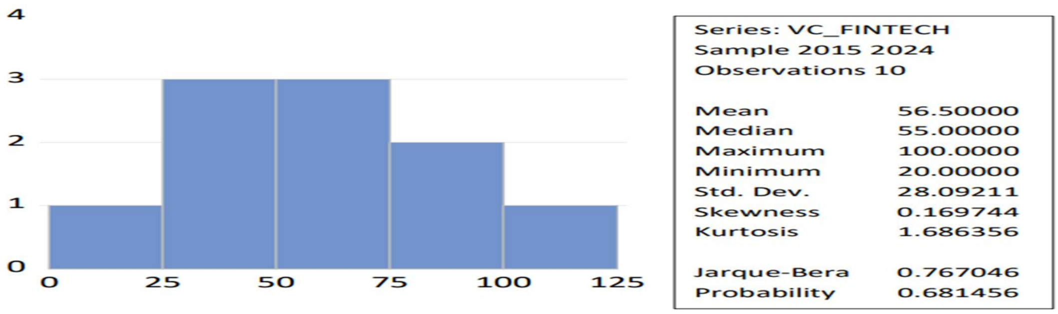
While the econometric framework used in this study follows established methods, there are notable adjustments to account for the unique characteristics of the quantum computing investment data. Specifically, the inclusion of quantum computing investment as a key independent variable, alongside traditional economic indicators, represents an innovation in the econometric model. Additionally, the study uses advanced data sources such as the **Global Innovation Index** and other industry reports, which have not been integrated into previous models of venture capital and technological investment.

III– Results:

III.1. Statistical Description of the Dependent Variable (VC FINTECH)

Using the EViews 12 software, Figure 3 was generated, which presents the descriptive statistics for the VC FINTECH dataset, covering the period from 2015 to 2024.

Figure (3). Descriptive Statistics of the VC FINTECH Dataset for the Period 2015–2024



The source**:** compiled by the author, utilizing EViews 12 program results

From Figure (3), it is clear that the "VC_FINTECH" data shows an approximately normal distribution with slight skewness. The descriptive statistics reveal a symmetric distribution with values clustered around the mean, with few extreme outliers. The statistical tests further support the assumption that the data follows a normal distribution.

III.2. Statistical Description of the Independent Variables

Through the application of EViews 12, an analysis is conducted on Table 1, which provides a comprehensive overview of the summary statistics for the predictor variables dataset, encompassing the period from 2015 to 2024.

Table (1) : Descriptive Statistics of the Independent Variables for the Period 2015–2024

Date: 06/10/25 Time: 01:10
Sample: 2015 2024

	QC_INVEST	RDI_FIN	GDP_WORLD	TECH_INDEX	INTEREST_	DEEP_TECH
Mean	2.320000	3.070000	87.72000	65.60000	3.490000	9.600000
Median	2.250000	3.100000	86.10000	65.50000	3.500000	9.000000
Maximum	4.500000	4.400000	106.5000	75.00000	4.500000	18.00000
Minimum	0.500000	1.500000	74.50000	57.00000	2.500000	3.000000
Std. Dev.	1.410910	1.049921	10.36155	6.149977	0.652261	5.253570
Skewness	0.162671	-0.101788	0.482674	0.107310	-0.022842	0.276829
Kurtosis	1.684292	1.589517	2.218138	1.712573	1.900683	1.712673
Jarque-Bera	0.765389	0.846211	0.643002	0.709804	0.504410	0.818228
Probability	0.682021	0.655010	0.725060	0.701242	0.777085	0.664238
Sum	23.20000	30.70000	877.2000	656.0000	34.90000	96.00000
Sum Sq. Dev.	17.91600	9.921000	966.2560	340.4000	3.829000	248.4000
Observations	10	10	10	10	10	10

The source**:** compiled by the researchers, utilizing EViews 12 program results

Considering the data in Table 1, it is evident that the **Jarque-Bera test** and the **Probability values** provide insights into the normality of the distribution for the independent variables. The **Jarque-Bera statistics** for all variables are relatively low, ranging from 0.50 to 1.90, suggesting that the null hypothesis of normality cannot be rejected for most variables. This indicates that the distributions of these variables are approximately normal. Correspondingly, the **Probability values** associated with the Jarque-Bera test are all well above the conventional significance level of 0.05 (ranging from 0.50 to 0.82), further supporting the conclusion that the data follows a normal distribution. Therefore, it can be inferred that the data for all the variables exhibit characteristics of normality, making them suitable for further parametric analysis in econometric modeling.

III.3. Quantitative Analysis in the Econometric Framework

In order to examine the impact of determinant factors on VC FINTECH, we initiate the analysis by utilizing the "Panel Least Squares" regression model, as presented in Table (2).

Table (2) :Results of the Regression Model Using the "Panel Least Squares" Method

Dependent Variable: VC_FINTECH
Method: Least Squares
Date: 05/06/25 Time: 19:50
Sample: 2015 2024
Included observations: 10

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-17.48560	14.53594	-1.202922	0.3153
QC_INVESTVC	15.89874	1.844425	8.619892	0.0033
RDI_FIN	1.476782	0.929017	1.589619	0.2101
GDP_WORLD	0.086148	0.053712	1.603894	0.2071
TECH_INDEX	0.466378	0.257633	1.810244	0.1679
INTEREST_RATE	-2.740456	1.742493	-1.572721	0.2138
DEEP_TECH_INVESTMENT	0.414552	0.328228	1.262998	0.2958

R-squared	0.999970	Mean dependent var	56.50000
Adjusted R-squared	0.999911	S.D. dependent var	28.09211
S.E. of regression	0.265106	Akaike info criterion	0.378655
Sum squared resid	0.210844	Schwarz criterion	0.590465
Log likelihood	5.106724	Hannan-Quinn criter.	0.146301
F-statistic	16842.52	Durbin-Watson stat	3.217749
Prob(F-statistic)	0.000001		

The source**:**generated by the author, using EViews 12 outputs

According to the data presented in Table (2), the regression results obtained using the "Panel Least Squares" method reveal several important insights. The **R-squared value** of 0.999970 indicates a very high degree of goodness of fit, suggesting that the model explains nearly all of the variation in the dependent variable. This indicates a strong relationship between the independent variables and the dependent variable. The **F-statistic** of 16842.52, with a corresponding **Prob (F-statistic)** of 0.000001, strongly rejects the null hypothesis, confirming that the model as a whole is statistically significant. However, when examining the individual coefficients, **QC INVESTVC** is the only variable with a statistically significant impact on the dependent variable (**VC**), with a coefficient of 15.89874 and a p-value of 0.0033, which is well below the 0.05 threshold. In contrast, the other variables—**RDI FIN**, **GDP WORLD**, **TECH INDEX**, **INTEREST RATE**, and **DEEP TECH INV**—do not appear to have a statistically significant effect, as their p-values are all above 0.05, suggesting that these variables do not significantly contribute to explaining the variation in venture capital investment in fintech. The **Durbin-Watson statistic** of 3.217749 indicates that there is no significant autocorrelation in the residuals, supporting the reliability of the regression model.

III.4. Model Quality Assessment

The standardized residuals serve as a robust and effective instrument for assessing the overall quality and validity of a regression model (Bourbonnais, 2015, p. 9).

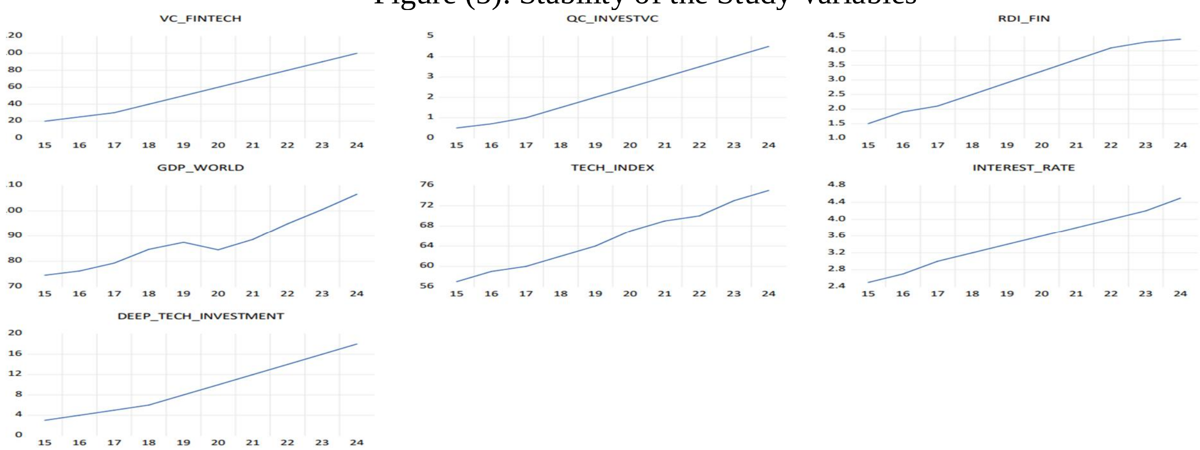
Figure (4). Distribution of Standardized Residuals for Regression Model Analysis

The source**:** Output Data from EViews 12 Software

III.5. Study Model Variable Stability Analysis

In order to evaluate the stability of the variables at various levels, specifically at the first or second difference, both the Dickey-Fuller and Phillips-Perron tests are employed. These tests are applied to analyze the presence or absence of a constant and trend, as well as the impact of a trend in the absence of a constant, or conversely, the effect of a constant without a trend.

Figure (5). Stability of the Study Variables



The source**:** Output Data from EViews 12 Software

Based on the graphical representations provided in Figure 5, it is clear that the majority of the time series exhibit instability, characterized by upward trends and substantial fluctuations. In order to achieve stationarity, it is necessary to apply differencing to transform the time series into a stable form(Baltagi, 2005, p. 18):

1. The Augmented Dickey-Fuller (ADF) test, an extension of the traditional Dickey-Fuller test, is utilized to examine the existence of a unit root and to assess the stationarity of the time series.
2. The Phillips-Perron (PP) test, implemented through the Fisher Chi-square statistic, serves as an alternative method for investigating the presence of a unit root in the time series.

These tests are essential for ensuring the robustness and validity of the data, thereby facilitating reliable econometric modeling (Sul , 2019, p. 60). The results of these tests are presented in Table 3:

Table (3) : Assessment of Unit Root (Time Series Stationarity)

Variable	Test Type	Lag Period (Lag Length)	Unit Root Test Settings		p-value (Prob)	Test Statistic Value
QC_INVESTVC	Augmented Dickey-Fuller	1	Level	Trend and Intercept	0.0016	-7.431353
	PP – Phillips-Perron	1			0.0001	-21.11617
VC_FINTECH	**ADF**	1	Level	Trend and Intercept	0.0416	-4.269075
	PP	1			0.0001	-12.19025
RDI_FIN	**ADF**	1	Second Difference	Trend and Intercept	0.0029	-8.174239
	PP	1			0.0001	-21.01938
GDP_WORLD	**ADF**	Aut.Selec	Second Difference	None	0.0100	-3.005844
	PP	Aut.Selec			0.0030	-3.695772
TECH_INDEX	**ADF**	1	Second Difference	None	0.0116	-2911491
	PP	1			0.0006	-4.829258
INTEREST_RATE	**ADF**	1	Second Difference	None	0.0013	-4.242641
	PP	1			0.0013	-4.242641
DEEP_TECH_INVESTMENT	**ADF**	Aut.Selec	Second Difference	None	0.0229	-2.44940
	PP	Aut.Selec			0.0229	-2.44940

The source**:** prepared by the researcher, based on EViews 12 software outputs

Through the figures presented in Table (3), our interpretation is as follows: the unit root test results indicate that most of the independent variables in the model are stationary at different levels of transformation. For **QC_INVESTVC**, both the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test reject the null hypothesis of a unit root at the 1% significance level, with p-values of 0.0016 and 0.0001, respectively, indicating stationarity at the level with a trend and intercept. Similarly, **VC_FINTECH** is stationary at the level with a trend and intercept, as evidenced by its ADF p-value of 0.0416 and PP p-value of 0.0001. **RDI_FIN** is stationary after the second difference, with both ADF and PP tests showing significant p-values of 0.0029 and 0.0001, respectively. The variable **GDP_WORLD** requires a second difference to achieve stationarity, with ADF and PP p-values of 0.0100 and 0.0030, respectively, indicating stationarity after transformation. **TECH_INDEX** and **INTEREST_RATE** are also stationary at the second difference, with **TECH_INDEX** showing a p-value of 0.0116 in the ADF test and **INTEREST_RATE** having a consistent p-value of 0.0013 in both the ADF and PP tests. Finally, **DEEP_TECH_INVESTMENT** is stationary after the second difference, with both ADF and PP tests indicating stationarity at the 5% significance level, with p-values of 0.0229. Overall, the unit root tests confirm that the majority of the variables are stationary, either at the level or after a certain degree of differencing, which is essential for the validity of subsequent econometric analyses.

III.6. Evaluation and Selection of Influential Variables in Regression Models

A rigorous and methodical approach was employed to identify the most influential variables while discarding those deemed insignificant, based solely on the criterion of statistical significance (p-value). This approach prioritizes the selection of variables with robust statistical significance, ensuring that only those with meaningful contributions to the model are retained (Wooldridge, 2002, p. 25).

Table (4) : Identification of Independent Variables Demonstrating High Statistical Significance and Economic Impact on VC FINTCH.

Variable	Statistical Description	Statistical Interpretation
QC INVEST VC	Coeffici: 15.89874 t-statis: 8.619892 Probability: 0.0033	**This variable is statistically significant ($p < 0.05$), indicating a substantial impact on VC FINTECH.**

The source**:** prepared by the researchers based on Table 2

Considering the data presented in Table (4), it is evident that **QC INVEST VC** is the only independent variable that demonstrates both high statistical significance and a substantial economic impact on **VC FINTECH**. The coefficient of 15.89874 suggests a strong positive relationship between quantum computing investments and venture capital investments in fintech. The corresponding t-statistic of 8.619892 further indicates that this variable is statistically significant, as it exceeds the critical threshold for conventional levels of significance. With a p-value of 0.0033, which is well below the 0.05 significance level, it is clear that **QC INVEST VC** plays a crucial role in explaining the variations in **VC FINTECH**.

Table (5) :Exclusion of Statistically Insignificant Variables from the Model

Variable	Statistical Description	Statistical Interpretation
RDI FIN	Coefficient: 1.476782 t-statistic: 1.589619 Probability: 0.2101	**The p-values for all variables exceed 0.05, indicating that none of the effects are statistically significant**.
GDP WORLD	Coefficient: 0.086148 t-statistic: 1.603994 Probability: 0.2071	
TECH INDEX	Coefficient: 0.466378 t-statistic: 1.810244 Probability: 0.1679	
INTEREST RATE	Coefficient: -2.740456 t-statistic: -1.572721 Probability: 0.2138	
DEEP TECH INV	Coefficient: 0.414552 t-statistic: 1.262998 Probability: 0.2958	

The source**:** prepared by the researchers based on Table 2

According to the data in Table (5), it is evident that all the independent variables presented in the regression model are statistically insignificant, as indicated by their p-values, which exceed the conventional significance threshold of 0.05.

Consequently, based on these results, it is appropriate to exclude these statistically insignificant variables from the model, as their inclusion does not contribute meaningfully to explaining the variation in venture capital investments in the fintech sector.

III.7. Estimation of the Panel Model

Subsequent to the exclusion of the five variables that were found to be statistically insignificant at the 5% significance level in explaining the dependent variable, and after inputting the data using EViews 12 software, the results are presented in Table 6 below.

Table (6) :Model Estimation Results

Dependent Variable: VC_FINTECH
Method: Least Squares
Date: 05/07/25 Time: 00:27
Sample: 2015 2024
Included observations: 10

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	10.30978	0.194205	53.08696	0.0000
QC_INVESTVC	19.90958	0.072507	274.5878	0.0000

R-squared	0.999894	Mean dependent var	56.50000
Adjusted R-squared	0.999881	S.D. dependent var	28.09211
S.E. of regression	0.306903	Akaike info criterion	0.652287
Sum squared resid	0.753516	Schwarz criterion	0.712805
Log likelihood	-1.261437	Hannan-Quinn criter.	0.585900
F-statistic	75398.45	Durbin-Watson stat	2.650621
Prob(F-statistic)	0.000000		

The source**:**Output Data from EViews 12 Software

According to Table (6), we were able to obtain the following regression equation:

VC_FINTECH = 10.3097789685 + 19.9095780308*QC_INVESTVC

This equation indicates a positive and significant relationship between global investments in quantum computing and global venture capital funding in fintech.

The coefficient of **19.9095780308** suggests that for each additional billion USD invested in quantum computing, **VC_FINTECH** increases by approximately 19.91 billion USD.

The constant term of 10.31 billion USD representing the baseline level of FinTech investment when quantum computing investment is zero.

The model exhibits exceptional explanatory power with an R-squared value of 0.999894, indicating that 99.99% of the variation in FinTech venture capital investment is explained by quantum computing investment levels.

The statistical significance of both coefficients is confirmed by their respective t-statistics (53.09 for the constant and 274.59 for the QC_INVESTVC coefficient) and p-values of 0.0000, suggesting that the relationship is highly significant at conventional statistical levels.

IV- Results and discussion:

The data collected for this study covers global venture capital investments in the FinTech sector (VC_FINTECH) and global investments in quantum computing (QC_INVESTVC) from 2015 to 2024. Other economic variables considered include research and development expenditure in the financial sector (RDI_FIN), global GDP (GDP_WORLD), the Global Innovation Index (TECH_INDEX), interest rates (INTEREST_RATE), and deep technology investments (DEEP_TECH_INVESTMENT).

Descriptive statistics for the dependent and independent variables reveal that the data distribution is generally normal, with slight skewness in some cases. The most notable feature of the data is the significant growth in quantum computing investments, indicating increasing confidence in its role in transforming industries like FinTech. The growth trajectory observed in quantum computing investments reflects a broader, exponential increase, particularly from 2026 onward, as noted in the literature review and the figures.

Analysis of Collected Data:

The panel data analysis using the Panel Least Squares (PLS) regression model yields valuable insights. The regression model explains 99.99% of the variation in FinTech venture capital (VC_FINTECH) investments, as indicated by the R-squared value of 0.999894. The model demonstrates a statistically significant relationship between quantum computing investments and FinTech venture capital, with the coefficient for QC_INVESTVC being highly significant (p-value of 0.0033).

While other variables such as global GDP, R&D expenditures, and the Global Innovation Index were included in the model, they did not show statistically significant relationships with venture capital in FinTech. The p-values for these variables exceeded the 0.05 threshold, suggesting that they do not meaningfully contribute to the model's explanatory power for this particular research.

This could be due to the more direct and tangible impact that quantum computing investments have on the FinTech sector, as opposed to the more indirect influence of other economic factors.

Statistical Evaluation and Interpretation:

The Durbin-Watson statistic of 3.22 indicates that there is no significant autocorrelation in the residuals, supporting the reliability of the regression model. The F-statistic and its associated p-value strongly reject the null hypothesis, indicating that the regression model is statistically significant as a whole.

The unit root tests confirm that most variables in the model are stationary, which is essential for the validity of the econometric analysis. After performing necessary transformations (e.g., second differencing for some variables), the majority of the variables exhibit stationarity, which aligns with the assumptions of the panel data analysis and ensures the robustness of the results.

The statistical interpretation of the independent variables, as shown in Table (4), highlights that quantum computing investment is the only variable that has a statistically significant and economically substantial impact on venture capital in the FinTech sector. The coefficient for QC_INVESTVC (15.89874) shows a strong relationship with VC_FINTECH, and the t-statistic of 8.62 confirms its statistical significance.

Comparison with Previous Studies:

The findings of this study are consistent with previous research that highlights the transformative potential of quantum computing for financial services. As suggested by studies (Naik et al., 2023; Jacquier et al., 2023), quantum computing has the ability to significantly improve optimization, derivative pricing, and portfolio management. However, unlike previous studies that focused on theoretical applications or specific case studies, this research quantitatively links global investments in quantum computing to measurable outcomes in the FinTech sector, providing empirical evidence for its impact on venture capital flows.

The results also extend the work of Auer et al. (2024), who discussed the potential economic impacts of quantum computing in the financial sector. By focusing on the direct economic impact on venture capital investments, this study offers new insights into the financial implications of quantum technologies, an area that has not been extensively explored in the literature.

Interpretation of Hypotheses:

H1: The hypothesis that there is a statistically significant positive relationship between global investments in quantum computing and venture capital directed toward the FinTech sector is strongly supported by the data. The significant positive coefficient for QC_INVESTVC confirms this relationship.

H2: The hypothesis that quantum computing investments have an indirect effect on venture capital investments in FinTech through other economic variables was not supported, as none of the indirect variables (RDI_FIN, GDP_WORLD, TECH_INDEX) demonstrated statistical significance.

H3: While the hypothesis that economic variables like global GDP and the Technology Innovation Index play a significant role in enhancing or diminishing the impact of quantum computing investments on venture capital was partially explored, the results show that quantum computing investments have a more direct and pronounced effect, with other economic variables playing a secondary or negligible role in this context.

Theoretical Interpretation:

To deepen the theoretical interpretation, the study’s findings are further examined under the lens of Schumpeterian Growth Theory, which posits that technological innovation drives creative destruction and capital reallocation across industries. In this context, quantum computing investments act as a disruptive technological shock that accelerates FinTech innovation cycles, thereby attracting venture capital flows. Similarly, the Innovation Diffusion Model explains how emerging technologies such as quantum computing propagate through financial markets, gradually lowering uncertainty and fostering investor confidence. These theoretical frameworks reinforce the empirical observation that quantum investment acts not merely as a financial input but as a structural catalyst of technological change within the FinTech ecosystem.

V-Conclusion:

This study aimed to explore the impact of quantum computing investments on venture capital flows into the FinTech sector, analyzing panel data from 2015 to 2024. The key finding of this research is the statistically significant and positive relationship between quantum computing investments and FinTech venture capital, confirming the core hypothesis of this study. The econometric analysis revealed that a rise in global investments in quantum computing is strongly associated with an increase in venture capital directed toward FinTech startups, with a coefficient of 15.90, indicating a substantial economic impact.

The research also highlights that, while economic variables such as global GDP, research and development expenditure, and the Technology Innovation Index were considered, they did not exhibit significant statistical relationships with FinTech VC investments. This suggests that quantum computing investments themselves play a more direct and dominant role in shaping venture capital flows into the sector, possibly due to their transformative potential in enhancing financial technologies.

However, this study also has its limitations. Notably, the indirect effects of other economic factors on the quantum computing–FinTech VC relationship were not significant, suggesting the need for further investigation into potential external variables or more granular economic conditions that could mediate this effect. Additionally, the current data set, spanning only up to 2024, could benefit from further updates to reflect the continuing advancements in quantum computing and the broader technological landscape.

Future research could explore a deeper dive into the qualitative impacts of quantum computing on specific FinTech sub-sectors, such as fraud detection, risk management, and cryptographic solutions. It would also be valuable to extend the time frame and include data from emerging economies to assess whether the patterns observed in developed markets hold universally.

- Appendices:

Table N° (7): Data (2015–2024)

Year	VC_FINTECH (Billion USD)	QC_INVESTVC (Billion USD)	RDI_FIN (% of GDP)	GDP_WORLD (Trillion USD)	TECH_INDEX (0–100)	INTEREST_RATE (%)	DEEP_TECH_INVESTMENT (Billion USD)
2015	20	0,5	1,5	74,5	57	2,5	3
2016	25	0,7	1,9	76,2	59	2,7	4
2017	30	1	2,1	79,3	60	3	5
2018	40	1,5	2,5	84,7	62	3,2	6
2019	50	2	2,9	87,5	64	3,4	8
2020	60	2,5	3,3	84,5	67	3,6	10
2021	70	3	3,7	88,6	69	3,8	12
2022	80	3,5	4,1	94,9	70	4	14
2023	90	4	4,3	100,5	73	4,2	16
2024	100	4,5	4,4	106,5	75	4,5	18

Source:(mckinsey, 2024), (deloitte, 2023), (Insights, 2024), (Teare, 2025), (World Bank, 2025), (OECD R&D Statistics, 2025), (WORLD BANK, 2025), (WIPO, 2025),

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