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Are Financial Stocks Driven by Substantive Factors or Virtual Factors? Comparing Taiwan and China Markets

Summary: This study employs information economics and the financial intermediary theory to explore the influences of private information in virtual communities and financial technology (fintech) derived from virtual currency on financial stocks. The paper conducts robust analyses on 67,166 data observations of the stock markets in China and Taiwan and finds that virtual currency development causes a structural change in the financial industry. The financial stocks in Taiwan are obviously driven by virtual factors, whereas those in China are subject to both pull from substantial factors and push from virtual factors. The research findings also suggest that the non-fundamental herding behavior driven by private information interferes with the value of financial stocks. However, financial innovations boost the competitiveness of the financial industry. It is advised to establish a policy to closely monitor the diffusion of private information and the exchange rate volatility between cryptocurrencies and home currencies to facilitate proactive financial risk management.

Keywords: Bitcoin, Fin-tech, Private information, Social media, Herging effect.

JEL: A14, D82, F65, G12.

Share prices are subject to the influence of substantial factors, as well as the influence of non-physical (or virtual) factors. Some studies have found that economic growth, information asymmetry, bank operating efficiency, corporate financial ratio, country risk, size, and financial supervision (Edward F. Buffie 1984; Panicos O. Demetriades and Khaled A. Hussein 1996; Thair Al Shaher, Ohoud Khasawneh, and Razan Salem 2011) are all substantial factors that influence financial stocks. In recent years, community conversations have flourished and through networking or mobile devices have greatly penetrated all levels of society. Many stock information boards, blogs, and interactive discussion groups have begun to affect specific securities (Meir Statman, Steven Thorley, and Keith Vorkink 2006; Chi M. Ho 2013; Ermanno Affuso and Kyre Dane Lahtinen 2018; Feng Mai et al. 2018). In other words, the value of the financial industry is certainly changing, driven by non-physical factors.

Social media discussions and financial innovations triggered by cryptocurrencies are in theory the virtual factors that influence share prices (Statman, Thorley, and Vorkink 2006; Mai et al. 2018; Ho 2020a, b), but there are inconsistent views and apparent contentions in the literature. Some studies indicate that the development of Bitcoin has nothing to do with economic growth (Eng-Tuck Cheah and John Fry 2015; Pavel Ciaian, Miroslava Rajcaniova, and d'Artis Kancs 2016), and that it does not influence the prices of financial products either (Dirk G. Baur, KiHoon Hong, and Adrian D. Lee 2018; Tony Klein, Pham H. Thu, and Thomas Walther 2018). However, other scholars point out that the direction of Bitcoin is related to the currencies in emerging markets (Jon Carrick 2016), has a positive influence on the financial industry (Julia Molnár 2018), and is driven by other market forces (Ciaian, Rajcaniova, and Kancs 2016). These differences in the literature may be due to the variance of supervisory systems in different markets. There are also structural differences in terms of influences on share prices. In addition, the inconsistent level of market developments and the shift in industrial and substantial factors also lead to changes in conclusions derived from models. Therefore, this paper seeks to address these shortcomings with an adjusted approach. First, it is necessary to consider the idiosyncratic and substantial factors of individual markets where the ideas about the governance of virtual factors are different. The CAPM time-series model (Elie Bouri, Rangan Gupta, and David Roubaud 2019; Syed J. H. Shahzad et al. 2021) is constructed to observe the interaction between substantial factors and virtual factors on share prices in order to interpret the inconsistencies in the literature.

1. Literature and Hypothesis

Past studies focus on economic bubbles, supervision, and efficiency (Shaen Corbet et al. 2018), and a lack of understanding on virtual factors will add to unnecessary volatility in the financial market (Bouri, Shahzad, and David Roubaud 2019; Imran Yousaf et al. 2021). At the same time, virtual factors are all related to psychological biases (Taofik Hidajat 2019). The model explanatory power of herding behavior driven by non-fundamentals (Siddharth Bhambhwani, Stefanos Delikouras, and George M. Korniotis 2019) compensates for the insufficiency of traditional financial theories (Ladislav Kristoufek 2013). Finally, understanding the interaction between substantial factors and virtual factors in the industry helps in policy recommendations covering financial risk management and supervision (Bouri, Gupta, and Roubaud 2019).

1.1 Private Information of Virtual Currency and Financial Stock

The Internet disseminates information and creates virtual groups where community members share their views and discuss specific events. Investors like to browse the discussions or articles posted on community websites and make investments based on these interactive discussions, which indirectly affects the commodity prices in financial markets, and many studies have proved this point (Werner Antweiler and Murray Z. Frank 2004; Statman, Thorley, and Vorkink 2006; Ho 2013; Affuso and Lahtinen 2019). The Herd Behavior in financial markets is a typical example. Hidajat (2019) indicates that Bitcon prices are driven by psychological biases, and herding behavior is the most frequently seen psychological bias. Some studies posit that cryptocurrencies have no intrinsic value (Cheah and Fry 2015), positing that the speculations (Florian Glaser et al. 2014; Chung Baek and Matt Elbeck 2015) have nothing to do with economic performances (Cheah and Fry 2015; Ciaian, Rajcaniova, and Kancs 2016), and are not related to traditional currencies or assets such as stocks, bonds, and gold (Klein, Thu, and Walther 2018; Bouri, Gupta, and Roubaud 2019). However, Ciaian, Rajcaniova, and Kancs (2016) suggest that Bitcoin prices are driven by Bitcoin itself as well as by other market forces. Carrick (2016) notes that Bitcoin is positively correlated with the Chinese yuan, but negatively correlated with currencies of other countries. Furthermore, herding behavior can be divided into fundamental driven herding and non-fundamental driven herding (Bhambhwani et al. 2019). The former focuses on information of fundamentals, while the latter is about private information and leading to financial market disability. Bouri, Gupta, and Roubaud (2019) offer that inadequate research on cryptocurrencies will result in inefficiency and volatility in financial markets. This is particularly the case for the herding of cryptocurrencies with high economic uncertainties (Yousaf et al. 2021). After the incorporation of liquid factors, Sonia Arsi, Khaled Guesmi, and Bouri (2021) observe more significant herding behaviors in a down market. In sum, the virtual factors driven by cryptocurrencies indeed have influences on financial markets.

Community conversations or postings may come from formal agencies or informal discussions, responses, and opinions about an event. In the Internet era and extensive mobile phone use, the Internet has strong penetration at the social level, which affects people's decision-making. Financial literature classifies the conversations and interactive suggestions in virtual communities as private information. In an efficiency market, stock prices will reflect public information or historical information, and information that may reflect changes in stock price is private information (Kent Daniel, David Hirshleifer, and Avanidhar Subrahmanyam 1999; Harrison Hong and Jeremy C. Stein 1999; Chun-Teck Lye, Jiunn-Shyan Khong, and Chee-Wooi Hooy 2019). Mai et al. (2018) used semantic analysis and VAR models to test the relationship between community and bitcoin value, and found that when a bullish forum posted a view of Bitcoin, the value of Bitcoin would go higher. However, even though some of the overall economic variables are controlled, the results have not changed, and not every message has a symmetrical impact on the value of Bitcoin.

From the perspective of the model of Eugene F. Fama and Kenneth R. French (1996), the scale, net market value ratio, and market excess return can explain the excess returns of financial stocks. However, the discussion of virtual currency in communities may affect people's willingness to hold bitcoin (Mai et al. 2018; Adam Hayes 2019). Once they consider buying Bitcoin, investors must withdraw money, which will reduce their savings, or borrow money from financial institutions, thereby changing the debt ratio and affecting financial stocks (Nsambu K. Frederick 2014; Adama Combey and Apélété Togbenou 2017). In this regard, through money multipliers, the supply of money will multiply and the market interest rate will slowly rise, which will affect the country's economic growth and change financial stocks (Demetriades and Hussein 1996). Moreover, investors will convert their home currency into bitcoins for investment. When this situation continues and the trading volume gradually expands, the depreciation pressure on the home country's currency is unfavorable to the overall financial industry (Siti N. Muhmad and Hafiza A. Hashim 2015). Finally, once investors own virtual currency, they will consider risk avoidance (Chen Y. Wu and Vivek

K. Pandey 2014; Konstantinos Gkillas and Paraskevi Katsiampa 2018; Gkillas and François Longin 2019). As financial stocks and virtual currencies are both financial assets, it is likely that investors will buy or sell to adjust their portfolios (Bouri, Gupta, and Roubaud 2019), as changes in supply and demand will change financial stocks. Therefore, the message content of communities concerning virtual currency will affect the financial sector through the debt ratio, exchange rate, interest rate, economic growth, and portfolio adjustment, thus, indirectly changing financial stocks.

While virtual currency is not a legitimate asset in the Taiwanese market, in the pursuit of wealth, investors will buy virtual currency, wait for it to appreciate, and sell for a profit. As the government is open to community discussion, the greater the fluctuations in Bitcoin, the stronger the discussions of community members (Antweiler and Frank 2004). The theory of an information economy indicates that, due to the limited capacity of community members, they do not wait for the optimal information to make decisions. In addition, interactions between individuals in communities (Joseph E. Stiglitz 1985; Michael Wessel, Ferdinand Thies, and Alexander Benlian 2017), knowledge sharing (Icek Ajzen and Martin F. Snippet 1980), and the exponential spread of community discussions (James B. Quinn et al. 1996), have begun to affect bitcoin sales (Mai et al. 2018). In this regard, adjustments will be actively made to avoid risks (Wu and Pandey 2014; Gkillas and Paraskevi 2018; Bouri, Gupta, and Roubaud 2019), as financial stocks are negatively affected by private information to a large extent (Daniel, Hirshleifer, and Subrahmanyam 1998; Ho 2013). Although China has witnessed the most prosperous bitcoin trading activities, the government has strict regulations for virtual currency and communities, thus, stock prices are affected normally by formal financial events, instead of being affected by community or online conversations. Even if people talk face to face or consider the trend of virtual currency, there is also asymmetry between private information (Stiglitz 1985). Moreover, the herd effect will offset each other’s power to buy and sell bitcoin, and such negative interference to financial stocks is low. Based on the above analysis, this study believes that the impact of private information, as derived from virtual currency on the financial stocks in the Taiwanese market, is higher than that of the mainland market, thus, this study offers H1.

H1: The impact of private information derived from virtual currency on financial stocks in the Taiwanese market is higher than that of the mainland market.

1.2 Fin-Tech and Financial Stock

The underlying technology for virtual currency is the blockchain, and the Fin-Tech formed by this technology has a major impact on the financial industry (Rainer Böhme et al. 2015; Molnár 2018). Blockchain is different from previous information processing methods, as it adopts the concept of a decentralized database and uses decentralized ledgers, instead of third-party equipment, to store and verify every transaction in the market. Through the anonymity and network trust, it constantly packs encrypted data, which is hugely different from the previous financial clearing, records, and transfer payments. Undoubtedly, it interrupts the original traditional financial service type, which causes rapid changes in the relationship between suppliers and consumers (Arthur Brieske et al. 2016). Ho (2020a) explored virtual currency development factors into model of Fama and French (1996) to examine relationships among financial stock value, bitcoin and interaction effect of bitcoin and Fin-Tech in Taiwan and China market. He found financial stocks in Taiwan's market are more greatly shocked by the bitcoin and interaction effect than those in China's market. In 2016, Nasdaq and the investment bank Keefe Bruyette and Woods (KBW) published the Fin-Tech Index (KFTX) to track the performance of those companies that use it, in order to provide or make use of the stock prices of Fin-Tech companies. Almost all of these companies have provided services through electronic, AI, APP, or cloud methods, such as VISA, ACIW, EVER, and Paypal, all of which are non-financial companies. In other words, third-party payments without a banking platform have replaced people's daily transactions, and their low service charges, simple loan procedures, and trading conditions are not good for financial stocks, as stock prices will be under downward pressure.

However, the financial intermediation theory has different views on Fin-Tech's impact on the financial industry. Michael P. Leahy et al. (2001) point out that financial innovation can help make the financial industry more efficient in using funds and promote the growth rate of the U.S. economy. Robert G. King and Ross Levine (1993) pointed out that a sound financial intermediation provides a pool of funds for both borrowers and lenders, which can reduce asymmetric information, facilitate social resource allocation, and provide consumers with stable cash flow. In addition, some literature holds that the financial industry has to play the roles of money flow (Raghuram G. Rajan 1996; Anil K. Kashyap, Rajan, and Jeremy C. Stein 2002), asset transfer, and information supervision (Ingo Walter 2003; Meyer Aaron, Francisco Rivadeneyra, and Samantha Sohal 2017). In this case, the online marketplace lender platform, as developed using the blockchain technology, makes it easier to reach consumers and reduce transaction costs (Molnár 2018). In addition, the banking industry can set up virtual branches or Neo-Banks to reduce the construction costs of physical banking, and based on such improved financial service processes, the insurance industry will use telematics-based insurance to secure new online life insurance contracts, and increase insurance premiums, which will bring about positive benefits for the entire economy. The traditional financial industry has lower costs and more competitiveness than new market competitors (Arnoud W. A. Boot 2016); in other words, the benefits of Fin-Tech can only have positive effect on financial stocks (Bobby Boon-Hui Chaia, Pek See Tan, and Thian Shong 2015). In the future, it will be combined with 5G transmission (Jing Wang 2018), and consumers will gradually adapt to and trust this financial innovation business model (Zhongqing Hu et al. 2019). In this way, the market value of the financial industry will be further enhanced.

In light of the development of Fin-Tech, non-financial companies may severely threaten the services of the financial industry, thus, reducing the profitability of banks and insurance companies. However, the financial intermediation theory, coupled with literature research, supports Fin-Tech's development in the traditional financial industry, and believes that the strength of the traditional financial industry is far better than non-financial companies (Molnár 2018; Hu et al. 2019), which implies that the marginal revenue of Fin-Tech in the financial industry is greater than the marginal cost. Thus, this study starts from this point. The Chinese market has a clear supervision system for virtual currency, and although it limits the use of Bitcoin, it allows third-party payments. In addition, the booming development of blockchain innovation in the private sector and the receipt of bitcoin donations as earthquake disaster funding by the public sector, show that Fin-Tech has extensive and profound impact on the Chinese market. Hence, from the perspective of the financial intermediation theory, Fin-Tech does have positive impact on financial stocks. Due to the extensive application of blockchain in the Chinese market, financial stocks have been great fluctuated by Fin-Tech. On the contrary, the Taiwanese market denies the legality of virtual currency, it does not allow third-party payments, and does not conduct financial supervision to regulate bitcoins, thus, the social and public sectors are not largely affected by Fin-Tech. In this regard, hypothesis H2 is proposed to prove this concept.

H2: The impact of Fin-Tech changes on mainland market financial stocks is higher than that of the Taiwan market.

2. Research Method

This section mainly describes the research subject, research period, main variables, and construction model. This paper hopes to understand whether financial stocks in emerging markets is affected by both substantive and virtual factors, and distinguishes the impact of different financial factors on financial stocks, which is of great importance to formulating national economic policies.

2.1 Research Subjects

The subjects of this research are two emerging markets in Asia, meaning the financial stocks in the two capital markets of Taiwan and China. At present, the Taiwanese market does not recognize the legal status of virtual currency, nor does it have clear financial supervision norms; the Chinese market has issued clear and strict financial supervision, and limits the use of virtual currency. These are the structural differences between the two markets for comparison by this study. The private information derived from virtual currency in this paper comes from the Bitcoin transaction quotation platform, while the Fin-Tech data is from the Fin-Tech Index (KFTX) of the Nasdaq exchange, and the remaining data are from the Taiwan Economic Journal (TEJ).

2.2 Research Period

In May 2015, the Bitcoin Index (NYXBT) was put on the market, and the relevant trading quotation platform began to operate, while the Fin-Tech Index (KFTX) was listed in July 2016. Under such considerations, the study period was set from July 19, 2016 to April 30, 2019. As there are nearly three years of data available for analysis, it is also possible to observe whether the January effect changes the stability of the model. After deduction of incomplete data and relevant comparison, about 44,727 pieces of daily data of Shanghai and Shenzhen financial stocks were collected from the Chinese market, and 22,439 pieces of daily data of financial stocks were collected from the Taiwanese market, thus, a total of 67,166 pieces of data were used as the calculation basis for this research model. Furthermore, Ho (2020a, b) used the same data in this paper for their studies. The earlier paper, with Bitcoin indexes as the kernel variables, explores the effect of the development of virtual currencies on financial stocks, by the capital asset pricing model (CAPM), portfolio theory and innovation diffusion theory (IDT). The subsequent paper explores the effect of exposures of virtual currencies on financial stocks, and calculates main variables based on the theory of exchange rate exposure. This paper uses the data of Bitcoin/Home currencies but deduces differently, because the links are information economics and financial intermediary theory. This paper emphasizes the destruction of private information in communities and the advantages of financial intermediaries. In the three papers, the effect of financial stocks has different significances, but the basic statistics of some variables are the same, which are specially explained for the purpose of differentiation.

2.3 Research Variables

In addition to exploring the changes in financial stocks by substantive and virtual factors, this study also hopes to understand the effect of these variables on different regions. In the model constructed by this paper which adopts a three-factors approach and Ho (2020a)'s model, the excess return of financial stocks is based on variables, scale, net market value ratio, and market excess return, which are substantive factors and control variables, while Bitcoin's private information and Fin-Tech Index (FTI) are virtual factors and independent variables. The calculation of the relevant variables is shown, as follows.

2.3.1 Excess Rate of Return on Financial Stocks ($R_i - R_f$)

The excess return of financial stocks is the daily return after considering Ex-Right or Ex-Dividend, as shown in Equation (1). Then, the daily return is subtracted from the market risk-free rate(R_f) to obtain the excess return of the financial stock, namely, a dependent variable.

$$R_{i,t} = (\frac{P_{i,t}\times(1+S\%+N\%)+Div_{i,t}}{P_{i,t-1}+(1+F\times N\%)+Div_{i,t-1}} - 1) \times 100\%, \tag{1}$$

where $R_{i,t}$: the return of financial stocks in period t, $P_{i,t}$: the stock price of i financial stocks in period t, $Div_{i,t}$: the dividends of i financial stocks in period t, $P_{i,t-1}$: the stock price of i financial stocks in the t-1 period, $Div_{i,t-1}$: the dividends of i financial stocks in the t-1 period, *S%* = stock interest rate, *N%* = cash allotment rate, *F* = cash increase capital per share underwriting price.

2.3.2 Size of Financial Stocks (SIZE)

The calculation of the size of individual stocks in this study is based on the natural logarithm of the market value of financial stocks. The substantive factor of this model is also the control variable, as shown in Equations (2).

$$SIZE_{i,t} = \ln(Market\ Value)_{i,t}. \tag{2}$$

2.3.3 Net Market Value Ratio (BMR)

The book-to-market ratio is the judgment of financial stocks as growth or value stocks. The method used in this study is to divide the book value of financial stocks by the natural logarithm of market value, and treat the result as a substantive factor and a control variable, as shown in Equation (3).

$$BMR_{i,t} = \ln\left(\frac{BV_{i,t}}{MV_{i,t}}\right), \tag{3}$$

where $BMR_{i,t}$: is the net value market value ratio of *i* financial stocks in period *t*, $BV_{i,t}$: is the book value of *i* financial stocks in period *t*, $MV_{i,t}$: is the market value of *i* financial stocks in period *t*.

2.3.4 Market Excess Rate of Return ($R_m - R_f$)

The calculation method for the excess return of the two emerging markets is the same, meaning both adopt the daily return, which is the difference between the market indices of the two business days before and after, in order to subtract the market risk-free interest rate (R_f) and obtain the excess return of the market, which is a substantive factor and a control variable, as shown in Equation (4).

$$R_{m,t} = \frac{P_{m,t} - P_{m,t-1}}{P_{m,t-1}} \times 100\%, \tag{4}$$

where $R_{m,t}$: is the return of market index in period *t*, $P_{m,t}$: is the value of market index stock in period *t*, and $P_{m,t-1}$: is the value of market index in the *t*-1 period.

2.3.5 Private Information of Virtual Currency (VP)

How to join the discussion of virtual currency on a social network is a difficult issue in both the Taiwanese and Chinese markets, which is mainly because the Chinese market has restrictions on community speech. According to Mai et al. (2018), if semantic analysis is used to search the structure of a particular word or string of words to predict stock price, the relevant information cannot be found in the Chinese market. According to information economics, prices are obtained through searching, the process is costly, the searched information is usually incomplete, and is mostly private information (Stiglitz 1985). This study uses the quotation information on the Bitcoin trading platform as proxy variables for private information. The direct quotation of Bitcoin to the home currency is not public information, but the highest price that a particular person is willing to pay to purchase a unit of virtual currency. Moreover, this type of quotation depends on the private information of the day, which is in line with the concept of private information by Daniel, Hirshleifer, and Subrahmanyam (1998). This paper calculates the change rate of the direct quotation price of Bitcoin to the home currency of two business days as the private information connotation of the home country's virtual currency. Furthermore, Ho (2020b) employs similar idea to calculate cryptocurrency exchange exposure in order to compare difference Asia markets and finds out cryptocurrency exchange exposure of China market more than Taiwan market. As a virtual factor and an independent variable, it is used to predict the change of the value of the financial stock, as shown in Equation (5).

$$VP_t = \frac{(Home\ Currency/Bitcoin)_t - (Home\ Currency/Bitcoin)_{t-1}}{(Home\ Currency/Bitcoin)_{t-1}} \times 100\%, \tag{5}$$

where VP_t: the change rate of private information in period t; $(Home\ Currency/Bitcoin)_t$: the direct quotation of a unit of bitcoin to the home currency in period t; $(Home\ Currency/Bitcoin)_{t-1}$: the direct quotation of a unit of bitcoin to the home currency in the t-1 period.

2.3.6 FTI

The Nasdaq exchange and investment bank, Keefe Bruyette and Woods (KBW), published the Fin-Tech Index (KFTX), which contains 49 stocks related to FTI. In this study, the KFTX index return is used as the proxy variable of FTI, as well as the virtual factor and the model's independent variable. The related calculation method is like that of the market return, as shown in Equation (6).

$$FTI_t = \frac{KFTX_t - KFTX_{t-1}}{KFTX_{t-1}} \times 100\%, \tag{6}$$

where FTI_t: the rate of return of FTI in period t; $KFTX_t$: the value of FTI in period t; $KFTX_{t-1}$: the value of FTI in the t-1 period.

2.4 Model

Bouri, Gupta, and Roubaud (2019) examine the herding behavior associated with cryptocurrencies and notice that static models cannot clearly show this behavior, because of the structural breaks and non-linearity of data. The research then conducts a rolling window analysis and identifies significant herding behavior in the crypto market. Such effects actually change over time. Shahzad et al. (2021) explore the contagion effects of cryptocurrencies and conclude that the four-factor pricing model offers better explanatory power. They derive great estimates after adding heterogeneous disturbance of cryptocurrencies to the model. Therefore, this paper uses panel data to replace the statistic rolling analysis, in order to observe the hidden effects of time series. Moreover, this paper looks into the influence of virtual factors on the excess returns of financial stocks. As the calculation of social media discussions may overlap with the heterogeneity of cryptocurrencies, multicollinearity may interfere with the estimates. Therefore, the use of a four-factor model is out of the question.

From the perspective of the model of Fama and French (1996), and in addition to considering the impact of size, book value ratio, and market system risk on stock price (William F. Sharpe 1964; Fama and French 1992), this paper considers the concept of international index integration and co-movement (Gregory C. Chow, Changjiang Liu, and Linlin Niu 2011; Ho 2020a, b). Therefore, as constructed based on the Fama-French three-factor model, this model adds the two virtual economic variables of VP and FTI of virtual currency, and uses tracking data for analysis. The original model is shown in Equation (7).

$$R_{i,t} - R_{f,t} = \alpha_0 + \beta_1\left(R_{m,t} - R_{f,t}\right) + \beta_2 ln(SIZE)_{i,t} + \beta_3 ln(BMR)_{i,t} + \beta_4(VP)_{i,t} + \beta_5(FTI)_t + \varepsilon_{i,t}, \tag{7}$$

where $(R_{i,t} - R_{f,t})$ is the excess return of financial stocks in period *t*; $\left(R_{m,t} - R_{f,t}\right)$ the excess return of market in period *t*; $ln(SIZE)_{i,t}$: the market value of i financial company in period *t*; $ln(BMR)_{i,t}$ the net market price ratio of financial stocks in period *t*; VP_t: the rate of change of private information in period *t*; FTI_t the FTI return in period *t*, ε_t residual of the model, and β_i the model regression coefficient. Then, the paper adjusts the original Model (7) to two market feature models, where Model (8) is the Taiwanese market characteristic equation, and Model (9) is the Chinese market characteristic equation. The relevant variables are described in Equation (6), with only β_{iC}representing the regression coefficient of the Chinese market characteristic model and β_{iT} representing the regression coefficient of the Taiwanese market characteristic model.

$$R_{i,t} - R_{f,t} = \alpha_{0T} + \beta_{1T}(R_{m,t} - R_{f,t}) + \beta_{2T} ln(SIZE)_{i,t} + \beta_{3T}(BMR)_{i,t} + \beta_{4T}(VP)_t + \beta_{5T}(FTI)_t + \varepsilon_{i,t}; \tag{8}$$

$$R_{i,t} - R_{f,t} = \alpha_{0C} + \beta_{1C}(R_{m,t} - R_{f,t}) + \beta_{2C} ln(SIZE)_{i,t} + \beta_{3C}(BMR)_{i,t} + \beta_{4C}(VP)_t + \beta_{5C}(FTI)_t + \varepsilon_{i,t}. \tag{9}$$

This paper sets up a dummy variable *D* to separate Taiwan data and China data, where D_1 denotes the Taiwan market, and D_2 is the China market. The eigenvalues of these two markets in Equation (8) and Equation (9) are this way combined into Equation (10). As data are either about the Taiwan market or the China market, D_1+D_2=1. The aforesaid combination equation can be expanded into Equation (11). A similar approach is seen in Ho (2020a, b). We further classify the two into Equation (10) and verify the two null hypotheses

$$H_{10}{:}\beta_{4T} - \beta_{4C} \geq 0, H_{20}{:}\beta_{5T} - \beta_{5C} \geq 0.$$

$$R_{i,t} - R_{f,t} = D_1[\alpha_{0T} + \beta_{1T}\left(R_{m,t} - R_{f,t}\right) + \beta_{2T} ln(SIZE)_{i,t} + \beta_{3T}(BMR)_{i,t} + \beta_{4T}(VP)_t + \beta_{5T}(FTI)_t + \varepsilon_{i,t} + D_2[\alpha_{0C} + \beta_{1C}(R_{m,t} - R_{f,t}) + \beta_{2C} ln(SIZE)_{i,t} + \beta_{3C}(BMR)_{i,t} + \beta_{4C}(VP)_t + \beta_{5C}(FTI)_t + \varepsilon_{i,t}] \tag{10}$$

$$R_{i,t} - R_{f,t} = \alpha_{0C} + (\alpha_{0T} - \alpha_{0C})D_1 + \beta_{1C} R_{m,t} + (\beta_{1T} - \beta_{1C})D_1(R_{m,t} - R_{f,t}) + \beta_{2C} ln(SIZE)_{i,t} + (\beta_{2T} - \beta_{2C})D_1 ln(SIZE)_{i,t} + \beta_{3C}(BMR)_{i,t} + (\beta_{3T} - \beta_{3C})D_1(BMR)_{i,t} + \beta_{4C}(VP)_t + (\beta_{4T} - \beta_{4C})D_1(VP)_t + \beta_{5C}(FTI)_t + (\beta_{5T} - \beta_{5C})D_1(FTI)_t + \varepsilon_{i,t}. \tag{11}$$

3. Results and Discussion

The purpose of this section is to discuss and present the results of all data analysis. The content is divided into basic statistical analysis, variable correlation analysis, regression analysis, and robustness analysis.

3.1 Basic Statistics Analysis

There are six main variables in this study, the excess return of financial stocks ($R_i - R_f$), the net market value ratio (BMR), the market excess return ($R_m - R_f$), the size of individual stocks (SIZE), the private information of virtual currency (VP), and FTI. The basic narrative statistics include various values, such as Mean, Median, Maximum, Minimum, Std. dev, Skewness, Kurtosis, and Jarque-Bera, and are listed in Table 1. Taking the Taiwanese market as an example; the average return of financial stocks ($R_i - R_f$) is -0.009860, the maximum value is 0.315264, and the skew coefficient is 2.6967713. The median of VP of the virtual currency is 0.002968, the minimum value is -0.200288, and the kurtosis coefficient is 9.812504. For the remaining variables, please refer to the Taiwanese market value shown in Table 1; for example, from the perspective of the Chinese market, the average return of financial stocks ($R_i - R_f$) is -0.010578, the maximum value is 0.430341, and the skew coefficient is 2.696713. The median of VP of the virtual currency is 0.001241, the minimum value is -24.29679, and the kurtosis coefficient is 49.85485. For the remaining variable statistics, please refer to the Chinese market value in Table 1.

Table 1 Basic Statistics

Taiwan market	$(R_i - R_f)$	BMR	$(R_m - R_f)$	SIZE	FTI	VP
Mean	-0.009860	1.167762	0.000282	10.79667	0.000804	0.002398
Median	-0.010450	1.159330	-0.000260	10.55654	0.001000	0.002968
Maximum	0.315264	2.686562	0.332506	13.47454	0.052000	0.330835
Minimum	-0.109588	0.384637	-0.072392	6.901737	-0.059000	-0.200288
Std. dev.	0.009776	0.337082	0.009657	1.547419	0.009649	0.045443
Skewness	2.696713	0.625405	3.358225	-0.401509	-0.312557	0.405190
Kurtosis	72.57218	4.644570	79.55708	2.474632	8.391173	9.812504
Jarque-Bera	4552664.	3991.464	5521955.	860.9564	27539.68	44005.62
N			22,439			
China market	$(R_i - R_f)$	BMR	$(R_m - R_f)$	SIZE	FTI	VP
Mean	-0.010578	0.651098	-0.010573	12.27325	-0.426060	-0.420796
Median	-0.011000	0.650205	-0.012175	12.07251	0.000000	0.001241
Maximum	0.430341	22.36493	0.460421	19.67318	0.052000	0.333780
Minimum	-0.111806	-5.094659	-0.126942	8.334485	-24.51550	-24.29679
Std. dev.	0.025626	0.773087	0.022192	1.564123	2.607169	2.585622
Skewness	2.679029	-2.371084	4.159578	1.079325	-6.748360	-6.741936
Kurtosis	45.04139	35.00027	75.31438	5.778230	49.93115	49.85485
Jarque-Bera	3347420	1950294.	9874561	23068.58	4444176.	4430194.
N			44,727			

Notes: This table describes the basic statistics which are Mean, Median, Maximum, Minimum, Std. dev., Skewness, Kurtosis, and Jarque-Bera for all variables in both markets, including ($R_i - R_f$), (BMR), ($R_m - R_f$), (SIZE), (VP), and (FTI).Due to the different sample sizes, listing time and closing time in the two markets, the basic FTI statistics are calculated based on the actual number after data stack.

Source: Author's calculations.

There is an obvious gap between the two markets in terms of net market value ratio (BMR). With an average value of 1.167762 in the Taiwanese market, the financial stocks can be classified as value stocks; with a value of 0.651098 in the Chinese market, the financial stocks can be classified as growth stocks. It is worth mentioning that the volatility of VP of virtual currency is only 0.045443 in the Taiwanese market featuring open communities and online conversations, while such value is as high as 2.585622 in the Chinese market, which is probably because the Chinese market is a virtual currency transaction market with the largest transaction amount. In addition, China controls community speech, thus, while the volatility of private information is particularly large, the impact on financial stocks should be determined based on causality.

3.2 Correlation Analysis

Table 2 describes the correlation coefficient among the variables. According to the numerical analysis of the Taiwanese market, the VP of the virtual currency is significantly negatively correlated with the excess return $(R_i - R_f)$ of individual stocks (-0.0255, $p < 0.05$), but is significantly positively correlated with (FTI) (0.0416, $p < 0.05$). The significance of private information and excess return of individual stocks may be similar to those of Daniel, Hirshleifer, and Subrahmanyam (1998) and Ho (2013), which argued that private information can negatively interfere with the value of individual stocks or assets. In addition, this paper found that FTI was significantly positively correlated with the excess return of individual stocks (0.0895, $p < 0.05$), which seems to support the hypothesis of the financial intermediation theory on the relationship between financial stock value and FTI (Molnár 2018). After turning the focus of attention to the Chinese market, this study found that there was partly significant correlation among all variables in the correlation matrix, which was greatly different from the Taiwanese market. For example, the VP of virtual currency in the Chinese market had significant positive correlation with the excess return of individual stocks $(R_i - R_f)$ and FTI, with correlation coefficients of 0.0308 ($p < 0.05$) and 0.0322 ($p < 0.05$), respectively. Similar to the study of Mai et al. (2018), this study does not support the ideas of Daniel, Hirshleifer, and Subrahmanyam (1998) or Ho (2013). While this study agrees with the argument of Molnár (2018), meaning that there is significant positive correlation between FTI and the excess return on stocks (0.0699, $p < 0.05$), this correlation is only between single variables, and conclusions should be made upon causality after multivariate regression analysis. Regarding the correlation of other variables, please refer to Table 2. It is worth mentioning that the structures of the two market financial stocks are significantly different. As shown in Table 1, the financial stocks in the Taiwanese market were mostly value stocks, and were significantly negatively correlated with the SIZE (-0.2086, $p < 0.05$), while the SIZE was closely related to the net market value-to-market ratio (BMR) (0.5004, $p < 0.05$) in the Chinese market.

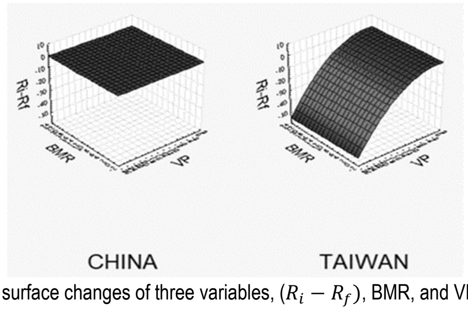
Figures 1 and 2 show the classification characteristics of the Taiwanese and the Chinese markets. Figure 1 is drawn with three variables: $(R_i - R_f)$, BMR, and VP; while Figure 2 is based on three variables: $(R_i - R_f)$, SIZE, FTI. According to the comparison shown in Figure 1, the excess return $(R_i - R_f)$ of financial stocks on the Taiwanese market first increased with the net market value-to-market ratio (BMR), increased to the highest with the VP; while there is not much change in the excess return $(R_i - R_f)$ of financial stocks, net market value ratio (BMR), or VP in the Chinese market. However, a closer look at the heights of the Z-axis movements in the two markets found that the excess return $(R_i - R_f)$ of financial stocks on the Chinese market increased as VP rose slightly, while the Taiwanese market saw a maximum value and then declined. According to the analysis shown in Figure 2, after the introduction of FTI in the Taiwanese market, the excess return $(R_i - R_f)$ of financial stocks did not seem to change with the size of the company (SIZE). However, after the introduction of FTI in the Chinese market, the excess return $(R_i - R_f)$ of financial stocks had substantive changes as the size of the company (SIZE) increased. Comparison of Figure 1 and Figure 2 reveals that there are significant differences in the financial environment between the two markets, which is consistent with the study of Shaher, Khasawneh, and Salem (2011).

Table 2 Correlation Coefficient Matrix

Taiwan market	$(R_i - R_f)$	**BMR**	$(R_m - R_f)$	**SIZE**	**FTI**	**VP**
$(R_i - R_f)$	1	-0.0158**	0.6741**	0.0076	0.0895**	-0.0255**
BMR		1	-0.0125	-0.2086**	0.0022	0.0075
$(R_m - R_f)$			1	0.0058	-0.0606**	0.0107
SIZE				1	-0.0001	-0.0029
FTI					1	0.0416**
VP						1
China market	$(R_i - R_f)$	**BMR**	$(R_m - R_f)$	**SIZE**	**FTI**	**VP**
$(R_i - R_f)$	1	-0.0984**	0.8266**	0.0115**	0.0699**	0.0308**
BMR		1	0.0001	0.5004**	-0.0048	-0.0222**
$(R_m - R_f)$			1	0.0094***	0.0133**	0.0216**
SIZE				1	0.0041	0.0814
FTI					1	0.0322**
VP						1

Notes: This table describes the Pearson product correlation coefficient values for all variables in the two markets, including $(R_i - R_f)$, (BMR), $(R_m - R_f)$, (SIZE), (VP), and (FTI). Only the significance of $p < 0.05$ is listed. ** $p < 0.05$.

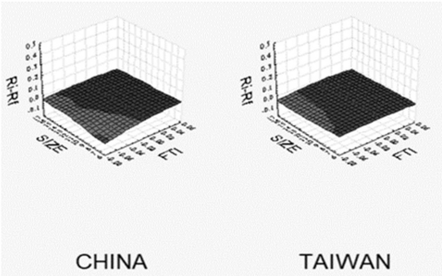
Source: Author's calculations.



Notes: Figure 1 compares the surface changes of three variables, $(R_i - R_f)$, BMR, and VP, in different markets. The graphic pattern indicates higher reactivity in the Taiwan market.

Source: Author's calculations.

Figure 1 Market Classification Characteristic



Notes: Figure 2 compares the surface changes of three variables, $(R_i - R_f)$, SIZE, and FTI, in different markets. The graphic pattern indicates higher reactivity in the China market because the surface color gradually changes and elevates.

Source: Author's calculations.

Figure 2 Market Classification Characteristic

3.3 Panel Regression Analysis

Before panel regression analysis, the test of Jerry Hausman (1978) should be conducted to track data regression. If the results of the Hausman test reject null hypothesis, then in this paper the fixed effect model shall be used for estimation; otherwise, the random effect model shall be used for estimation. It is found after verification of Hausman statistics of full model of Taiwan's market is 19.5067 ($p < 0.01$) and that of China's market is 36.2517 ($p < 0.01$), and both reject the null hypothesis estimated by the random effect - namely, the fixed effect shall be selected for the regression model for the estimations.

This study explores whether the changes in the financial stocks of the two markets are more affected by three factors, market excess return, or the book-to-market ratio; or by private information derived from virtual currency and Fin-Tech? Which market will have higher fluctuations? These questions can be analyzed and discussed based on Table 3. From the regression model of the Taiwanese market, as shown in Table 3, the dependent variable is the excess return $(R_i - R_f)$ of individual stocks, and the remaining variables are control variables or independent variables. Model A first added the three-factor model to FTI, which was significantly positively correlated with financial stocks (0.132389, $p < 0.01$); Model B then added the three-factor model to the virtual currency VP, which was significantly negatively correlated with financial stocks (-0.007148, $p < 0.01$). Finally, Model C simultaneously added both VP, as derived from virtual currency, and FTI to the three-factor model, showing the same direction and significance as those of Model A and Model B; that is, the development of FTI will increase the value of Taiwan's financial stocks. However, if virtual currency is not regulated by financial supervision, financial stocks will be impaired due to arbitrary communities or media network spread. Careful observation and comparison of the changes in the three models found that the substantive variable of SIZE in the three-factor model became insignificant, which means that financial stocks in the Taiwan market are driven by both virtual factors and substantive factors that exclude SIZE variable. The model Adjusted R^2 and F values are significant, indicating that the research model has good predictive power. Please refer to the results of Table 3 for the remaining regression coefficients.

Table 3 Analysis of Regression Model on Taiwanese Market

This table model of the cross-section fixed regression results of the Taiwanese market offers significance and *t*-stats of regression coefficients. There are three models, and the dependent variables and independent variables are described in the equation: $R_{i,t} - R_{f,t} = \alpha_0 + \beta_1(R_{m,t} - R_{f,t}) + \beta_2 ln(SIZE)_{i,t} + \beta_3 ln(BMR)_{i,t} + \beta_4 (VP)_{i,t} + \beta_5 (FTI)_t + \varepsilon_{i,t}$.

Dependent variable: $(R_i - R_f)$ Taiwan market

Independent Variables	Model A		Model B		Model C	
	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Intercept	-0.009570***	-10.07728	-0.009492***	-9.847503	-0.009555***	-10.07514
BMR	-0.000871***	-3.073766	-0.000787***	-2.735949	-0.000824***	-2.909971
$(R_m - R_f)$	0.690035***	139.9429	0.682411***	136.5982	0.690577***	140.2342
SIZE	3.96E-05	0.495442	3.49E-05	0.430297	3.48E-05	0.435626
FTI	0.132389***	26.85106			0.134004***	27.19320
VP			-0.007148***	-6.729087	-0.008319***	-7.953595
Adjusted R^2	0.470885		0.454938		0.472353	
F-statistic	313.0099***		293.6239***		310.0252***	
N	22,439					

Notes: *** $p < 0.01$.

Source: Author's calculations.

From the results of the regression model analysis of the Chinese market in Table 4, while Model A's three-factor model added the FTI variable, it was significantly positively correlated with financial stocks (0.154167, $p < 0.01$); Model B added virtual currency VP to the three-factor model, and it was also significantly positively correlated with financial stocks (0.006930, $p < 0.01$). Model C added virtual currency VP and FTI to the model, and the results show that FTI was significantly positively correlated with financial stocks (0.153293, $p < 0.01$), and virtual currency VP was also significantly positively correlated with financial stocks (0.005908, $p < 0.01$). The conclusion of Model C is different as that observed in the Taiwanese market. FTI and VP will increase financial stocks in the Chinese market. Similarly, observing and comparing the changes of the three models found that the three substantive variables $(R_m - R_f)$, BMR, and SIZE in the three-factor model, as well as the two virtual factors of FTI and VP, have significant impact on financial stocks; that is, the role of financial stocks on the Chinese market is driven by both the substantive factors and virtual factors of the digital economy. Finally, the model Adjusted R^2 and F values show that the model has good predictive power. Please refer to the results of Table 4 for the remaining regression coefficients.

To explore whether financial stocks is more affected by substantive factors or virtual factors, this study needs to determine whether the two research hypotheses are true. Table 5 shows the fixed effect panel regression model analysis that integrates the two markets' data after tests for the Hausman statistics, which is 13214.94 ($p < 0.01$) and rejects the random effect hypothesis. From the variable D1*VP of Table 5, the influence of the private message (VP) of the virtual currency on financial stocks on the Taiwanese market is relatively large. The regression coefficient (-0.008259, $p < 0.01$) shows that the financial stocks on the Taiwanese market are more negatively affected by private information than on the Chinese market; that is, H1 is established, and the null hypothesis: H_{10}: β_{4T} −: $\beta_{4C} \geq 0$ is rejected. Then, this study discussed another variable, D1*FTI, to observe the impact of the change in FTI on financial stocks on the Chinese market. From the regression coefficient of D1*FTI (-0.020123, $p < 0.1$), financial stocks on the Taiwanese market are indeed less affected by FTI than on the Chinese market; that is, H2 is established, and the null hypothesis: H_{20}:$\beta_{5T} - \beta_{5C} \geq 0$ is rejected. It can be seen from regression coefficients D1, D1*($R_m - R_f$), D1* BMR, D1*VP, D1* SIZE, and D1*FTI in Table 5 that the structure of the two markets is significantly different. Finally, the Adjusted R^2 and F values are significant, indicating that the model has good predictive power. Please refer to the results of Table 5 for the remaining regression coefficients.

Table 4 Analysis of Regression Model on the Chinese Market

This table model of the cross-section fixed regression results of the Chinese market offers significance and *t*-stats of regression coefficients. There are three models, and the dependent variables and independent variables are described in the equation:

$$R_{i,t} - R_{f,t} = \alpha_0 + \beta_1(R_{m,t} - R_{f,t}) + \beta_2 ln(SIZE)_{i,t} + \beta_3 ln(BMR)_{i,t} + \beta_4(VP)_{i,t} + \beta_5(FTI)_t + \varepsilon_{i,t}$$

Dependent variable: $(R_i - R_f)$ China market

Independent Variables	Model A		Model B		Model C	
	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Intercept	-0.003553**	-2.132401	-0.003676**	-2.197119	-0.003450**	-2.070324
BMR	-0.001559***	-6.484723	-0.001565***	-6.484175	-0.001535***	-6.385927
$(R_m - R_f)$	0.952924***	310.6354	0.953380***	309.6584	0.952655***	310.5281
SIZE	0.000336**	2.443336	0.000357***	2.588093	0.000324**	2.360044
FTI	0.154167***	22.14673			0.153293***	22.01452
VP			0.006930***	4.749813	0.005908***	4.047838
Adjusted R^2	0.686771		0.683520		0.686879	
F-statistic	789.5395***		780.0108***		783.6252***	
N			44,727			

Notes: *** $p < 0.01$.

Source: Author's calculations.

According to the results in Table 3, the effect of size is insignificant in Taiwan's market, indicating that the changes in the market size of financial stocks during the sample period cannot explain the effect on excess returns. Maybe due to the global quantitative easing, the interest margin is low and there are no returns to scale on financial stocks. Of course, there may be another reason. Maybe the development of financial technology or the application of virtual network changes the structure of the excess returns on financial stocks. In order to confirm this idea, the other two models in Table 3 are compared, and it found that this inference is reasonable. As the sizes of financial stocks vary greatly in the Chinese market, according to the results in Table 4, that the size change affects stock prices and excess returns. The market of ethnic Chinese allows investors to invest in each other and has a great number of large enterprises, therefore China's market surely attracts a lot of capital, and the difference in the size of the two markets in Table 5 can explain the excess returns on financial stocks in the two different regions.

Table 5 Analysis of Two Markets Regression Model

The model of this table is to test the difference between the regression coefficients in the two markets. The model depends on the dependent variables and the independent variables, as follows:

$$R_{i,t} - R_{f,t} = \alpha_{0C} + (\alpha_{0T} - \alpha_{0C})D_1 + \beta_{1C}R_{m,t} + (\beta_{1T} - \beta_{1C})D_1(R_{m,t} - R_{f,t}) + \beta_{2C}ln(SIZE)_{i,t} + (\beta_{2T} - \beta_{2C})D_1 ln(SIZE)_{i,t} + \beta_{3C}(BMR)_{i,t} + (\beta_{3T} - \beta_{3C})D_1(BMR)_{i,t} + \beta_{4C}(VP)_t + (\beta_{4T} - \beta_{4C})D_1(VP)_t + \beta_{5C}(FTI)_t + (\beta_{5T} - \beta_{5C})D_1(FTI)_t + \varepsilon_{i,t}$$

Dependent variable: $(R_i - R_f)$ Merge Taiwan and China market (All data)

Variables	Coefficient	*t*-statistic	Variables	Coefficient	*t*-statistic
Intercept	-0.004013**	-2.547417	D1	-0.005633**	-2.008508
BMR	-0.001835***	-8.628559	D1*(R_m – R_f)	-0.262292***	-29.13703
(R_m – R_f)	0.952869***	359.4468	D1* SIZE	-0.000358*	-1.943193
SIZE	0.000392***	3.270920	D1* BMR	0.001011*	1.877552
FTI	0.154126***	25.61635	D1*VP	-0.008259***	-4.517628
VP	-6.06E-05	-1.110908	D1*FTI	-0.020123*	-1.915903
N		67,166			
Adjusted R^2		0.672339			
F-statistic		721.1642***			

Notes: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Source: Author's calculations.

3.4 Robustness Analysis

In this paper, the two factors of virtual currency development are included in the model for discussion. Although there are preliminary conclusions, the self-correlation between the January effect, the model in the financial market, and heteroskedasticity may affect the research results; therefore, it is necessary to consider the above issues and conduct panel data of robustness analysis. Table 6 shows the result of robustness analysis of the regression model. Model A considers the model's self-correlation and heteroskedasticity and uses Newly-West Regression, as the research data belongs to the time series and involves structural differences between the two markets. The regression coefficients of the two variables D1*VP (-0.008274, $p < 0.01$) and D1*FTI (-0.020056, $p < 0.01$) show that the direction and significant results have not changed, which is in line with the conclusions of Table 4-5. Model B shows the result after removing all January data from the two markets and re-conducting pool regression. The coefficients of D1*VP (-0.019195, $p < 0.01$) and D1*FTI (-0.002510, $p < 0.1$) show that the directionality and significance of Table 5 remain unchanged. Bouri, Gupta, and Roubaud (2019) also suggest that there are non-linearity problems with crypto data. Therefore, Model C combines the data from both markets for non-linear estimates. After iterative calculations with the Quasi-Newton method, the model criterion is based on the loss function. The regression coefficient of Model C shows that the variable D1*VP(-0.008273, $p < 0.1$) is in the same direction as D1*FTI(-0.023671, $p < 0.1$) in Table 5. In other words, this paper confirms the existence of H1 and H2, while rejecting the two null hypotheses H_{10} and H_{20}, and the result has great robustness.

Table 6 Regression Model Robustness Analysis

The model is the Newly-West Regression for testing both market data, the POOL after deducting the January data, and the Quasi-Newton Regression for testing both markets. The difference between the regression coefficients in different markets, the model dependent variable, and the independent variable are, as follows.

$$R_{i,t} - R_{f,t} = \alpha_{0C} + (\alpha_{0T} - \alpha_{0C})D_1 + \beta_{1C}R_{m,t} + (\beta_{1T} - \beta_{1C})D_1(R_{m,t} - R_{f,t}) + \beta_{2C}ln(SIZE)_{i,t} + (\beta_{2T} - \beta_{2C})D_1 ln(SIZE)_{i,t} + \beta_{3C}(BMR)_{i,t} + (\beta_{3T} - \beta_{3C})D_1(BMR)_{i,t} + \beta_{4C}(VP)_t + (\beta_{4T} - \beta_{4C})D_1(VP)_t + \beta_{5C}(FTI)_t + (\beta_{5T} - \beta_{5C})D_1(FTI)_t + \varepsilon_{i,t}$$

Dependent variable: $(R_i - R_f)$	**Model A Newly-West regression**		**Model B POOL (exclude January data)**		**Model C Quasi-Newton regression**
Variables	**Coefficient**	***t*-statistic**	**Coefficient**	***t*-statistic**	**Coefficient**
Intercept	-0.002722***	-3.866317	-0.006609***	-3.462821	-0.002139*
BMR	-0.000815***	-4.246124	-0.001648***	-4.854337	-0.000836*
$(R_m - R_f)$	0.953804***	59.89360	0.173830***	35.17523	0.976765*
SIZE	0.000223***	3.507790	2.86E-05	0.202096	0.000195
FTI	0.154355***	12.47306	0.139725***	12.87989	0.157970*
VP	1.83E-05	0.673661	0.009803***	4.206354	0.000017*
D1	-0.007333***	-9.095077	-0.006515*	-1.655356	0.007917*
D1*$(R_m - R_f)$	-0.262854***	-9.769258	0.522157***	32.87259	-0.285815*
D1* SIZE	-0.000209***	-2.998925	1.98E-05	0.096175	-0.000182
D1* BMR	0.000616***	2.636253	0.001259*	1.875645	0.000637*
D1*VP	-0.008274***	-6.808034	-0.019195***	-4.721786	-0.008273*
D1*FTI	-0.020056*	-1.748076	-0.002510*	-1.832710	-0.023671*
N	67,166		61,137		65,535
Adjusted R^2	0.672520		0.062082		0.83804
F-statistic	12515.95***		24.12373***		Loss Fuction=9.13985

Notes: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Source: Author's calculations.

The results of the robustness analysis support Ho (2013), Carrick (2016), Ciaian, Rajcaniova, and Kancs (2016), Mai et al. (2018), and Hidajat (2019). Even with the substantial factors in the model taken into account, the private information-led and non-fundamental-driven herding behaviors still interfere with the value of financial stocks (Bhambhwani et al. 2019). This finding is different from Klein, Thu, and Walther (2018). In addition, the economies of scale and the reduction of transaction costs due to financial innovations in the financial industry support the intrinsic value of financial intermediaries. Obviously, blockchain technology creates new niches for the financial industry (Leahy et al. 2001; Molnár 2018) and far outweighs any adverse effects on financial stocks (Ho 2020a, b). This means the digital influence driven by virtual factors will contribute to economic growth (Molnár 2018). As mentioned by Bouri, Gupta, and Roubaud (2019) and Yousaf et al. (2021), ignoring virtual factors may lead to unexpected volatility and market inefficiency. Finally, the coefficients of *D1**$(R_m - R_f)$*, D1* SIZE, and D1* BMR* indicate structural differences in the substantial factors between these two markets. This is also the reason for inconsistency in the literature.

4. Conclusion and Suggestions

Under the framework of virtual currency development, this study explores the impact of private information and FTI on financial stocks. After some experimental design and model analysis, this paper supports several important findings. H1's community decision-making individuals feature bounded rationality and interaction, and the spread of private information has negative impact on financial stocks, which is in line with conclusion of Stiglitz (1985), Daniel, Hirshleifer, and Subrahmanyam (1998), Ho (2013), and Mai et al. (2018); that is, the null hypothesis (H_{10}:$\beta_{4T} - \beta_{4C} \geq 0$) is rejected, and the opposite hypothesis $\beta_{4T} - \beta_{4C} \leq 0$ is established. There are similar financial supervision mechanisms to regulate the dissemination of false statements in the Taiwanese and Chinese markets; however, according to the results of H1 and other related analysis, the Taiwanese market should introduce stricter financial supervision policies, while the Chinese market should moderately open the community to reduce the fluctuation of private information. H2 intends to verify the existing advantages of the financial industry stressed by the financial intermediation theory. After introducing FTI, it can help to enhance the competitive position; that is, the null hypothesis(H_{20}:$\beta_{5T} - \beta_{5C} \geq 0$) is rejected, while the opposite hypothesis $\beta_{5T} - \beta_{5C} \leq 0$ is accepted, and this result is in line with that of Molnár (2018). However, due to clear financial supervision in the Chinese market, third-party payments and blockchain innovations are flourishing, and are more affected by FTI. In contrast, the Taiwanese market does not recognize the environment of bitcoin or third-party payments. The introduction of FTI has relatively small impact on financial stocks, and corresponds to Figure 2 of this study.

This paper continues to observe the impact of the three factors of Fama and French (1996) and the two variables of VP and FTI on financial stocks. In terms of regression results, financial stocks in the Taiwan market are driven by all virtual factors and two substantive factors, while financial stocks in the China market are affected by all substantive factors and virtual factors. Thus, the impact of virtual currency development and the impact of country or regional risks on financial stocks cannot be ignored (Shaher, Khasawneh, and Salem 2011). In addition, the regression results of Tables 5 and 6 show that there is a clear difference in the financial environment between the two markets. This model compares two emerging Asian markets. In terms of the development of virtual currency, the two markets have two different financial supervision systems, and it is difficult to explain whether the conclusions of other regions are the same.

The paper makes a number of contributions and suggestions for future studies. First, it expands the research on the influence of herding behavior and financial innovations arising from the development of cryptos on financial stocks. The diffusion of private information should be modulated and controlled in a timely manner with policy tools. It is necessary to keep a close eye on the exchange volatility between cryptocurrencies and home currencies, in order to conduct stress tests on the financial industry and perform proactive risk management. Many recent studies cover how COVID-19 is connected with financial markets and cryptocurrencies. Amid economic uncertainties or during the pandemic, do herding behaviors caused by virtual factors magnify the impact of non-fundamental information on financial markets? Does the combat against disinformation or closure of social media groups mitigate the non-fundamental volatility? The results are not yet clear. Whether blockchain technology is a blessing or bane to the financial industry needs more evidence for confirmation. Finally, there are basic structural differences and non-normality assumption problems with the data on the two markets. Hence, the estimates produced with the least squares method may be biased. The quantile-based approach of regression is an alternative option as it does not require normal distributions. It can also resolve the model problems due to abnormal data values and analyze the relations between different metric variables. Khaled Mokni, Ahmed Bouteska, and Mohamed S. Nakhli (2022) produce some demonstrations. Follow-up studies may discuss the abovementioned issues.

References

Aaron, Meyer, Francisco Rivadeneyra, and Samantha Sohal. 2017. "Fin-Tech: Is This Time Different? A Framework for Assessing Risks and Opportunities for Central Banks." Bank of Canada Staff Discussion Paper 2017-10.

Affuso, Ermanno, and Kyre D. Lahtinen. 2018. "Social Media Sentiment and Market Behavior." *Empirical Economics*, 57(1): 105-127. http://dx.doi.org/10.1007/s00181-018-1430-y

Ajzen, Icek, and Martin F. Snippet. 1980. *Understanding Attitudes and Predicting Social Behavior*. New Jersey: Prentice-Hall.

Antweiler, Werner, and Murray Z. Frank. 2004. "Is All That Talk Just Noise? The Information Content of Internet Stock Message Boards." *Journal of Finance*, 59(3): 1259-1294. http://dx.doi.org/10.1111/j.1540-6261.2004.00662.x

Arsi, Sonia, Khaled Guesmi, and Elie Bouri. 2021. "Herding Behavior and Liquidity in the Cryptocurrency Market." *Asia-Pacific Journal of Operational Research*, 39(4). http://dx.doi.org/10.1142/S0217595921400212

Baek, Chung, and Matt Elbeck. 2015. "Bitcoins as an Investment or Speculative Vehicle? A First Look." *Applied Economics Letters*, 22(1): 30-34. http://dx.doi.org/10.1080/13504851.2014.916379

Baur, Dirk G., KiHoon Hong, and Adrian D. Lee. 2018. "Bitcoin: Medium of Exchange or Speculative Assets?" *Journal of International Financial Markets, Institutions and Money*, 54: 177-189. http://dx.doi.org/10.1016/j.intfin.2017.12.004

Bhambhwani, Siddharth, Stefanos Delikouras, and George M. Korniotis. 2019. "Do Fundamentals Drive Cryptocurrency Prices?" Center for Economic and Policy Research Discussion Paper 13724.

Böhme, Rainer, Nicolas Christin, Benjamin Edelman, and Tyler Moore. 2015. "Bitcoin: Economics, Technology, and Governance." *Journal of Economic Perspectives*, 29(2): 213-238. http://dx.doi.org/10.1257/jep.29.2.213

Boot, Arnoud W. A. 2016. "Understanding the Future of Banking: Scale and Scope Economics, and Fin-Tech." In *The Future of Large, Internationally Active Banks*, ed. Asli Demirgüç-Kunt, Douglas D. Evanoff, and George G. Kaufman, 429-447. Singapore: World Scientific Studies International Economics. http://dx.doi.org/10.1142/9789813141391_0025

Bouri, Elie, Rangan Gupta, and David Roubaud. 2019. "Herding Behaviour in Cryptocurrencies." *Finance Research Letters*, 29(C): 216-221. http://dx.doi.org/10.1016/j.frl.2018.07.008

Bouri, Elie, Syed J. H. Shahzad, and David Roubaud. 2019. "Cryptocurrencies as Hedges and Safe-Havens for US Equity Sectors." *The Quarterly Review of Economics and Finance*, 75(C): 294-307. http://dx.doi.org/10.1016/j.qref.2019.05.001

Brieske, Arthur, Thomas-Frank Dapp, Kevin Garlan, and Matthaeus Sielecki. 2016. "FinTech 2.0: Creating New Opportunities through Strategic Alliance." *Deutsche Bank*, February 08. https://bravenewcoin.com/insights/fintech-2-0--creating-new-opportunities-through-strategic-alliance.

Buffie, Edward F. 1984. "Financial Repression, the New Structuralisms', and Stabilization Policy in Semi-Industrialized Economic." *Journal of Development Economics*, 14(3): 305-322. http://dx.doi.org/10.1016/0304-3878(84)90061-0

Carrick, Jon. 2016. "Bitcoin as a Complement to Emerging Market Currencies." *Emerging Markets Finance and Trade*, 52(10): 2321-2334. http://dx.doi.org/10.1080/1540496X.2016.1193002

Chaia, Bobby Boon-Hui, Pek See Tan, and Thian Shong. 2016. "Banking Services That Influence the Bank Performance." *Procedia - Social and Behavioral Sciences*, 224(15): 401-407. http://dx.doi.org/10.1016/j.sbspro.2016.05.405

Cheah, Eng-Tuck, and John Fry. 2015. "Speculative Bubbles in Bitcoin Markets? An Empirical Investigation into the Fundamental Value of Bitcoin." *Economics Letters*, 130(C): 32-36. http://dx.doi.org/10.1016/J.ECONLET.2015.02.029

Chow, Gregory C., Changjiang Liu, and Linlin Niu. 2011. "Co-movements of Shanghai and New York Stock Prices by Time-Varying Regressions." *Journal of Comparative Economics*, 39(4): 577-583. http://dx.doi.org/10.1016/j.jce.2011.06.001

Ciaian, Pavel, Miroslava Rajcaniova, and d'Artis Kancs. 2016. "The Economics of Bit Coin Price Formation." *Applied Economics*, 48(19): 1799-1815. http://dx.doi.org/10.1080/00036846.2015.1109038

Combey, Adama, and Apélété Togbenou. 2017. "The Bank Sector Performance and Macroeconomics Environment: Empirical Evidence in Togo." *International Journal of Economics and Finance*, 9(2): 180-188.

Corbet, Shaen, Brian Lucey, Andrew Urquhart, and Larisa Yarovaya. 2018. "Cryptocurrencies as a Financial Asset: A Systematic Analysis." *International Review of Financial Analysis*, 62(C): 182-199. http://dx.doi.org/10.1016/J.IRFA.2018.09.003

Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam. 1998. "Investor Psychology and Security Market Under- and Over-Reactions." *The Journal of Finance*, 53(6): 1839-1885.

Demetriades, Panicos O., and Khaled A. Hussein. 1996. "Does Financial Development Cause Economic Growth? Time-Series Evidence from 16 Countries." *Journal of Development Economics*, 51(2): 387-411. http://dx.doi.org/10.1016/S0304-3878(96)00421-X

Fama, Eugene F., and Kenneth R. French. 1992. "The Cross-Section of Expected Stock Returns." *Journal of Finance*, 47(2): 427-465. http://dx.doi.org/10.2307/2329112

Fama, Eugene F., and Kenneth R. French. 1996. "Multifactor Explanations of Asset Pricing Anomalies." *The Journal of Finance*, 51(1): 56-84. http://dx.doi.org/10.1111/j.1540-6261.1996.tb05202.x

Frederick, Nsambu K. 2014. "Factors Affecting Performance of Commercial Banks in Uganda: A Case for Domestic Commercial Banks." Paper presented at the 25th International Business Research Conference, Cape Town, South Africa.

Gkillas, Konstantinos, and Paraskevi Katsiampa. 2018. "An Application of Extreme Value Theory to Cryptocurrencies." *Economics Letters*, 164(C): 109-111. http://dx.doi.org/10.1016/j.econlet.2018.01.020

Gkillas, Konstantinos, and François Longin. 2019. "Is Bitcoin the New Digital Gold? Evidence from Extreme Price Movements in Financial Markets." *SSRN Electronic Journal*. http://dx.doi.org/10.2139/ssrn.3245571

Glaser, Florian, Martin Haferkorn, Moritz Christian Weber, and Kai Zimmermann. 2014. "How to Price a Digital Currency? Empirical Insights on the Influence of Media Coverage on the Bitcoin Bubble." *Banking and Information Technology*, 15(1).

Hausman, Jerry. 1978. "Specification Tests in Econometrics." *Applied Econometrics*, 46(6): 1251-1271. http://dx.doi.org/10.2307/1913827

Hayes, Adam. 2019. "The Socio-Technological Lives of Bitcoin." *Theory Culture & Society*, 36(4): 49-72. http://dx.doi.org/10.1177/0263276419826218

Hidajat, Taofik. 2019. "Behavioural Biases in Bitcoin Trading." *Fokus Ekonomi: Jurnal Ilmiah Ekonomi*, 14(2): 337-354. http://dx.doi.org/10.34152/fe.14.2.337-354

Ho, Chi Ming. 2013. "Private Information, Overconfidence and Intraday Trading Behavior: Empirical Study of the Taiwan Stock Market." *Applied Financial Economics*, 23(4): 325-345. http://dx.doi.org/10.1080/09603107.2012.720012

Ho, Chi Ming. 2020a. "Does Virtual Currency Development Harm Financial Stocks' Value? Comparing Taiwan and China Markets." *Economic Research*, 33(1): 361-378. http://dx.doi.org/10.1080/1331677X.2019.1702076

Ho, Chi Ming. 2020b. "Impact of Cryptocurrency Exchange Rate on Financial Stock Exposure: Comparison between Two Emerging Markets." *Financial and Credit Activity Problems of Theory and Practice*, 4(35): 28-36. http://dx.doi.org/10.18371/fcaptp.v4i35.221733

Hong, Harrison, and Jeremy C. Stein. 1999. "A Unified Theory of Under-Reaction, Momentum Trading and Overreaction in Asset Markets." *The Journal of Finance*, 54(6): 2143-2184. http://dx.doi.org/10.1111/0022-1082.00184

Hu, Zhongqing, Shuai Ding, Shizheng Li, Luting Chen, and Shanlin Yang. 2019. "Adoption Intention of Fintech Services for Bank Users: An Empirical Examination with an Extended Technology Acceptance Model." *Symmetry*, 11(3): 340-356. http://dx.doi.org/10.3390/sym11030340

Kashyap, Anil K., Raghuram G. Rajan, and Jeremy C. Stein. 2002. "Banks as Liquidity Providers: An Explanation for the Coexistence of Lending and Deposit-Taking." *Journal of Finance*, 57(1): 33-73. http://dx.doi.org/10.1111/1540-6261.00415

King, Robert G., and Ross Levine. 1993. "Finance, Entrepreneurship, and Growth Theory and Evidence." *Journal of Monetary Economics*, 32(3): 513-542.

Klein, Tony, Pham H. Thu, and Thomas Walther. 2018. "Bitcoin Is Not the New Gold - A Comparison of Volatility, Correlation, and Portfolio Performance." *International Review of Financial Analysis*, 59(C): 105-116. http://dx.doi.org/10.1016/j.irfa.2018.07.010

Kristoufek, Ladislav. 2013. "Bitcoin Meets Google Trends and Wikipedia: Quantifying the Relationship between Phenomena of the Internet Era." *Scientific Reports*, 3(1). http://dx.doi.org/10.1038/srep03415

Leahy, Michael Patrick, Sebastian Schich, Gert D. Wehinger, Florian Pelgrin, and Thorsteinn Thorgeirsson. 2001. "Contributions of Financial Systems to Growth in OECD Countries." OECD Economics Department Working Paper 280. http://dx.doi.org/10.1787/888167575648

Lye, Chun-Teck, Jiunn-Shyan Khong, and Chee-Wooi Hooy. 2019. "Board Gender Diversity, Investor Protection, and Private Information-Based Trading." *Global Economic Review*, 48(4): 419-439. http://dx.doi.org/10.1080/1226508X.2019.1636701

Mai, Feng, Zhe Shan, Qing Bai, Xin Wang, and Roger H. L. Chiang. 2018. "How Does Social Media Impact Bitcoin Value? A Test of the Silent Majority Hypothesis." *Journal of Management Information Systems*, 35(1): 19-52. http://dx.doi.org/10.1080/07421222.2018.1440774

Mokni, Khaled, Ahmed Bouteska, and Mohamed S. Nakhli. 2022. "Investor Sentiment and Bitcoin Relationship: A Quantile-Based Analysis." *The North American Journal of Economics and Finance*, 60(C). http://dx.doi.org/10.1016/j.najef.2022.101657

Molnár, Julia. 2018. “What Does Financial Intermediation Theory Tell Us about Fintechs?” *Budapest Management Review*, 49(5): 38-46. http://dx.doi.org/10.14267/VEZTUD.2018.05.04

Muhmad, Siti N., and Hafiza Aishah Hashim. 2015. “Using the Camel Framework in Assessing Bank Performance in Malaysia.” *International Journal of Economics, Management and Accounting*, 23(1): 109-127.

Quinn, James Brian, Philip Anderson, Paul Anderson, and Sydney Finkelstein. 1996. “Managing Professional Intellect: Making the Most of the Best.” *Harvard Business Review*, 74(2): 71-80.

Rajan, Raghuram G. 1996. “Why Banks Have a Future: Toward a New Theory of Commercial Banking.” *Journal of Applied Corporate Finance*, 9(2): 114-128. http://dx.doi.org/10.1111/j.1745-6622.1996.tb00119

Shaher, Thair Al, Ohoud Khasawneh, and Razan Salem. 2011. “The Major Factors That Affect Banks’ Performance in Middle Eastern Countries.” *Journal of Money, Investment and Banking*, 20: 101-109.

Shahzad, Syed J. H., Elie Bouri, Tanveer Ahmad, Muhammad A. Naeem, and Xuan V. Vo. 2021. “The Pricing of Bad Contagion in Cryptocurrencies: A Four-Factor Pricing Model.” *Finance Research Letters*, 41(2). http://dx.doi.org/10.1016/j.frl.2020.101797

Sharpe, William F. 1964. “Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk.” *The Journal of Finance*, 19(3): 425-442.

Statman, Meir, Steven Thorley, and Keith Vorkink. 2006. “Investor Overconfidence and Trading Volume.” *The Review of Financial Studies*, 19(4): 1531-1565.

Stiglitz, Joseph E. 1985. *Principal and Agent: Allocation, Information and Markets*. London: Palgrave Macmillan. http://dx.doi.org/10.1007/978-1-349-20215-7

Walter, Ingo. 2003. “Strategies in Financial Services, the Shareholder, and the System: Is Bigger and Broader Better?” Hamburg Institute of International Economics Discussion Paper 205. http://dx.doi.org/10.2139/ssrn.333800

Wang, Jing. 2018. “From Aperture Satellite to ‘Internet Finance’: Institutionalization of ICTs in China’s Financial Sector since 1991.” *Telecommunications Policy*, 42(7): 566-574. http://dx.doi.org/10.1016/j.telpol.2018.04.004

Wessel, Michael, Ferdinand Thies, and Alexander Benlian. 2017. “Opening the Floodgates: The Implications of Increasing Platform Openness in Crowdfunding.” *Journal of Information Technology*, 32(4): 344-360. http://dx.doi.org/10.1057/s41265-017-0040-z

Wu, Chen Y., and Vivek K. Pandey. 2014. “The Value of Bitcoin in Enhancing the Efficiency of an Investor’s Portfolio.” *Journal of Financial Planning*, 29(9): 44-53.

Yousaf, Imran, Shoaib Alil, Elie Bouri, and Anupam Dutta. 2021. “Herding on Fundamental/Non-Fundamental Information during the COVID-19 Outbreak and Cyber-Attacks: Evidence from the Cryptocurrency Market.” *Sage Journals*, 11(3): 1-8. http://dx.doi.org/10.1177/21582440211029911