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Fintech vs. Traditional financial services: how are investors reacting?

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Master in Finance

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Abstract

Financial technology (fintech) has experienced dramatic growth in the 21st century while the traditional finance sector is facing challenges of innovative and convenient services brought by financial technology in the U.S after the 2008 crisis.

This dissertation intends to study whether investors view U.S fintech differently from traditional finance under the influence of macroeconomic variables (total non-farm payroll, S&P500 index, the spread of 10-year and 2-year Government Bonds, and 3-month LIBOR). We establish multiple linear regression models for U.S fintech (the KFTX index as a representative) and traditional finance (represented by the S&P 500 Financials Services Select Sector Index) respectively to investigate the relationship between the above four macroeconomic variables from 2016 to 2020 and then obtain their comparative model by the difference between their log returns in empirical analysis.

We observe that total non-farm payroll, and S&P 500 index are both statistically relevant in explaining the variations of the S&P 500 Financials Services Select Sector Index and the KFTX index while the S&P 500 Financials Services Select Sector Index is also influenced by the positive and statistically significant effects of 3-month LIBOR and the spread of 10-year and 2-year Government Bonds. In addition, we figure out that when 3-month LIBOR or 10-year and 2-year Government Bonds spread rises, investors are inclined to buy more traditional financial stock represented by the S&P 500 Financials Services Select Sector Index than the fintech assets represented by the KFTX index.

Keywords: Fintech, Traditional finance, Macroeconomic variables, Multiple linear regression method

JEL Classification: G12, G20

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Resumo

A tecnologia financeira (fintech) experimentou um crescimento dramático no século 21, enquanto o setor financeiro tradicional está enfrentando desafios de serviços inovadores e convenientes trazidos pela tecnologia financeira nos EUA após a crise de 2008.

Esta dissertação pretende estudar se os investidores veem a fintech dos EUA de forma diferente das finanças tradicionais sob a influência de variáveis macroeconômicas (folha de pagamento não agrícola total, índice S & P500, spread de títulos do governo de 10 e 2 anos e LIBOR de 3 meses). Estabelecemos vários modelos de regressão linear para fintech dos EUA (o índice KFTX como representante) e finanças tradicionais (representado pelo índice S&P 500 Financials Services Select Sector), respectivamente, para investigar a relação entre as quatro variáveis macroeconômicas acima de 2016 a 2020 e, em seguida, obter seu modelo comparativo pela diferença entre seus retornos de log na análise empírica.

Observamos que o total da folha de pagamento não agrícola e o índice S&P 500 são estatisticamente relevantes para explicar as variações do S&P 500 Financials Services Select Sector Index e do índice KFTX, enquanto o S&P 500 Financials Services Select Sector Index também é influenciado pelo índice positivo e efeitos estatisticamente significativos da LIBOR de 3 meses e do spread dos títulos do governo de 10 e 2 anos. Além disso, descobrimos que quando o spread da LIBOR de 3 meses ou dos títulos do governo de 10 e 2 anos aumenta, os investidores tendem a comprar mais ações financeiras tradicionais representadas pelo S&P 500 Financials Services Select Sector Index do que os ativos fintech representados por o índice KFTX.

Palavras-chave: Fintech, Finanças tradicionais, Variáveis macroeconômicas, Método de regressão linear múltipla.

Classificação JEL: G12, G20

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Glossary

ADF - Augmented Dickey-Fuller

AR (1) - First-order Autoregression

ARCH - Autoregressive Conditional Heteroscedasticity

ATM - Automated Teller Machine

AI - Artificial Intelligence

AIC - The Akaike information criterion

CPI - Consumer Price Index

FRED - Federal Reserve Economic Data

GARCH - Generalized Autoregressive Conditional Heteroscedasticity

GDP – Gross Domestic Product

GICS - The Global Industry Classification Standard

LM - Lagrange multiplier

IPO - Initial Public Offering

KBW - Keefe, Bruyette & Woods

KFTX - The KBW NASDAQ Financial Technology Index

LIBOR - London Interbank Offered Rate

M&A - Mergers and Acquisitions

MLRM – Multiple Linear Regression Model

OLS – The Ordinary Least Squares Method

P2P - Peer-to-Peer

PE - Private Equity

SIC - Schwarz's Information Criterion

VC - Venture Capital

VIF – Variance Inflation Factor

VIX - The Chicago Board Options Exchange's CBOE Volatility Index

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1. Introduction

Fintech, a portmanteau word of financial and technology, first appeared in the mid-1950s with credit cards allowing customers to carry no cash. After several decades' development, it is innovated as a new financial industry that using a series of emerging technologies to improve financial services to customers, including digital payment, peer-to-peer (P2P) lending platform, online-only insurance and banking, cloud computing, blockchain, big data analysis, Artificial intelligence (AI) and so on.

Technology has developed dramatically in the 21st century, and it has completely changed everything. However, banks are facing increased supervision, especially in terms of their relationships with customers after the 2008 financial crisis. With the help of technological development, the financial technology industry has rapidly adapted to its operations in recent years, and more and more financial technology companies have expanded to a certain extent that it has never seen before. The global venture capital (VC) investment of fintech companies skyrockets 500% from 2011 to 2015.

On the one hand, some people think that the emergence of fintech start-ups poses a threat to the traditional financial sector. With the rapid rise of Fintech, its innovative services can better meet people's needs, and traditional finance will gradually be replaced. On the other hand, others believe that Fintech and traditional finance can take advantage of each other to enhance cooperation and achieve a win-win situation.

The KBW NASDAQ Financial Technology Index (KFTX) as the first index of fintech was launched in 2016 to track the performance of the fintech sector. It is worthwhile to make a comparative analysis for U.S fintech (KFTX index as a representative) and traditional finance (represented by S&P 500 Financials Services Select Sector Index) to study the reaction of investors in the macroeconomic environment and compare which index has better returns.

Thus, this research aims to figure out if investors see U.S fintech in a different way than they look to traditional finance and analyzes how investors react to different economic variables.

The empirical research is based on the Ordinary Least Squares method (OLS) which is applied to the quantitative analysis, common and widely supported by the existing literature, we established three multiple linear regressions: one is a multiple linear regression using the log return of the KFTX index as the dependent variable (RK); the other is a log return using the S&P 500 Financials Services Select Sector Index (RF); the third regression is for the comparative model which is the differences between both two log returns (△RKRF).

Besides, we deal with the error's first autocorrelation [AR (1)] problem for the original estimation of the comparative model and the regression of KFTX, which is based on the generalized differences method.

A large number of scholars have used empirical analysis to prove that macroeconomic fluctuations will have an impact on the stock market. Investors will also make investment decisions based on changes in macroeconomic conditions. We consider macroeconomic factors as the explanatory variables, including 3-month LIBOR in USD, the difference between the yields on the 10-year Government Bonds and those on the 2-year Government Bonds, non-farm payroll, and S&P 500 index.

We find that 3-month LIBOR, the spread of 10-year and 2-year Government Bonds, total non-farm payroll, and S&P 500 index all have a positive and statistically significant relevance with the S&P 500 Financials Services Select Sector Index, while the KFTX index is only positive and statistically significant related to the total non-farm payroll and S&P 500 index. Besides, when 3-month LIBOR or 10-year and 2-year Treasury bonds spread rises, investors are inclined to buy more traditional financial stocks represented by the S&P 500 Financials Services Select Sector Index than the fintech assets represented by the KFTX index.

This dissertation consists of five sections, besides the introduction. Section 2 presents the literature review including the background of Fintech, the introduction of the KFTX index, the different empirical analyses, methodologies, and conclusions for the relationship between Fintech and traditional finance, and studies on the influence of macroeconomics determinants on the stock returns. Section 3 shows the empirical analysis by presenting the methodology for the regressions, and data description. The results of the empirical analysis are illustrated in Section 4. Section 5 demonstrates the discussion and conclusion.

2. Literature review

2.1 The emergence and development of Fintech

The term fintech is formed by the contraction of "financial and technology", which represents innovative start-ups that aim to use creative technologies, like the internet, communication technology, and the automated processing of information, to redesign traditional financial services (Milian et al., 2019). The US Financial Stability Board (FSB, 2017) defined Fintech as a technology-based innovation in financial services, which could lead to new business models and processes, generate new applications, services, or products, significantly impact on financial markets and institutions and the financial service providers.

Fintech companies not only contain some famous and elder companies but also newly-born start-up companies. Most people consider that fintech appeared when they use mobile payment to shop without a credit card or transfer money through an online payment app instead of going to the bank. Fintech has come to pervade every corner of our lives, bringing much more convenience than traditional financial services.

The 1950s brought us credit cards to ease the burden of carrying cash. In the 1960s, ATMs (Automated Teller Machines) were introduced to people that allow them to withdraw or transfer money at any time without going to the bank counter Lerner (2013). Electronic stock trading appeared on exchange trading floors in the 1970s. The 1980s witnessed the growth of bank mainframe computers and more complicated data and record-keeping systems. With the boom of the Internet and E-Trade models, the phone-driven retail stock brokering model was gradually replaced by online stock brokerage websites in the 1990s (Desai, 2015).

What's more, it is also important to pay attention that some risk management, treasury management, trade processing, and data analysis tools related to the institutional level for traditional financial services companies were become more sophisticated (Desai, 2015). Bloomberg, Thomson Reuters, SunGard, and Misys are a few players at the institutional level that support the needs of traditional financial services companies.

Through five decades of developments in the 20th century, technology has always played an important role in the financial sector in ways that most people were using it every day and might not realize.

A study made by Duval (2016) indicated that while these technologies became mainstream and widely adopted by traditional financial institutions and their customers, the banking sector was not significantly negatively affected. By contrast, the data from the U.S. Federal Deposit

Insurance Corporation (FDIC) illustrated that the volume of bank branches in the country dramatically increased from approximately 18,000 to over 82,000 from 1950 to 2014.

However, after the 2008 financial crash, the enthusiasm towards fintech has been growing year after year. According to Google Trends, the global monthly enthusiasm of Fintech underwent a dramatic upward trend since 2015. In 2014, the monthly average score was 5.7 and then climbed sharply to the peak value of 100 in Nov 2017 despite some initial fluctuations, then keep the monthly average value around 85.6 in 2018, which indicated that fintech remained popular in these two years.

At the same time, the Fintech adoption index, across 20 markets and over 22,000 online interviews, surveyed by EY (2017) showed that the global adoption rate of Fintech services has grown steadily to 33% in 2017 while achieving 16% in 2015, the year of the index was first published. In addition, they compare two barriers, lack of awareness of Fintech and preference for traditional financial services providers, to analyze the relationship between Fintech adoption and awareness of Fintech. And they have observed that these two selected barriers rapidly declined from 2015 to 2017, which indicates that more populations were aware of Fintech.

Indeed, the phenomenon of Fintech in recent years has attracted a lot of attention from the media, investors, and established financial institutions. Many digital retail financial services were innovated in the 21st century that we are very familiar with, with many customers almost using them every day.

The most popular part of Fintech is mobile payment, which provides mobile wallets and payment apps, such as Alipay, Apple pay, Google Wallet, and PayPal, which innovate the world to cashless. With the mobile payment apps, people not only can shop and purchase online without using cash or credit card but also can pay or transfer money to others, all this just need internet and a computer or smartphone.

EY (2017) compared the adoption rate between 2015 and 2017 among Fintech categories (money transfer and payment, savings and investments, financial planning, insurance, and borrowing), and they found that money transfer and payment services were continuing to be the top one, increased to 50% in 2017 from 18% in 2015, furthermore, 65% of consumers intended to use these fintech services in the future.

The other big trend of Fintech is borrowing services that improved the lending process to become much easier and faster, as well as lower the interest rates for individuals and companies to grant a loan between each other. Lending Club was the first peer-to-peer (P2P) lending platform to be listed on NYSE in 2014. Moreover, its stock soar more than 60% on its first trading day and ended up 56%, leading to its market value dramatically increasing to $8.5

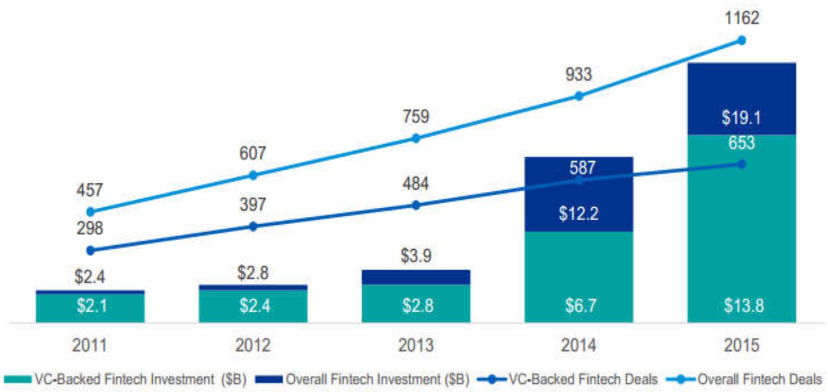
billion, recorded as the largest U.S. technological IPO of 2014.

Besides, financial information provider (Bloomberg), online-only banking and insurance, Artificial intelligence (AI) asset management/Robo-advisors, equity crowdfunding platforms, big data analysis, blockchain (Bitcoin), credit reporting, and financial products selling online platform are also playing an important part in Financial technology evolution today.

Fintech globally investments underwent an upward trend since 2014. According to the report of KPMG International (2016), 2015 was the year that fintech was booming by all measures.

Figure 1 shows the trend of annual global fintech financing between VC-Back Fintech companies and overall fintech investment (including fintech funding by angel investors, angel groups, private equity firms, mutual funds, hedge funds, VC, corporate and corporate VC investors), which is analyzed by KPMG International (2016) and CB Insights, they show that over $13.8 billion across 653 deals were deployed to a wide variety of fintech companies globally, more than double the value of venture capital (VC) investment in fintech in 2014, up 106%. This increase of more than 100% is even more significant given that the 2011 fintech investment was only $2.1 billion.

Figure 2.1.1: Annual Global Fintech Financing Trend

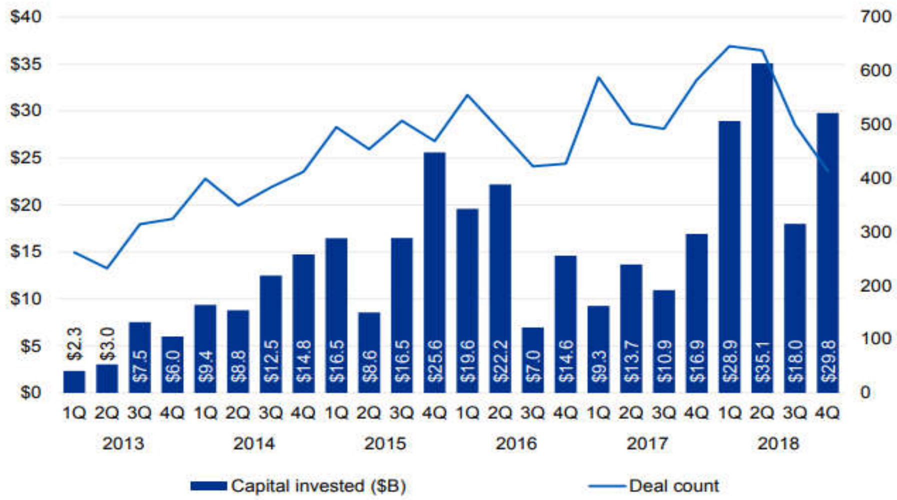


Source 1: The Pulse of Fintech, 2015 in Review, Global Analysis of Fintech Venture Funding, KPMG International and CB Insights (data provided by CB Insights) 9th March 2016.

What's more, confidence in Fintech accelerated this trend, financial technology investment increased significantly in 2018, reached multiple record highs.

KPMG International (2019) analyzed the global investment in fintech companies, including mergers and acquisitions (M&A), venture capital (VC), and private equity (PE) investments from 2013 to 2018, and the result is presented in Figure 2 as below. The total investment activities are more than doubling from $50.8 billion with 2165 deals in 2017 to $111.8 billion with 2196 deals in 2018.

Figure 2.1.2: Total investment activity (VC, PE, and M&A) in Fintech from 2011 to 2015



Source 2: Pulse of Fintech 2018, Global Analysis of Investment in Fintech, KPMG International (data provided by PitchBook) 4th January 2019.

The increase of fintech start-ups is attacking traditional finance by delivering a totally different approach to clients. They provide better financial services to customers, save clients' time, lower financial services fees, provide customized services, and put all their attention to the customers who are the top priority again.

2.2 The change of finance environment after the financial crisis

From 2007 to 2008, the traditional financial business witnessed a huge financial crisis over the world, which led to a recession and deterioration in the financial industry.

With the deterioration of the economic situation and the aggravation of the sovereign debt crisis, the highly prosperous banking sector suffered a hard hit in 2008, especially for large international commercial banks. Lehman Brothers, the American Investment Bank, declared bankruptcy in September 2008. In the same year, the liquidity crisis at the American International Group (AIG), the world's largest insurance company, exacerbated the collapse of global financial markets.

The 2008 financial crisis has resulted in numerous shifts in terms of liquidity and capital for banks, subsequent bank bailouts, and banker bonus scandals, marking an essential turning point in the financial services sector. Great changes have taken place in the financial market after the financial disaster.

Basel III, developed by the members of the Basel Committee on Banking Supervision in

2010, is an internationally agreed, global, and more robust regulatory framework on the banking system. It was designed in response to the deficiencies in financial regulation revealed by the financial crisis from 2007 to 2008, aim to improve capital requirements of banks by increasing bank liquidity and reducing bank leverage, and strengthen the regulation, supervision, and risk management of banks.

In particular, the Basel Committee on Banking Supervision (BCBS) defined a group of large banking financial institutions as Systemically Important Financial Institutions (SIFIs) and increased the regulatory capital requirements of banks.

Therefore, the banking industry faced double pressure after the crisis. On the one hand, banking financial institutions became the "culprit" of the financial crisis in global public opinion. The government used the public purse to inject into the banking system to avoid the collapse of SIFIs, which directly led to the loss of confidence in the traditional financial sector, especially among young people. Gallup polls revealed that between 2007 and 2012, confidence in banks of Americans fell by half (20 percentage points), and it was just 21% at the end of 2012 (Jacobe, 2013).

On the other hand, the strengthening of supervision measures for the banking sector has increased the pressure on the regulatory capital of the banking sector, directly reducing its business scope and space, which limits the development of the banks. Due to the traditional financial business innovation lagging behind the pace of development of the digital economy and constant changes in the pattern of consumption, it is unable to meet the need of customers (Bulmash and Trivoli, 1991).

After the financial disaster in 2008, industry experts and consumers began questioning the future of traditional banking. The anger of customers on banks prompted them to gradually change their view on Finance, especially on banks, looking for products and alternative services that satisfy their needs (Worthington and Welch, 2011).

Since then, customers were reluctant to buy products or services within banks and traditional financial institutions. On the contrary, customers expect financial services and products can be easy to use, have 24-hour access, be automated, and be more transparent (Goldman Sachs, 2015). They actively seek and obtain various financial products and services through different ways to build financial solutions that meet their personal needs.

Changes in customers' attitudes and behaviors have brought significant innovation to the financial industry. Meanwhile, the new technologies play an essential part in this evolution, giving an opportunity for the new competitor that has not been affected and blamed in the crisis, to provide banking services to their customers in the form of financial technology (Fintech), which has quickly won the recognition and favor of the public and public opinion (Li et al., 2017).

With the development and creativity of science and technology, as well as the foundation of widespread use of the Internet, Fintech start-ups create a series of emerging technologies to improve financial services to customers, including digital payment, peer-to-peer lending platform, online-only insurance and banking, cloud computing, blockchain, big data analysis, AI and so on.

Compared to the traditional financial services, this innovation and creativity of Fintech services bring much more convenience to human life, allow customers to experience timesaving, cheaper financial services, and customer personalized services.

2.3 Financial technology in the United States

2.3.1 United States: The leader of FinTech

The U.S. financial industry and high-tech industry are both extremely developed, and the combination of the financial industry and high-tech is also at the forefront of the world. The White House Economic Committee and the U.S. International Trade Agency have both elaborated on the background of the birth of FinTech and emphasized the fundamental role of information technology in the industry and the social soil provided by the changes in the regulatory environment after the financial crisis. Using social media, artificial intelligence, big data, and other methods to help technology companies capture the needs of people who cannot be covered by the banking system, especially the needs of young people, subverts the traditional business model of the banking industry.

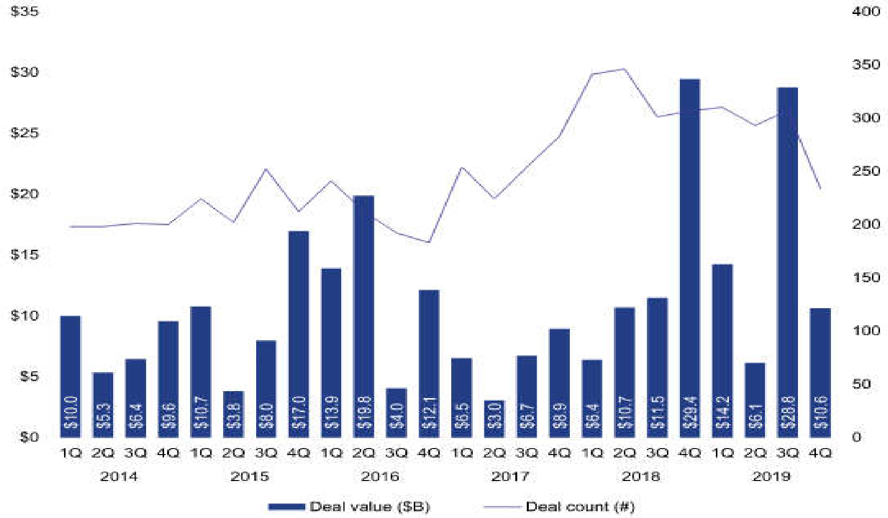
At present, the development of the financial technology industry in the United States, which is mainly driven by technology, is already at the international leading level, and the industrial ecology is quite mature.

Technology and the internet promote the development of financial technology. According to research data, E-Trade, an online brokerage firm established in 1992, is the first financial institution that can be found to introduce information technology. The Security First Network Bank (SFNB), established in 1995 in the United States, is the world's first online bank. As for American companies that have entered the global rankings and are recognized as being included in the FinTech category, the P2P lending platform Prosper Market (Prosper Market Inc, Prosper), which was born in 2005, is the earliest company established.

According to the data of Venture Scanner, the statistics of the research company, there are about 1,100 Fintech companies in the United States until April 2017, mainly located near the technology city of Silicon Valley and the traditional financial center Manhattan, New York; 21 of them have entered KPMG's Leading 50 list.

Figure 3 presents the total investment activities in Fintech in the United Stated which is analyzed by KPMG International (2020), they illustrated that fintech investment across VC, M&A, and PE in the U.S. reached a record US$59.8 billion in 1,144 transactions in 2019, accounting for 44% of total global fintech investment.

Figure 2.3.1: Total investment activity (VC, PE, and M&A) in Fintech in the U.S from 2014 to 2019 Q4



Source 3: Pulse of Fintech 2019, Global Analysis of Investment in Fintech, KPMG International (data provided by PitchBook) 31st December 2019.

2.3.2 KBW Nasdaq Financial Technology Index (KFTX)

According to Nasdaq Global Indexes, US investment banks Keefe, Bruyette & Woods (KBW) and Nasdaq jointly launched the first financial technology index in July 2016, KBW NASDAQ Financial Technology Index (KFTX), to track the performance of financial technology companies listed in the U.S stock market.

Since financial technology is an emerging field, it is not easy to classify financial technology companies into a specific industry, so the eligibility of the index is not limited to securities in a specific industry category. Companies with fee-based revenues and use technology to provide specialized financial products and services that are more digital can be included in this index.

KFTX index initially included 49 constituent stocks, not only well-known traditional financial services companies which are actively promoting digital financial services, such as Visa, MasterCard, American Express, PayPal, etc., but also emerging innovative financial technology companies, like the P2P online lending platform Lending Club. Although there are no large banks in the index, companies are providing financial technology services for banks, such as Fiserv, FIS, and so on.

According to reports, when the index was released, the total market cap of the constituent companies was as high as 785 billion US dollars, accounting for 18% of the investable US financial sector, and 4% of the total value of the US stock market.

From the date the KFTX index was released, it underwent an overall upward trend. Due to the impact of COVID-19, the KFTX index dropped significantly in January 2020. However, the index has rebounded from a low of 1285.46 to 2084.12 since March 2020. As the stock market closed on 6th November 2020, the index has grown by 13% in the past year.

2.4 Fintech VS. Traditional Financial

With the development and application of a series of new-generation information technologies such as cloud computing, big data, blockchain, mobile internet, artificial intelligence, etc., fintech has grown rapidly in the 21st century and quickly occupied most of the market share in recent years, which has indeed posed a threat to the traditional financial industry. Traditional industries are undergoing a financial technology revolution.

Although Fintech has its outstanding advantages, some deficiencies cannot be ignored. Philippon (2016) pointed out that financial technology may continuedly reduce the cost of obtaining financial services, but it also faces new risks and regulatory challenges. Foley et al. (2019) emphasized the negative impact of financial technology. They estimate that about 76 billion US dollars of illegal activities are related to bitcoin and cryptocurrency each year, which almost represent the combined illegal drug market in the United States and Europe.

The traditional financial industry is like an awakened sleeping lion, accelerating its adaptation to the changes in the market environment, and leveraging its advantages in financial resources, speeding up the competition for this emerging market in the past few years.

The study from Duval (2016) pointed out that the attitudes of traditional banks towards fintech companies are also changing, fintech companies and banks can have relationships such as competition, cooperation, or investment. She even believes that the cooperation between the traditional financial industry and Fintech startups is the current trend.

Traditional banks have financial resources, while Fintech companies have technical capabilities. While fierce competition, both parties can take advantage of each other and have greater cooperation.

In 2017, China's four largest state-owned banks respectively reached cooperation agreements with Fintech companies. China Construction Bank, Alibaba Group, and Ant Financial Services Group signed a strategic cooperation agreement in Hangzhou to jointly explore innovative cooperation models between commercial banks and Internet financial companies; Industrial and Commercial Bank of China and JD Finance have launched comprehensive cooperation; Agricultural Bank of China and Baidu formally announced strategic cooperation; Bank of China announced the establishment of a joint financial technology laboratory with Tencent.

Through a detailed analysis of the financial technology and banking industry in Europe and the United States from 2008 to 2015, Romānova and Kudinska (2016) indicated that the development of financial technology has prompted the traditional financial industry to increase investment in financial technology.

In order to clarify the relationship between fintech digital banking startups and the traditional financial banks, Li et al. (2017) examined the impact of 47 retail banks' stock returns in the US from 2010 to 2017 and suggested fintech and traditional banks have complementarity.

Chen and Zhang (2018) studied the relationship between fintech and the traditional financial sector by applying the Granger Causality Test and Toda Yamamoto's version of the Granger Causality Test to examine the relationship between the KFTX index and S&P 500 Financials Services Select Sector Index, S&P 500 Banks Index, S&P 500 Insurance Index from 2007 to 2016. They pointed out that the interactive relationship between the index of fintech and banks, and between the index of fintech and the financial selected sector are disappearing as time-varying during the financial crisis (Chen and Zhang, 2018). Moreover, they also indicate no significant effect between the fintech sector and the traditional financial sector in the post-crisis period.

Yudaruddin (2019) used the GMM approach to provide empirical studies for analyzing the effect of fintech start-ups on bank performance in Indonesia during 2009-2018. He concluded that all categories of fintech start-ups do not have a negative effect on bank performance, but if fintech is specific to P2P lending, the performance of a small bank can be disturbed.

2.5 The effect of macroeconomic variables on stock returns

Macroeconomic factors play an important role on the stock market. Since the intrinsic value of stocks is determined by the company's operating performance, that is, the value of stocks is obtained by discounting the company's future cash flow. Therefore, changes in the macro environment can affect the company's operating performance, which in turn affects the stock price. In addition, macroeconomic prosperity and recession will be transmitted to stock prices by affecting investors' confidence in the stock market.

Law and Ibrahim (2014), and Rachman (2012) suggest that investors should consider macroeconomic variables when making investment decisions, because they may cause fluctuations in stock prices and returns.

The spread of the 10-year and 2-year Government bonds (T10Y2Y) is generally considered to be a warning of severe weakness in the stock market. Investors and economists look at the spread of two distinct U.S. Treasury bill rates to expect the economy heading shortly. The spread steepens when the market with stronger growth, higher inflation, and/or an increase in interest rates by the Federal Reserve, also means long-term rate rise more than short-term.

The 3 - month London Interbank Offered Rate (LIBOR3M) is a benchmark interest rate. Major global banks lend to one another in the international interbank market for short-term loans refer to this rate. LIBOR is applied to calculate the interest and other payments under many loans, derivatives, bonds, and other financial transactions worldwide. It takes into account the liquidity premium of various instruments traded in the money markets and is also an indicator of the health of the entire banking system.

Total Nonfarm Payroll (NFP), an essential economic indicator related to employment in the U.S., measures the number of workers in the economy of the U.S that excludes proprietors, private household employees, unpaid volunteers, farm employees, and the unincorporated self-employed. The expansion of the non-farm payrolls indicates that the economy is growing. Lucey et al. (2008) showed that the increase in the number of non-farm payrolls in the United States has a significant impact on the returns of the British stock market.

A large number of scholars have studied the relationship between stock price trends and macroeconomic indicators (industrial production, CPI, broad money M2, Government Bonds yields, S&P 500 index, JPY/USD exchange rate, interest rate) for the US and other regions of the world. Chen et al. (1986), Bulmash and Trivoli (1991), Choi (1995), Boyd et al. (2005), Ratanapakorn and Sharma (2007) investigate the effects of macroeconomic variables in the US, while Garcia and Liu (1999), Resatoglu and Çukur (2007), Gay (2008), Riman et al. (2014)

examined the same effects in the global scope.

Ratanapakorn and Sharma (2007) analyzed the relationship between S&P500 and six different macroeconomic variables from 1975 to 1999 by using the Granger causality test and the variance decomposition (VDC). The variables consist of industrial production index, M1 narrow money supply, treasury bill rate, 10-year Government Bond yields, inflation rate, JPY/USD exchange rate. They indicated that there is a negative link between the S&P 500 and the 10-year Government Bond yields while the S&P 500 has a positive relation with M1, inflation, exchange rate, industrial production, and treasury bill. Moreover, they observed that government bond interest rates are more able to explain US stock prices than the other five macroeconomic variables.

Narayan and Sahminan (2018) applied the robust ordinary least squares estimation approach to investigate the macroeconomic impact on Indonesian fintech companies from 1998 to 2017. The result shows that the fintech sector can decline inflation as costs are reduced, and have a positive effect on the rupiah–US dollar exchange rate result from more cross-border activities.

Foo et al. (2017) used canonical correlation analysis (CCA) to investigate the relationship between macroeconomy and peer-to-peer lending which is an essential part of fintech. Initially, they chose a series of macroeconomic variables to do OLS regressions and AIC stepwise regressions, including gross domestic product (GDP), unemployment rate, the inflation (CPI) and household debt, the first-difference in the yields of the 10-year Government Bonds (Δ 10Y-rf), the difference between the 10-year Government Bond yields and the 1-year Treasury Bill rate (rf-slope), the S&P 500 Index (SPX), the first differenced VIX index (ΔVIX), the small-minus-big (SMB) factor and the high-minus-low (HML) factor. According to the OLS regression, they found that the 10-year Government Bonds yields and the HML and SMB factors are statistically and economically significant, and the change in VIX is positively significant to predict shorter-term loans. Besides, CPI shows a significance for lower grade credit spreads in AIC stepwise regressions while the unemployment rate shows significance in OLS.

Zare et al. (2015) presented that short-term interest rates and oil prices have a negative influence on stock prices while money supply positively affects the stock prices in Malaysia.

El-Nader and Alraimony (2012), Owusu-Nantwi and John (2011) analyzed the effect of macroeconomic variables on the Amman Stock Market (ASE) by using OLS and ARCH / GARCH and shows that money supply, exchange rates, and interest rates have a negative influence on the stock.

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3. Empirical Analysis

The analysis performed in the previous section suggests that stock returns are influenced by different macroeconomics factors. This section presents the estimation of equations for the returns of Fintech, traditional finance, and the differences between both stock returns for the period from 2016 to 2020. The fundamental goal is to evaluate the impact that the main macroeconomic determinates had on the returns of fintech, traditional finance, and both difference of the returns. Had the investors been stimulated to invest in the securities we are analyzing whenever the variables related to those parameters rise? This is the question for which we are trying to answer.

In this chapter, we will show the characteristics of the collected data to form a suitable representative sample for our analysis. We will also present the methods used to process the data under consideration.

3.1 Methodology

To see how investors react to different macroeconomic variables, we collect measurable information, expressed in numerical form, and then rely on quantitative research for studying and sorting.

It has been found that many time series data, especially macroeconomic data that is nonstationary, often show obvious time trends, such as interest rates increase over time. This trend can be attributed to technological progress, the growth of labor and its quality, etc. If using the time series data involving nonstationary to run the regression, which can be led to the spurious regression and the result is unreliable. The Augmented Dicky-Fuller (ADF) unit root tests can help to check the stationarity of the data.

Ordinary Least Squares Method (OLS) is a method traditionally used in various studies in the literature; in other words, we apply this approach to establish a multiple linear regression model (MLRM) to compare the difference in the returns between financial technology and traditional finance and evaluate the relevance of investors' responses to different economic variables.

In this study, we consider the returns of the KBW Nasdaq Financial Technology Index (KFTX), the returns of the S&P 500 Financials Services Select Sector Index (FINANCIALS), and the differences between both returns (△K_F) as three dependent variables respectively to run the three regressions model. The explanatory variables are the 3-month USD liber

(LIBOR3M), the difference between the yields on the 10-year Government Bonds and those on the 2-year Government Bonds (T10Y2Y), total nonfarm payroll (NFP), and S&P 500 index (SP500).

The equations of OLS regression we use in this research are expressed as follows:

$$(\triangle K\_F)_t = \beta_1 + \beta_2\, NFP_t + \beta_3\, SP500_t + \beta_4\, T10Y2Y_t + \beta_5\, LIBOR3M_t + \varepsilon_t \tag{1}$$

$$KFTX_t = \beta_1 + \beta_2\, NFP_t + \beta_3\, SP500_t + \beta_4\, T10Y2Y_t + \beta_5\, LIBOR3M_t + \varepsilon_t \tag{2}$$

$$FINANCIALS_t = \beta_1 + \beta_2\, NFP_t + \beta_3\, SP500_t + \beta_4\, T10Y2Y_t + \beta_5\, LIBOR3M_t + \varepsilon_t \tag{3}$$

Where KFTX reflects the returns of the KBW Nasdaq Financial Technology Index; FINANCIALS reflects the returns of the S&P 500 Financials Services Select Sector Index; (△K_F) reflects the differences between the KBW Nasdaq Financial Technology Index and the S&P 500 Financials Services Select Sector Index; NFP is the variable measures total nonfarm payroll in the U.S; SP500 is regarded as the S&P 500 index; T10Y2Y represents the spread of 10-year Government Bonds and the 2-year Government Bonds; LIBOR3M is the 3- month London Interbank Offered Rate; β_1 is a constant term C; $\beta_2, \beta_3, \beta_4, \beta_5$, are coefficients; ε_t is the error at period t.

One of the assumptions of the multiple linear regression model is that there is no autocorrelation, meaning that the errors $\varepsilon_{i \text{ and }} \varepsilon_{j,}$ with $i \neq j$, are linearly independent. However, when we are dealing with time-series data, the violation of the assumption generally occurs, making the errors correlate with the residuals.

After obtaining the OLS regression, we use the Durbin-Watson (D-W) test to check the error's first-order autocorrelation [AR (1)] and then confirm the residuals' autocorrelation by computing the Breusch-Godfrey (B-G) LM test. We found that the initial OLS regression for the comparative model (△K_F), and the OLS regression of KFTX exist the error's first-order autocorrelation.

Several standard models are applied to deal with the linear regression model with AR (1) errors for stationary time-series, however, the most common for autocorrelated regression errors is the first-order autoregressive process, AR (1), we suppose:

$$\varepsilon_t \; = \rho\varepsilon_{t-1} + v_t \tag{4}$$

Where ε_{t-1} is the error at period t-1; ρ is the autocorrelation coefficient, $0 \leq |\rho| < 1$; v_t is an error term, the 'random shocks', is assumed to be Gaussian white noise, $v_t \sim N(0, \sigma^2_v)$.

This process is known as the Cochrane-Orcutt (CORC) iterative procedure, which is based on the generalized differences method. Then we estimate the OLS model with AR (1) to make the errors linearly independent, and the procedures for the regression of the comparative model are as follow:

As $$(\triangle \mathrm{K\_F})_{t-1} = \beta_1 + \beta_2 NFP_{t-1} + \beta_3 SP500_{t-1} + \beta_4 T10Y2Y_{t-1} + \beta_5 LIBOR3M_{t-1} + \varepsilon_{t-1} \tag{5}$$

Thus $$\varepsilon_{t-1} = (\triangle \mathrm{K\_F})_{t-1} - \beta_1 - \beta_2 NFP_{t-1} - \beta_3 SP500_{t-1} - \beta_4 T10Y2Y_{t-1} - \beta_5 LIBOR3M_{t-1} \tag{6}$$

If we replace equations (6) and (1) into equation (4), we get:

$$\begin{aligned}(\triangle \mathrm{K\_F})_t = {} & \beta_1 + \beta_2 NFP_t + \beta_3 SP500_t + \beta_4 T10Y2Y_t + \beta_5 LIBOR3M_t + \\ & \rho[(\triangle \mathrm{K\_F})_{t-1} - \beta_1 - \beta_2 NFP_{t-1} - \beta_3 SP500_{t-1} - \beta_4 T10Y2Y_{t-1} - \\ & \beta_5 LIBOR3M_{t-1})] + v_t\end{aligned} \tag{7}$$

And we perform the same procedures to the regression of KFTX, the equation (2) is replaced as equation (8):

$$\begin{aligned}KFTX_t = {} & \beta_1 + \beta_2 NFP_t + \beta_3 SP500_t + \beta_4 T10Y2Y_t + \beta_5 LIBOR3M_t + \\ & \rho(KFTX_{t-1} - \beta_1 - \beta_2 NFP_{t-1} - \beta_3 SP500_{t-1} - \beta_4 T10Y2Y_{t-1} - \\ & \beta_5 LIBOR3M_{t-1}) + v_t\end{aligned} \tag{8}$$

The EViews can be directly applied to estimate a model with AR (1) errors.

3.2 Data description

The empirical analysis focuses on the US market to compare the difference between the fintech sector and the traditional financial sector. KBW Nasdaq Financial Technology Index (KFTX) is selected to represent fintech and the S&P 500 Financials Services Select Sector Index (FINANCIALS) to represent traditional finance industries.

Both indices in this empirical analysis are average monthly series which are computed by daily close price exported from Investing.com. The time range of data is from 18th July 2016 to 30 Oct 2020, which is decided by the launch date of the KFTX index, a total of 51 monthly observations. After that, we compute the monthly returns of both indices by using logs, which are represented by RK, RF respectively, and next obtain the log difference proxy by △RKRF. These three variables are also the dependent variables in this empirical analysis.

The continuously compounded monthly returns of the variables are calculated as the following equation:

$$R_t = ln\left(\frac{Pt}{Pt-1}\right) = ln\,(P_t) - ln\,(P_{t-1}) \tag{9}$$

Where R_t is regarded as the monthly return of each index at period t, P_t and P_{t-1} are the average monthly price for the current month t and previous month t-1.

Based on the content we found in the literature or the economic intuition, four macroeconomic factors are initially chosen as explanatory variables for this research, including 3-month USD LIBOR, the difference between the yields on the 10-year and 2-year Government Bonds, total nonfarm payroll, and S&P 500 index.

Since the economic data used in this study is a time series of monthly data, we use the x-12 Seasonally adjusted method by *EViews* to eliminate seasonal effects on the 3-month USD LIBOR, the difference between the yields on the 10-year Government Bonds and those on the 2-year Government Bonds, and total nonfarm payroll.

Table 1 Variable Description and Source

Variables	Description	Source
KFTX	KBW Nasdaq Financial Technology Index (monthly average).	Investing.com
FINANCIALS	S&P 500 Financials Services Select Sector Index, consists of companies included in the S&P 500 as members of the GICS® financials sector (monthly average)	Investing.com
LIBOR3M	3-month LIBOR in USD (%) (monthly, seasonally adjusted)	FRED Economic Data
T10Y2Y	The spread between 10-Year Treasury Constant Maturity and 2-Year Treasury Constant Maturity. (monthly average, seasonally adjusted)	FRED Economic Data
NFP	Total nonfarm payroll of all employees in the U.S. (monthly, seasonally adjusted).	FRED Economic Data
SP500	S&P 500 index, a stock market index that tracks the stocks of 500 large-capitalization U.S. companies (monthly average)	Investing.com

The final format of all the explanatory variables are as follows: DLNLIBOR3M represents the log difference of 3-month LIBOR in USD; DLNT10Y2Y, the nature log difference of the spread between 10-year Treasury Constant Maturity and 2-year Treasury Constant Maturity; DLNSP500 respectively proxy the log return of the average monthly data of S&P 500. Last, obtain log returns from monthly data of total nonfarm payroll, respectively marked as DLNNFP.

We emphasize that these variables are finally presented in the form of logarithmic first differences, which also represent a continuously compounded return or the change, so the new series is in general stationary and the errors are not autocorrelated. Moreover, the first natural logarithm of the variables can help to stabilize the variance and get the residuals homoskedasticity.

An explanation and the steps are illustrated in the next section. All the empirical results were obtained through *EViews 9.0*.

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4. Empirical Result

4.1 Stationary

When we analyze time-series data in the regression model, we must ensure the stationarity of the series. We initially applied the Augmented Dickey-Fuller (ADF) test which is known as a unit root test of random walk series, to check the stationary of each variable. The null hypothesis of the ADF test assumes that the time series has a unit root, which means that the time series is non-stationary, leading to unreliable estimation and spurious regression.

First, we test the original time series with an automatic lag-length selection using Schwarz's Information Criterion (SIC) and the choice of the equation is from the Trend and Intercept, Intercept to None. The results can be seen in the tables below, which show that the original series of all variables are found to be non-stationary. However, all the series become stationary after the first differencing.

The variables of SP500 and KFTX are stationary with t-values of -3.84 and -3.18 greater than the critical values at 5% and 10% respectively, while the other four variables are not statistically significant at those levels. Thus, we do not reject the null hypothesis in the ADF test for the original series of FINANCIALS, NFP, T10Y2Y, and LIBOR3M, and we conclude that they are non-stationary.

Table 2 Augmented Dickey-Fuller test for the level of series[1]

	Lags	t-statistic	p-value
KFTX	0	-3.180832	0.0998
FINANCIALS	0	-2.216232	0.4706
NFP	0	-2.449209	0.3511
SP500	0	-3.839597	0.0224
T10Y2Y	0	-0.383097	0.9857
LIBOR3M	2	0.552475	0.9992

KFTX: KBW Nasdaq Financial Technology Index; FINANCIALS: S&P 500 Financials Services Select Sector Index; NFP: Total nonfarm payroll; SP500: S&P500 index; T10Y2Y: The spread between 10-Year and 2-Year Government Bond yields; LIBOR3M: 3-month LIBOR.

For regression analysis involving unit roots, the time series is not stationary, resulting in the invalid t-statistic value, and we may encounter the problem of spurious regression. To solve this problem, a common procedure is to transform the original levels to the first differences.

Therefore, we compute the first differences of the natural log of all the original time series

[1] See the original tables with results in Annex A –Table 11, Table 12,Table 13, Table 14, Table 15,andTable 16.

to achieve stationary and obtain the difference between the log-returns of the KFTX index and the S&P 500 Financials Services Select Sector Index, resulting in compounding rates of returns. And then we re-process the ADF test, with the results presented in Table 3:

Table 3 Augmented Dickey-Fuller test for the first difference[2]

	Lags	t-statistic	p-value
△RKRF	1	-3.580218	0.0420
RK	0	-6.533878	0.0000
RF	0	-6.517724	0.0000
DLNNFP	0	-6.981848	0.0000
DLNSP500	0	-6.657292	0.0000
DLNT10Y2Y	1	-6.755070	0.0000
DLNLIBOR3M	0	-6.396462	0.0000

△RKRF: the difference between the log-returns of the KBW Nasdaq Financial Technology Index and the S&P 500 Financials Services Select Sector Index; RK: the log difference of KBW Nasdaq Financial Technology Index; RF: the log difference of S&P 500 Financials Services Select Sector Index; DLNNFP: the log difference of Total nonfarm payroll; DLNSP500: the log difference of S&P500 index; DLNT10Y2Y: the log difference of the spread between 10-Year and 2-Year Government Bond yields; DLNLIBOR3M: The log difference of 3-month LIBOR.

The results indicate that all variables are significant at a 95% confidence interval, moreover, the probability value is also below 5%. Therefore, we conclude for the absence of a unit root at their first difference and that the transformed series are stationary at a 5% significant level.

4.2 The multiple linear regressions

After converting the original data into the form of logarithmic first-order difference, we established a series of stable variables and estimated the parameters by multiple linear regression.

4.2.1 The regression of the comparative model (△RKRF)

The first trial includes all the transformed variables described in the previous section. We take the difference between the log-returns of the KBW Nasdaq Financial Technology Index and the S&P 500 Financials Services Select Sector Index as the dependent variable, and the log difference of Total nonfarm payroll, the log difference of S&P500 index, the log difference of the spread between the yields on the 10-Year and 2-Year Government Bonds, and the 3-month LIBOR, as explanatory variables.

[2] See the original tables with results in Annex A – Table 17, Table 18, Table 19, Table 20, Table 21, Table 22, and Table 23.

We estimate the parameters of the equation (1) with the first differences of the natural log by the OLS method, and compute the Durbin -Watson (D-W) test and the Breusch - Godfrey (B-G) LM test to detect the presence of autocorrelation. The results are as follow:

Table 4 The regression of the comparative model (△RKRF, estimation result)[3]

- Dependent Variable: △RKRF
- Method: Least Squares

Explanation Variables	Coefficient	t-statistic	p-value
DLNNFP	-0.152196	0.170390	-0.893221
DLNSP500	-0.167940	0.092756	-1.810546
DLNT10Y2Y	-0.027079	0.011885	-2.278357
DLNLIBOR3M	-0.083419	0.024345	-3.426502
C	0.007993	0.003788	2.110181
R-squared	0.270964	**F-statistic**	4.274249
Adjusted R-squared	0.207569	**Prob(F-statistic)**	0.005041
Durbin-Watson stat	1.333856		

△RKRF: the difference between the log-returns of the KBW Nasdaq Financial Technology Index and the S&P 500 Financials Services Select Sector Index; DLNNFP: the log difference of Total nonfarm payroll; DLNSP500: the log difference of S&P500 index; DLNT10Y2Y: the log difference of the spread between the yields on the 10-Year and 2-Year Government Bonds; DLNLIBOR3M: 3-month LIBOR.

Table 4 shows that the D-W statistic in the OLS regression of the initial comparative model (△RKRF) is 1.333856, to confirm if we reject the null hypothesis, which is No First Order Autocorrelation ($\rho = 0$), we search for the critical value through the Durbin-Watson Table[4] at the alpha 0.05 significance. Since there is not a row for sample size 51, Evans (2014) mentions that when we do not find a row for sample size, so go to the next lowest sample size with a tabulated row. Thus, we refer to n=50, k=5 (including the intercept), the critical values are d_L=1.335 > 1.333856, d_U=1.771, which indicate that the D-W statistic is on region Ⅰ: the residual (RESID) points for positive first-order autocorrelation. Therefore, we reject the null and we cannot assume the absence of the autocorrelation. Next, we confirm the autocorrelation of the residuals by using the Breusch-Godfrey test (2 legs):

Table 5 Breusch-Godfrey LM test for the comparative model (△RKRF)[5]

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	2.9120	Prob. F (2,44)		0.0649
Obs*R-squared	5.9615	Prob. Chi-Square (2)		0.0508
Variable	Coefficient	Std. Error	t-Statistic	Prob.
RESID (-1)	0.3579	0.1541	2.3221	0.0249
RESID (-2)	-0.0144	0.1592	-0.0902	0.9285

[3] See the original table with results in Annex A–Table 24.
[4] Evans (2014)
[5] See the original table with results in Annex A–Table 25

In the initial model where the explanatory variable is △RKRF, Table 5 indicates that the probability associated with the test value is higher than the significance level (0.05), we do not reject the general assumption of no autocorrelation. However, the probability of the RESID (-1) is lower than the level of significance (0.05), we reject the null hypothesis of the RESID (-1) series. Once each coefficient of the residuals violates the null hypothesis and not independent variables, the distribution of F for finite samples is not known, leading to different possibilities. Thus, we can conclude that the error's first-order autocorrelation exists in the initial comparative model (△RKRF) based on the OLS method.

Since both the Durbin -Watson (D-W) test and the Breusch - Godfrey (B-G) LM test point out to a first-order autocorrelation in the residuals [AR(1)] in the initial comparative model (△RKRF), we deal with the error's first autocorrelation problem base on the generalized differences method and re-estimate a model with AR(1) errors directly in *EViews*.

The equation (7) can be written in the form:

$$\triangle \mathrm{RKRF}_t = \beta_1(1-\rho) + \beta_2 DLNNFP_t + \beta_3 DLNSP500_t + \beta_4 DLNT10Y2Y_t + \beta_5 DLNLIBOR3M_t + \rho(\triangle \mathrm{RKRF}_{t-1} - \beta_2 DLNNFP_{t-1} - \beta_3 DLNSP500_{t-1} - \beta_4 DLNT10Y2Y_{t-1} - \beta_5 DLNLIBOR3M_{t-1}) + v_t \tag{10}$$

And we get the results shown in Table 6:

Table 6 The regression of the comparative model (△RKRF, re-estimation result)[6]

- Dependent Variable: △RKRF
- Method: ARMA Generalized Least Squares (Gauss-Newton)

Explanation Variables	Coefficient	t-statistic	p-value
DLNNFP	-0.147475	-0.853598	0.3978
DLNSP500	-0.140645	-1.585056	0.1200
DLNT10Y2Y	-0.026548	-2.374712	0.0219
DLNLIBOR3M	-0.096587	-3.516786	0.0010
C	0.007609	1.408292	0.1659
AR (1)	0.353102	2.439925	0.0187
R-squared	0.355795	**F-statistic**	4.970710
Adjusted R-squared	0.284217	**Prob(F-statistic)**	0.001044
Durbin-Watson stat	1.943741		

△RKRF: the difference between the log-returns of the KBW Nasdaq Financial Technology Index and the S&P 500 Financials Services Select Sector Index; DLNNFP: the log difference of Total nonfarm payroll; DLNSP500: the log difference of S&P500 index; DLNT10Y2Y: the log difference of the spread between the yields on the 10-Year and 2-Year Government Bonds; DLNLIBOR3M: 3-month LIBOR; AR(1): the error's first autocorrelation.
The autocorrelation coefficient ρ is 0.353102.

[6] See the original table with results in Annex A–Table 26.

The results in Table 6 show that after the AR (1) procedure the D-W test is 1.94, close to 2, is on the no reject region, which means that the first-order autocorrelation problem in the initial model has been solved. And we can conclude the absence of autocorrelation in the transformed model as we do not reject the null in the D-W and B-G LM test[7].

As we can see, the transformed comparative model (△RKRF) is statistically significant. This is confirmed by the p-value (0.001) associated with the F test (F-Statistic) < α, where α = 0,05 is the default significance level. Thus, we reject the null hypothesis that all the coefficients of the determinant are equal to zero and conclude that the model is statistically significant. This means that the changes on the dependent variable rely on at least one explanatory variable.

Next, we use the adjusted R-squared to see the linear relationship between the dependent and all the explanatory variables. Since the adjusted R-squared is a modified version of R-squared, it is more suitable for comparing the explanatory power of regression models with different numbers of predictors, and showing whether additional input variables improve the regression model.

In the transformed model, the adjusted R-squared is 0.2842, higher than the one, 0.2076, in the initial estimate model, which indicates that the transformed model fits better. And it means 28.42% of the dependent variables (the difference between the log-returns of the KBW Nasdaq Financial Technology Index and the S&P 500 Financials Services Select Sector Index) can be explained by the changes in the independent variables in this re-estimated comparative model.

In addition, Table 6 indicates that two factors, DLNT10Y2Y and DLNLIBOR3M, have a negative and significant influence on the dependent variable since the significances of their respective parameters are lower than the significance level (0.05), while the p-values of DLNNFP and DLNSP500 are higher than 0.05.

The estimated equation (11) is given by:

$$\begin{aligned} \triangle RKRF_t = \; & 0.0049 - 0.1475DLNNFP_t - 0.1406DLNSP500_t - 0.0265DLNT10Y2Y_t - \\ & 0.0966DLNLIBOR3M_t + 0.3531(\triangle RKRF_{t-1} - 0.1475DLNNFP_{t-1} - \\ & 0.1406DLNSP500_{t-1} - 0.0265DLNT10Y2Y_{t-1} - 0.0966DLNLIBOR3M_{t-1}) \end{aligned} \quad (11)$$

Since the coefficient estimates of variables, DLNT10Y2Y and DLNLIBOR3M, can be considered negative and statistically significant, they can be interpreted as follows. By increasing the log return of the yield spread between 10-Year and 2-Year Government Bonds or 3-month LIBOR by 1 percentage point (p.p), the difference between the log-returns of KFTX and FINANCIALS will be decreased by 0.0265 p.p or 0.0966 p.p respectively, which means

[7] See the B-G LM test results in Annex B.

that investors may buy more traditional finance stocks than fintech when the spread 10-year and 2-year Government bonds rate or the 3-month LIBOR increase.

Although the coefficients of DLNNFP and DLNSP500 show a negative but no statistically significant relevance in explaining the difference between the log-returns of KFTX and FINANCIALS, from Table 9 and Table 10 in the next chapters, we can find the existence of a positive statistical influence on those variables with the regression related only to KFTX or FINANCIALS, so we did not exclude these two independent variables from the model. At the same time, we can also get the answer from the respective regression models of KFTX and FINANCIALS, whenever LIBOR3M or T10Y2Y increases, whether the decline of the dependent variables in the comparative model (△RKRF) results from the decrease in KFTX or the increase in FINANCIALS.

4.2.2 The regression of the KFTX

In this section, we take the log difference of the KBW Nasdaq Financial Technology Index (KFTX) as the dependent variable in the first trial and the explanatory variables are the log difference of total nonfarm payroll, the log difference of S&P500 index, the log difference of the spread between the yields on the 10-Year and 2-Year Government Bonds; and the 3-month LIBOR.

After estimating the parameters of the equation (2) with the first differences of the natural log by the OLS method, we use the Durbin -Watson (D-W) test and the Breusch - Godfrey (B-G) LM test to check the error's first-order autocorrelation, and the results are shown below:

Table 7 The regression of the KFTX (estimation results)[8]

- Dependent Variable: RK
- Method: Least Squares

Explanation Variables	Coefficient	t-statistic	p-value
DLNNFP	0.313869	0.103781	3.024330
DLNSP500	1.097616	0.056496	19.42816
DLNT10Y2Y	-0.008225	0.007239	-1.136153
DLNLIBOR3M	-0.001008	0.014828	-0.068001
C	0.003819	0.002307	1.655401
R-squared	0.899044	**F-statistic**	102.4105
Adjusted R-squared	0.890265	**Prob(F-statistic)**	0.000000
Durbin-Watson stat	1.338877		

RK: the log difference of KBW Nasdaq Financial Technology Index; DLNNFP: the log difference of Total nonfarm payroll; DLNSP500: the log difference of S&P500 index; DLNT10Y2Y: the log difference of the yields spread between 10-Year and 2-Year Government Bonds; DLNLIBOR3M: 3-month LIBOR.

[8] See the original table with results in Annex A– Table 27.

In the initial regression of the log difference of KFTX by the OLS method, Table 7 presents that the D-W test is 1.338877. We search for the critical value through the Durbin-Watson Table[9] at the alpha 0.05 significance. For n=50, k=5 (including the intercept), the critical values are d_L=1.335 < 1.338877, d_U=1.771, the test is on the region Ⅱ, the inconclusive region, nothing can be concluded about the AR(1). Next, we compute the Breusch-Godfrey test until the second order to test the error's autocorrelation:

Table 8 Breusch-Godfrey LM test for the regression of KFTX[10]

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	2.9064	Prob. F (2,44)		0.0652
Obs*R-squared	5.9514	Prob. Chi-Square (2)		0.0510
Variable	Coefficient	Std. Error	t-Statistic	Prob.
RESID (-1)	0.3621	0.1591	2.2761	0.0278
RESID (-2)	-0.0123	0.1634	-0.0755	0.9402

In the initial model where the explanatory variable is RK, The B-G LM test results in Table 8 show that the probability associated with the test value is higher than the significance level (0.05), we do not reject the general null hypothesis. However, the probability of the RESID (-1) is 0.0278, which is lower than the 0.05 significant level. Thus, we reject the null hypothesis of the RESID (-1) series and conclude that there is the autocorrelation of the first order in the initial regression of the log difference of KFTX based on the OLS method.

Due to a first-order autocorrelation in the residuals [AR (1)] occurring after the D-W test and the B-G LM test, we solve the error's first autocorrelation problem by directly using the *EViews* to transform the model with AR (1) errors. We could rewrite the equation (2) as:

$$\begin{aligned} RK_t = {} & \beta_1(1-\rho) + \beta_2 DLNNFP_t + \beta_3 DLNSP500_t + \beta_4 DLNT10Y2Y_t + \\ & \beta_5 DLNLIBOR3M_t + \rho(RK_{t-1} - \beta_2 DLNNFP_{t-1} - \beta_3 DLNSP500_{t-1} - \\ & \beta_4 DLNT10Y2Y_{t-1} - \beta_5 DLNLIBOR3M_{t-1}) + v_t \end{aligned} \tag{12}$$

And the results are shown below:

[9] Evans (2014)
[10] See the original table with results in Annex A–Table 28.

Table 9 The regression of the KFTX (re-estimation results)[11]

- Dependent Variable: RK
- Method: ARMA Generalized Least Squares (Gauss-Newton)

Explanation Variables	Coefficient	t-statistic	p-value
DLNNFP	0.361572	3.428656	0.0013
DLNSP500	1.148077	21.64407	0.0000
DLNT10Y2Y	-0.008994	-1.341262	0.1866
DLNLIBOR3M	-0.009525	-0.561570	0.5772
C	0.003370	0.963779	0.3403
AR (1)	0.399247	2.805250	0.0074
R-squared	0.912312	**F-statistic**	93.63684
Adjusted R-squared	0.902569	**Prob(F-statistic)**	0.000000
Durbin-Watson stat	1.960685		

RK: the log difference of KBW Nasdaq Financial Technology Index; DLNNFP: the log difference of Total nonfarm payroll; DLNSP500: the log difference of S&P500 index; DLNT10Y2Y: the log difference of the yields spread between 10-Year and 2-Year Government Bonds; DLNLIBOR3M: 3-month LIBOR; AR(1): the error's first autocorrelation.
The autocorrelation coefficient ρ is 0.399247.

Table 9 shows the results of the transformed model of KFTX, the D-W test is 1.96, close to 2, is on the no reject region after the AR (1) procedure, which means that we successfully deal with the error's first-order autocorrelation problem in the initial model. And we can conclude there is no autocorrelation in the transformed model as we do not reject the assumption of the D-W and B-G LM test[12].

It can be assumed that the re-estimated model of KFTX is adequate which is confirmed by the p-value (0.0000) associated with the F test (F-Statistic) < α, where α = 0,05. Thus, we reject the null and conclude that the model is statistically significant. In addition, the adjusted R-squared is 0.9026 in the transformed model, higher than the one, 0.8903, in the initial model, which also shows that the transformed model fits better. In this re-estimated model, 90.26% of the log return of KFTX can be explained by the changes in the determinant variables.

Moreover, two factors, DLNNFP and DLNSP500, have a positive and statistically significant impact because the level of significance (p-value) is quite lower than the default significant level (0.05), while the DLNT10Y2Y and DLNLIBOR3M have a negative but no statistically significant impact.

The estimated equation is given by:

$$\begin{aligned} RK_t = {} & 0.0020 + 0.3616 DLNNFP_t + 1.1481 DLNSP500_t - 0.0090 DLNT10Y2Y_t - \\ & 0.0095 DLNLIBOR3M_t + 0.3992\ (RK_{t-1} - 0.3616 DLNNFP_{t-1} - \\ & 1.1481 DLNSP500_{t-1} + 0.0090 DLNT10Y2Y_{t-1} + 0.0095 DLNLIBOR3M_{t-1}) \end{aligned} \tag{13}$$

[11] See the original table with results in Annex A–Table 29.
[12] See the B-G LM test results in Annex B.

Since the coefficient of DLNNFP and DLNSP500 are positive and statistically significant, they can be explained as the log difference of Total nonfarm payroll or the log difference of the S&P500 index each increase by 1 percentage point (p.p), following the log-returns of KFTX will rise by 0.3616p.p or 1.1481 p.p respectively.

4.2.3 The regression of the FINANCIALS

We consider the log difference of the S&P 500 Financials Services Select Sector Index (FINANCIALS) as the dependent variable and take the log difference of total nonfarm payroll, the log difference of the S&P500 index, the log difference of the yields spread between the 10-Year and 2-Year Government Bonds; and the 3-month LIBOR as the explanatory variables.

Since there are no autocorrelation or heteroskedastic issues, we assess the regression model of FINANCIALS directly by the OLS method. The equation (3) is converted to equation (14):

$$RF_t = \beta_1 + \beta_2\, DLNNFP_t + \beta_3\, DLNSP500_t + \beta_4\, DLNT10Y2Y_t + \beta_5\, DLNLIBOR3M_t + \varepsilon_t \quad (14)$$

And the results are as follows:

Table 10 The regression of FINANCIALS (estimation results)[13]

- Dependent Variable: RF
- Method: Least Squares

Explanation Variables	Coefficient	t-statistic	p-value
DLNNFP	0.466066	3.358735	0.0016
DLNSP500	1.265556	16.75371	0.0000
DLNT10Y2Y	0.018854	1.947926	0.0575
DLNLIBOR3M	0.082411	4.156648	0.0001
C	-0.004174	-1.353067	0.1826
R-squared	0.872992	**F-statistic**	79.04518
Adjusted R-squared	0.861947	**Prob(F-statistic)**	0.000000
Durbin-Watson stat	1.626842		

RF: the log difference of S&P 500 Financials Services Select Sector Index; DLNNFP: the log difference of Total nonfarm payroll; DLNSP500: the log difference of S&P500 index; DLNT10Y2Y: the log difference of the yields spread between 10-Year and 2-Year Government Bonds; DLNLIBOR3M: 3-month LIBOR.

Regarding Table 10, the p-value (0.0000) is associated with the F test (F-Statistic) < α, where α = 0,05, and hence we reject the null and conclude that the model is statistically significant. In addition, we confirm the model of FINANCIALS is adequate because the adjusted R-square of the model is 0.8619, which means that 86.19% of the log return of

[13] See the original table with results in Annex A–Table 30.

FINANCIALS can be explained by the changes in the determinant variables. Moreover, the probabilities of the parameters of DLNNFP, DLNSP500, and DLNLIBOR3M are positive and statistically significant since the level of significance (p-value) is quite lower than the default significant level (0.05), while the coefficient of DLNT10Y2Y is statistically significant at the level of 10%.

The estimated equation is given by:

$$RF_t = -0.0042 + 0.4661DLNNFP_t + 1.2656DLNSP500_t + 0.0189DLNT10Y2Y_t + 0.0824DLNLIBOR3M_t \tag{15}$$

Since the coefficients of all the explanatory variables are positive and statistically significant, they can be concluded that when the log difference of total nonfarm payroll, the log difference of the S&P500 index, the yield difference of 10-year and 2-year Government Bonds, or the 3-month LIBOR each increase by 1 percentage point (p.p), the log-returns of FINANCIALS will rise by 0.4661p.p, 1.2656p.p, 0.0189p.p or 0.0824 p.p respectively.

The MLRM assumptions tests for all the above models are shown in Annex B.

5. Discussion and Conclusion

This paper aims to provide the results of empirical analysis, based on the OLS method, to measure the impact of macroeconomic variables (total nonfarm payroll, s&p500 index, 3-month LIBOR in USD, and 10-year and 2-year Government Bond spreads) on the monthly returns of fintech, traditional finance, as well as to compare the differences of both log returns from 2016 to 2020 in the U.S. The results of the three multiple regression models enable us to understand that every time these variables rise, they stimulate investors to buy the assets we are analyzing.

In addition, the Cochrane-Orcutt (CORC) iterative procedure, based on the generalized difference method, successfully helps to solve the first-order autocorrelation problem of the residuals in the initial estimated comparative model and the model of KFTX.

Regarding the results of the regression models, first of all, it can be concluded that the three multiple regression models we established are all statistically significant. The adjusted R-square associated with the transformed model of the KBW Nasdaq Financial Technology Index (KFTX, represent fintech) and the model of S&P 500 Financials Services Select Sector Index (FINANCIALS, a proxy for traditional finance industries) are 90.26% and 86.19%, the models fit quite adequately. However, the adjusted R-square of the transformed comparative model (△RKRF) is 28.42%, the model does not fit well.

Secondly, from the transformed comparative model (△RKRF) which is the differences between the log-returns of the KBW Nasdaq Financial Technology Index (KFTX, represent fintech) and the S&P 500 Financials Services Select Sector Index (FINANCIALS, a proxy for traditional finance industries), we saw that the relationship between 3-month LIBOR, or 10-year and 2-year Government Bonds spread with the dependent variable are negative and statistically significant. In particular, after we build models for KFTX and FINANCIALS respectively, we can confirm that whenever LIBOR3M or 10-year and 2-year Government Bonds increases, the decline of the dependent variables in the comparative model (△RKRF) results from the increase in FINANCIALS. Because 3-month LIBOR, or 10-year and 2-year Government Bonds spreads are a positive and statistically significant influence on the dependent variable in the model of FINANCIALS, while these two explanatory variables present a negative but no statistically significant influence in the transformed model of KFTX.

Therefore, it can be concluded that whenever the 3-month LIBOR or the spread between 10-year and 2-year Government Bonds rise, investors are inclined to buy more traditional financial stock represented by the S&P 500 Financials Services Select Sector Index than the fintech assets represented by the KFTX index.

LIBOR3M rises or 10-Y and 2-Y Government Bonds spread increase indicate a strengthening economy. In an environment where economic growth, interest rates are rising, the traditional financial sector has always been one of the sectors most sensitive to changes in interest rates. The traditional financial companies represented by S&P 500 Financials Services Select Sector Index, including entities such as banks, insurances, brokerage firms, etc., have benefited from the increase in interest income, and their profit margins will usually historically expand as interest rates rise. Investors expect such stocks to have better value and return, stimulating them to buy more.

However, we are unable to confirm the negative relationship between the KFTX index with LIBOR3M or 10-Y and 2Y Government Bonds spread since the statistical is not significant. Because when the interest rate increases, the fintech start-up represented by the KFTX index needs to spend more on debts, and corporate profits will be affected. The rising interest rates will also affect the enthusiasm of venture capital, and will also affect the financial technology business model that relies on debt or warehouse financing. In addition, financial technology is an emerging concept that relies on technological innovation and development, and its risks and the instability of corporate profits are higher than traditional finance, which will affect investors' willingness to invest in stocks.

Last, after we analyze the transformed model of KFTX and the model of FINANCIALS, we can conclude that total non-farm payroll and S&P 500 index are positive and statistically significant related to fintech and traditional finance. Because the increase of total nonfarm payroll and S&P 500 both pointed out that the employment situation is developing well and the income of residents increases, which will drive all aspects of the market, so that corporate profits will also increase, and the US economic situation will further improve. That is, when the economy develops well, it will drive the stock market to rise. At the same time, when the economy grows, residents have more funds for investment, which will increase the liquidity of the stock market to a certain extent, thereby stimulating the stock market to rise; and the KFTX index and the S&P 500 Financial Services Select Industry Index will also rise with the market. However, we cannot confirm whether investors will buy more financial technology assets or traditional finance in response to the increase in these two macroeconomic factors.

In the future, as the development of fintech becomes longer, when people's understanding of fintech becomes more and more comprehensive, they may have a different perception (value, risk, and return) of fintech from traditional finance. Moreover, traditional finance will also have more technological innovations to seek development or more cooperation with fintech. At that time, comparing the performance of the two may have different results. This is an interesting, and worthy of observation and research point.

Our research contains some shortcomings and limitations. First, since fintech is a new concept that has only been well-known to the public in the 21st century, the related literature and research are still not sufficient and still need to be improved. Most of the articles in the previous research discussed the relationship between the financial technology industry and the traditional financial industry based on theory, rather than empirical analysis. Then, there are relatively few reference materials available for our empirical analysis.

Another limitation may be the sample size and the monthly data we use. Since fintech is related to technological innovation, the time when investors realize technological innovation and the impact of changes in macroeconomic factors on stocks are also lagging (this is reflected in the statistically significant AR (1) in the model). However, since the KFTX index was only released in July 2016, until 2020, the monthly, quarterly, and annual sample sizes available to us are limited, and we can only make compromises between the frequency and length of the analysis or our sample period. In the future, as the development time of fintech becomes longer and the available sample size increases, this problem can be solved and we could consider different sample frequencies (daily data, quarterly data, etc.) or different regions to compare the performance of fintech and traditional finance by empirical analysis which will help to obtain a more effective conclusion.

From the results of the poor fit of the comparative model and the existence of statistically significant AR (1), it can be seen that the third limitation may be caused by the choice of the model and the independent variables. Since the OLS model is a relatively basic multiple regression model, and its classical assumptions are more restrictive, however, economic data is a complex time series, usually with lag, autocorrelation, and other problems. In addition to macroeconomic factors, independent variables may also include other potential determinants, such as microeconomic factors, and are also related to the previous period changes of dependent variables and some independent variables. In further research, a more detailed selection of representative samples of fintech, traditional finance, and determinant variables could be considered, and try to apply more diversified methods to examine the relationship between fintech and traditional finance.

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Annex A

Table 11 Augmented Dickey-Fuller test for the level of series
- Variable: KFTX (The KBW Nasdaq Financial Technology Index)

Null Hypothesis: KFTX has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.180832	0.0998
Test critical values:	1% level	-4.148465	
	5% level	-3.500495	
	10% level	-3.179617	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(KFTX)
Method: Least Squares
Date: 09/23/21 Time: 20:49
Sample (adjusted): 2016M08 2020M10
Included observations: 51 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
KFTX(-1)	-0.348683	0.109620	-3.180832	0.0026
C	369.0528	111.5134	3.309494	0.0018
@TREND("2016M07")	7.040364	2.349151	2.996983	0.0043

R-squared	0.174168	Mean dependent var	19.90518
Adjusted R-squared	0.139759	S.D. dependent var	83.51492
S.E. of regression	77.45942	Akaike info criterion	11.59441
Sum squared resid	287998.2	Schwarz criterion	11.70804
Log likelihood	-292.6574	Hannan-Quinn criter.	11.63783
F-statistic	5.061609	Durbin-Watson stat	1.673399
Prob(F-statistic)	0.010125		

Table 12 Augmented Dickey-Fuller test for the level of series
- Variable: FINANCIALS (The S&P 500 Financials Services Select Sector Index)

Null Hypothesis: FINANCIALS has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.216232	0.4706
Test critical values:	1% level	-4.148465	
	5% level	-3.500495	
	10% level	-3.179617	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FINANCIALS)
Method: Least Squares
Date: 09/23/21 Time: 20:53
Sample (adjusted): 2016M08 2020M10
Included observations: 51 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FINANCIALS(-1)	-0.165960	0.074884	-2.216232	0.0314
C	73.61425	29.83618	2.467281	0.0172
@TREND("2016M07")	-0.052160	0.243943	-0.213820	0.8316

R-squared	0.120019	Mean dependent var	1.787377
Adjusted R-squared	0.083354	S.D. dependent var	24.23663
S.E. of regression	23.20455	Akaike info criterion	9.183596
Sum squared resid	25845.64	Schwarz criterion	9.297233
Log likelihood	-231.1817	Hannan-Quinn criter.	9.227020
F-statistic	3.273331	Durbin-Watson stat	1.785912
Prob(F-statistic)	0.046489		

Table 13 Augmented Dickey-Fuller test for the level of series
- Variable: NFP (Total nonfarm payroll)

Null Hypothesis: NFP has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.449209	0.3511
Test critical values:	1% level	-4.148465	
	5% level	-3.500495	
	10% level	-3.179617	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(NFP)
Method: Least Squares
Date: 09/23/21 Time: 20:54
Sample (adjusted): 2016M08 2020M10
Included observations: 51 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
NFP(-1)	-0.226196	0.092355	-2.449209	0.0180
C	33761.61	13645.58	2.474179	0.0169
@TREND("2016M07")	-19.71574	28.04960	-0.702888	0.4855

R-squared	0.117202	Mean dependent var	-41.94118
Adjusted R-squared	0.080419	S.D. dependent var	3072.611
S.E. of regression	2946.474	Akaike info criterion	18.87163
Sum squared resid	4.17E+08	Schwarz criterion	18.98527
Log likelihood	-478.2265	Hannan-Quinn criter.	18.91505
F-statistic	3.186298	Durbin-Watson stat	1.816589
Prob(F-statistic)	0.050196		

Table 14 Augmented Dickey-Fuller test for the level of series
- Variable: SP500 (The S&P500 index)

Null Hypothesis: SP500 has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.839597	0.0224
Test critical values:	1% level	-4.152511	
	5% level	-3.502373	
	10% level	-3.180699	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(SP500)
Method: Least Squares
Date: 09/23/21 Time: 22:19
Sample (adjusted): 2016M09 2020M10
Included observations: 50 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
SP500(-1)	-0.489571	0.127506	-3.839597	0.0004
D(SP500(-1))	0.281200	0.144127	1.951064	0.0572
C	1079.652	278.7306	3.873460	0.0003
@TREND("2016M07")	10.23378	2.789472	3.668714	0.0006

R-squared	0.244407	Mean dependent var	24.82438
Adjusted R-squared	0.195129	S.D. dependent var	118.2887
S.E. of regression	106.1222	Akaike info criterion	12.24368
Sum squared resid	518048.8	Schwarz criterion	12.39664
Log likelihood	-302.0920	Hannan-Quinn criter.	12.30193
F-statistic	4.959769	Durbin-Watson stat	2.094731
Prob(F-statistic)	0.004578		

Table 15 Augmented Dickey-Fuller test for the level of series
- Variable: T10Y2Y (The spread between 10-Year and 2-Year Government Bond yields)

Null Hypothesis: T10Y2Y has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.383097	0.9857
Test critical values:	1% level	-4.148465	
	5% level	-3.500495	
	10% level	-3.179617	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(T10Y2Y)
Method: Least Squares
Date: 09/23/21 Time: 22:19
Sample (adjusted): 2016M08 2020M10
Included observations: 51 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
T10Y2Y(-1)	-0.020922	0.054613	-0.383097	0.7033
C	-0.006127	0.060555	-0.101176	0.9198
@TREND("2016M07")	0.000525	0.001295	0.405319	0.6870

R-squared	0.025785	Mean dependent var	-0.003803
Adjusted R-squared	-0.014808	S.D. dependent var	0.088559
S.E. of regression	0.089212	Akaike info criterion	-1.938571
Sum squared resid	0.382025	Schwarz criterion	-1.824934
Log likelihood	52.43355	Hannan-Quinn criter.	-1.895147
F-statistic	0.635207	Durbin-Watson stat	1.650659
Prob(F-statistic)	0.534221		

Table 16 Augmented Dickey-Fuller test for the level of series
- Variable: LIBOR3M (3-month LIBOR)

Null Hypothesis: LIBOR3M has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.552475	0.9992
Test critical values:	1% level	-4.148465	
	5% level	-3.500495	
	10% level	-3.179617	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LIBOR3M)
Method: Least Squares
Date: 09/23/21 Time: 22:21
Sample (adjusted): 2016M08 2020M10
Included observations: 51 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LIBOR3M(-1)	0.014047	0.025425	0.552475	0.5832
C	0.104313	0.053249	1.958970	0.0559
@TREND("2016M07")	-0.005296	0.001287	-4.116536	0.0002

R-squared	0.260930	Mean dependent var	-0.010476
Adjusted R-squared	0.230136	S.D. dependent var	0.152861
S.E. of regression	0.134123	Akaike info criterion	-1.123092
Sum squared resid	0.863475	Schwarz criterion	-1.009455
Log likelihood	31.63884	Hannan-Quinn criter.	-1.079668
F-statistic	8.473265	Durbin-Watson stat	1.904270
Prob(F-statistic)	0.000705		

Table 17 Augmented Dickey-Fuller test for the first difference
- Variable: △RKRF (The difference between the log-returns of the KBW Nasdaq Financial Technology Index and the S&P 500 Financials Services Select Sector Index)

Null Hypothesis: △RKRF has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.580218	0.0420
Test critical values:	1% level	-4.156734	
	5% level	-3.504330	
	10% level	-3.181826	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(△RKRF)
Method: Least Squares
Date: 09/23/21 Time: 22:23
Sample (adjusted): 2016M10 2020M10
Included observations: 49 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
△RKRF (-1)	-0.661971	0.184897	-3.580218	0.0008
△RKRF (-1))	-0.144139	0.150697	-0.956477	0.3439
C	-0.004213	0.008897	-0.473561	0.6381
@TREND("2016M07")	0.000372	0.000308	1.205159	0.2344

R-squared	0.400263	Mean dependent var	0.000202
Adjusted R-squared	0.360281	S.D. dependent var	0.035729
S.E. of regression	0.028577	Akaike info criterion	-4.194316
Sum squared resid	0.036749	Schwarz criterion	-4.039882
Log likelihood	106.7608	Hannan-Quinn criter.	-4.135724
F-statistic	10.01097	Durbin-Watson stat	1.932836
Prob(F-statistic)	0.000036		

Table 18 Augmented Dickey-Fuller test for the first difference
- Variable: RK (The log difference of KBW Nasdaq Financial Technology Index)

Null Hypothesis: RK has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.533878	0.0000
Test critical values:	1% level	-4.152511	
	5% level	-3.502373	
	10% level	-3.180699	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(DLNKFTX)
Method: Least Squares
Date: 09/23/21 Time: 22:24
Sample (adjusted): 2016M09 2020M10
Included observations: 50 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RK(-1)	-0.953988	0.146006	-6.533878	0.0000
C	0.018352	0.014840	1.236662	0.2224
@TREND("2016M07")	-0.000204	0.000484	-0.420968	0.6757

R-squared	0.476023	Mean dependent var	0.000313
Adjusted R-squared	0.453726	S.D. dependent var	0.066569
S.E. of regression	0.049201	Akaike info criterion	-3.127662
Sum squared resid	0.113777	Schwarz criterion	-3.012941
Log likelihood	81.19155	Hannan-Quinn criter.	-3.083975
F-statistic	21.34928	Durbin-Watson stat	1.979337
Prob(F-statistic)	0.000000		

Table 19 Augmented Dickey-Fuller test for the first difference
- Variable: RF (The log difference of S&P 500 Financials Services Select Sector Index)

Null Hypothesis: RF has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.517724	0.0000
Test critical values:	1% level	-4.152511	
	5% level	-3.502373	
	10% level	-3.180699	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(DLNFINANCIALS)
Method: Least Squares
Date: 09/23/21 Time: 22:25
Sample (adjusted): 2016M09 2020M10
Included observations: 50 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RF(-1)	-0.951077	0.145922	-6.517724	0.0000
C	0.023349	0.017462	1.337127	0.1876
@TREND("2016M07")	-0.000710	0.000577	-1.230786	0.2245

R-squared	0.474767	Mean dependent var	-4.61E-05
Adjusted R-squared	0.452417	S.D. dependent var	0.077966
S.E. of regression	0.057694	Akaike info criterion	-2.809206
Sum squared resid	0.156444	Schwarz criterion	-2.694485
Log likelihood	73.23016	Hannan-Quinn criter.	-2.765520
F-statistic	21.24208	Durbin-Watson stat	1.995825
Prob(F-statistic)	0.000000		

Table 20 Augmented Dickey-Fuller test for the first difference
- Variable: DLNNFP (The log difference of Total nonfarm payroll)

Null Hypothesis: DLNNFP has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.981848	0.0000
Test critical values:	1% level	-4.152511	
	5% level	-3.502373	
	10% level	-3.180699	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(DLNNFP)
Method: Least Squares
Date: 09/23/21 Time: 22:26
Sample (adjusted): 2016M09 2020M10
Included observations: 50 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLNNFP(-1)	-1.019512	0.146023	-6.981848	0.0000
C	0.002924	0.006684	0.437532	0.6637
@TREND("2016M07")	-0.000123	0.000222	-0.552640	0.5831

R-squared	0.509142	Mean dependent var	7.12E-05
Adjusted R-squared	0.488254	S.D. dependent var	0.031518
S.E. of regression	0.022547	Akaike info criterion	-4.688298
Sum squared resid	0.023893	Schwarz criterion	-4.573577
Log likelihood	120.2075	Hannan-Quinn criter.	-4.644612
F-statistic	24.37532	Durbin-Watson stat	2.005752
Prob(F-statistic)	0.000000		

Table 21 Augmented Dickey-Fuller test for the first difference
- Variable: DLNSP500 (The log difference of S&P500 index)

Null Hypothesis: DLNSP500 has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.657292	0.0000
Test critical values:	1% level	-4.152511	
	5% level	-3.502373	
	10% level	-3.180699	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(DLNSP500)
Method: Least Squares
Date: 09/23/21 Time: 22:26
Sample (adjusted): 2016M09 2020M10
Included observations: 50 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLNSP500(-1)	-0.970734	0.145815	-6.657292	0.0000
C	0.008162	0.012333	0.661815	0.5113
@TREND("2016M07")	2.27E-05	0.000407	0.055911	0.9556

R-squared	0.485324	Mean dependent var	0.000246
Adjusted R-squared	0.463423	S.D. dependent var	0.056666
S.E. of regression	0.041509	Akaike info criterion	-3.467688
Sum squared resid	0.080981	Schwarz criterion	-3.352966
Log likelihood	89.69219	Hannan-Quinn criter.	-3.424001
F-statistic	22.15979	Durbin-Watson stat	1.991455
Prob(F-statistic)	0.000000		

Table 22 Augmented Dickey-Fuller test for the first difference
- Variable: DLNT10Y2Y (The log difference of the spread between 10-Year and 2-Year Government Bond yields)

Null Hypothesis: DLNT10Y2Y has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.755070	0.0000
Test critical values:	1% level	-4.156734	
	5% level	-3.504330	
	10% level	-3.181826	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(DLNT10Y2Y)
Method: Least Squares
Date: 09/23/21 Time: 22:27
Sample (adjusted): 2016M10 2020M10
Included observations: 49 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLNT10Y2Y(-1)	-1.273902	0.188585	-6.755070	0.0000
D(DLNT10Y2Y(-1))	0.370529	0.138347	2.678254	0.0103
C	-0.106277	0.097269	-1.092603	0.2804
@TREND("2016M07")	0.003603	0.003191	1.129363	0.2647

R-squared	0.538817	Mean dependent var	0.002219
Adjusted R-squared	0.508071	S.D. dependent var	0.445907
S.E. of regression	0.312749	Akaike info criterion	0.591274
Sum squared resid	4.401529	Schwarz criterion	0.745708
Log likelihood	-10.48621	Hannan-Quinn criter.	0.649866
F-statistic	17.52504	Durbin-Watson stat	2.028339
Prob(F-statistic)	0.000000		

Table 23 Augmented Dickey-Fuller test for the first difference
- Variable: DLNLIBOR3M (The log difference of 3-month LIBOR)

Null Hypothesis: DLNLIBOR3M has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.396462	0.0000
Test critical values:	1% level	-4.152511	
	5% level	-3.502373	
	10% level	-3.180699	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(DLNUSDLIBOR3M)
Method: Least Squares
Date: 09/23/21 Time: 22:28
Sample (adjusted): 2016M09 2020M10
Included observations: 50 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLNLIBOR3M(-1)	-0.936399	0.146393	-6.396462	0.0000
C	0.112735	0.045325	2.487283	0.0165
@TREND("2016M07")	-0.005175	0.001602	-3.229496	0.0023

R-squared	0.465514	Mean dependent var	-0.003104
Adjusted R-squared	0.442770	S.D. dependent var	0.186600
S.E. of regression	0.139293	Akaike info criterion	-1.046348
Sum squared resid	0.911921	Schwarz criterion	-0.931627
Log likelihood	29.15870	Hannan-Quinn criter.	-1.002661
F-statistic	20.46746	Durbin-Watson stat	2.028936
Prob(F-statistic)	0.000000		

Table 24 The regression of the comparative model △RKRF (estimation result)

- Dependent Variable: △RKRF
- Method: Least Squares

Dependent Variable: △RKRF
Method: Least Squares
Date: 09/23/21 Time: 14:36
Sample (adjusted): 2016M08 2020M10
Included observations: 51 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLNNFP	-0.152196	0.170390	-0.893221	0.3764
DLNSP500	-0.167940	0.092756	-1.810546	0.0767
DLNT10Y2Y	-0.027079	0.011885	-2.278357	0.0274
DLNUSDLIBOR3M	-0.083419	0.024345	-3.426502	0.0013
C	0.007993	0.003788	2.110181	0.0403

R-squared	0.270964	Mean dependent var	0.008644
Adjusted R-squared	0.207569	S.D. dependent var	0.029237
S.E. of regression	0.026027	Akaike info criterion	-4.366503
Sum squared resid	0.031160	Schwarz criterion	-4.177109
Log likelihood	116.3458	Hannan-Quinn criter.	-4.294130
F-statistic	4.274249	Durbin-Watson stat	1.333856
Prob(F-statistic)	0.005041		

Table 25 Breusch-Godfrey LM test for the comparative model △RKRF

- Dependent variable: △RKRF

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	2.912000	Prob. F(2,44)	0.0649
Obs*R-squared	5.961464	Prob. Chi-Square(2)	0.0508

Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 09/23/21 Time: 15:54
Sample: 2016M08 2020M10
Included observations: 51
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLNNFP	0.020048	0.165499	0.121136	0.9041
DLNSP500	0.037781	0.091352	0.413581	0.6812
DLNT10Y2Y	0.005099	0.011819	0.431389	0.6683
DLNUSDLIBOR3M	-0.000250	0.023577	-0.010623	0.9916
C	-0.000210	0.003642	-0.057696	0.9543
RESID(-1)	0.357890	0.154120	2.322144	0.0249
RESID(-2)	-0.014365	0.159210	-0.090224	0.9285

R-squared	0.116891	Mean dependent var	-2.01E-18
Adjusted R-squared	-0.003532	S.D. dependent var	0.024964
S.E. of regression	0.025008	Akaike info criterion	-4.412379
Sum squared resid	0.027517	Schwarz criterion	-4.147227
Log likelihood	119.5157	Hannan-Quinn criter.	-4.311057
F-statistic	0.970667	Durbin-Watson stat	2.001045
Prob(F-statistic)	0.456219		

Table 26 The regression of the comparative model △RKRF (re-estimation result)

- Dependent Variable: △RKRF
- Method: ARMA Generalized Least Squares (Gauss-Newton)

Dependent Variable: △RKRF
Method: ARMA Generalized Least Squares (Gauss-Newton)
Date: 09/27/21 Time: 15:27
Sample: 2016M08 2020M10
Included observations: 51
Convergence achieved after 7 iterations
Coefficient covariance computed using outer product of gradients
d.f. adjustment for standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLNNFP	-0.147475	0.172769	-0.853598	0.3978
DLNSP500	-0.140645	0.088732	-1.585056	0.1200
DLNT10Y2Y	-0.026548	0.011179	-2.374712	0.0219
DLNLIBOR3M	-0.096587	0.027464	-3.516786	0.0010
C	0.007609	0.005403	1.408292	0.1659
AR(1)	0.353102	0.144719	2.439925	0.0187

R-squared	0.355795	Mean dependent var	0.008644
Adjusted R-squared	0.284217	S.D. dependent var	0.029237
S.E. of regression	0.024736	Akaike info criterion	-4.448383
Sum squared resid	0.027534	Schwarz criterion	-4.221110
Log likelihood	119.4338	Hannan-Quinn criter.	-4.361535
F-statistic	4.970710	Durbin-Watson stat	1.943741
Prob(F-statistic)	0.001044		

Inverted AR Roots	.35

Table 27 The regression of KFTX (estimation result)
- Dependent Variable: RK
- Method: Least Squares

Dependent Variable: RK
Method: Least Squares
Date: 10/19/21 Time: 08:12
Sample (adjusted): 2016M08 2020M10
Included observations: 51 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLNNFP	0.313869	0.103781	3.024330	0.0041
DLNSP500	1.097616	0.056496	19.42816	0.0000
DLNT10Y2Y	-0.008225	0.007239	-1.136153	0.2618
DLNLIBOR3M	-0.001008	0.014828	-0.068001	0.9461
C	0.003819	0.002307	1.655401	0.1047

R-squared	0.899044	Mean dependent var	0.013575
Adjusted R-squared	0.890265	S.D. dependent var	0.047854
S.E. of regression	0.015852	Akaike info criterion	-5.358114
Sum squared resid	0.011560	Schwarz criterion	-5.168719
Log likelihood	141.6319	Hannan-Quinn criter.	-5.285740
F-statistic	102.4105	Durbin-Watson stat	1.338877
Prob(F-statistic)	0.000000		

Table 28 Breusch-Godfrey LM test for the regression of KFTX

- Dependent variable: RK

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	2.906430	Prob. F(2,44)	0.0652
Obs*R-squared	5.951392	Prob. Chi-Square(2)	0.0510

Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 10/19/21 Time: 08:12
Sample: 2016M08 2020M10
Included observations: 51
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLNNFP	-0.005156	0.101664	-0.050715	0.9598
DLNSP500	0.031658	0.056003	0.565283	0.5748
DLNT10Y2Y	0.003565	0.007157	0.498057	0.6209
DLNLIBOR3M	0.000775	0.014255	0.054388	0.9569
C	-0.000182	0.002219	-0.082072	0.9350
RESID(-1)	0.362066	0.159074	2.276081	0.0278
RESID(-2)	-0.012335	0.163378	-0.075497	0.9402

R-squared	0.116694	Mean dependent var	1.63E-18
Adjusted R-squared	-0.003757	S.D. dependent var	0.015205
S.E. of regression	0.015234	Akaike info criterion	-5.403766
Sum squared resid	0.010211	Schwarz criterion	-5.138613
Log likelihood	144.7960	Hannan-Quinn criter.	-5.302443
F-statistic	0.968810	Durbin-Watson stat	1.994058
Prob(F-statistic)	0.457424		

Table 29 The regression of the log difference of KFTX (re-estimation results)
- Dependent Variable: RK
- Method: ARMA Generalized Least Squares (Gauss-Newton)

Dependent Variable: RK
Method: ARMA Generalized Least Squares (Gauss-Newton)
Date: 09/27/21 Time: 15:29
Sample: 2016M08 2020M10
Included observations: 51
Convergence achieved after 11 iterations
Coefficient covariance computed using outer product of gradients
d.f. adjustment for standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLNNFP	0.361572	0.105456	3.428656	0.0013
DLNSP500	1.148077	0.053043	21.64407	0.0000
DLNT10Y2Y	-0.008994	0.006706	-1.341262	0.1866
DLNLIBOR3M	-0.009525	0.016962	-0.561570	0.5772
C	0.003370	0.003497	0.963779	0.3403
AR(1)	0.399247	0.142321	2.805250	0.0074

R-squared	0.912312	Mean dependent var	0.013575
Adjusted R-squared	0.902569	S.D. dependent var	0.047854
S.E. of regression	0.014937	Akaike info criterion	-5.456400
Sum squared resid	0.010040	Schwarz criterion	-5.229126
Log likelihood	145.1382	Hannan-Quinn criter.	-5.369552
F-statistic	93.63684	Durbin-Watson stat	1.960685
Prob(F-statistic)	0.000000		

Inverted AR Roots	.40

Table 30 The regression of the log difference of FINANCIALS (estimation results)
- Dependent Variable: RF
- Method: Least Squares

Dependent Variable: RF
Method: Least Squares
Date: 09/27/21 Time: 15:29
Sample (adjusted): 2016M08 2020M10
Included observations: 51 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLNNFP	0.466066	0.138762	3.358735	0.0016
DLNSP500	1.265556	0.075539	16.75371	0.0000
DLNT10Y2Y	0.018854	0.009679	1.947926	0.0575
DLNLIBOR3M	0.082411	0.019826	4.156648	0.0001
C	-0.004174	0.003085	-1.353067	0.1826

R-squared	0.872992	Mean dependent var	0.004931
Adjusted R-squared	0.861947	S.D. dependent var	0.057045
S.E. of regression	0.021195	Akaike info criterion	-4.777164
Sum squared resid	0.020665	Schwarz criterion	-4.587769
Log likelihood	126.8177	Hannan-Quinn criter.	-4.704791
F-statistic	79.04518	Durbin-Watson stat	1.626842
Prob(F-statistic)	0.000000		

Annex B Assumptions test for the MLRM

We present the assumption test result of the multiple linear regression model (MLRM) in this section, which includes normality test, multicollinearity test, heteroscedasticity test, and autocorrelation test.

Annex B.1 Normality test

Normality is the assumption that the underlying residuals are normally distributed, or approximately so. All the statistical inferences in the MLRM, the F-test (the overall significance) and the t-tests (the individual significance), for each estimated coefficient rely on it.

Commonly used normality test methods include normal probability plot, Histogram, Shapiro-Wilk (W) test, Kolmogorov-Smirnov (K-S) test, Skewness-Kurtosis test, the Jarque-Bera (JB) test, etc. The null hypothesis is the error following normality distribution.

We compute “Empirical Distribution Tests” in EViews to test the normality of the residual of the re-estimated comparative model which is the difference between the log-returns of the KFTX and FINANCIALS ($RESID_{\_\triangle RKRF}$), the residual of the re-estimated regression of the log difference of KFTX ($RESID_{\_RK}$), and the residual of the regression of the log difference of FINANCIALS ($RESID_{\_RF}$), including the Lilliefors (D), Cramér–von Mises (W^2), Watson (U^2), Anderson-Darling (A^2) test.

The Lilliefors (D) test is a normality test by adapting the K-S test which is an algorithm based on empirical cumulative distribution function (ECDF), and it is used to test the assumption that data come from a normally distributed population when the parameters of the distribution under the test are unknown. The Cramér–von Mises (W^2) test is an alternative to the K–S test, while the Watson (U^2) test is a modified version of the W^2 test. And the Anderson–Darling (A^2) test compares the empirical cumulative distribution function of the sample data with the expected distribution when the data is assumed to be normally distributed. If the measured difference is large enough, the test will reject the null hypothesis that the population is normally distributed. The above methods are also applicable to small sample sizes.

Our findings are shown in the following table:

Table 31 Empirical Distribution Test

	$RESID_{\_\triangle RKRF}$			$RESID_{\_RK}$			$RESID_{\_RF}$		
Method	**Value**	**Adj. Value**	**Prob.**	**Value**	**Adj. Value**	**Prob.**	**Value**	**Adj. Value**	**Prob.**
Lilliefors (D)	0.0580	NA	> 0.1	0.0854	NA	> 0.1	0.1178	NA	0.0744
Cramer-von Mises (W^2)	0.0200	0.0202	0.9668	0.0474	0.0479	0.5420	0.1035	0.1045	0.0976
Watson (U^2)	0.0195	0.0197	0.9654	0.0464	0.0468	0.5130	0.0916	0.0925	0.1177
Anderson-Darling (A^2)	0.1638	0.1663	0.9394	0.2641	0.2682	0.6839	0.6406	0.6506	0.0896

$RESID_{\_\triangle RKRF}$: the residual of the re-estimated comparative model of the difference between the log-returns of KFTX and FINANCIALS; $RESID_{\_RK}$: the residual of the re-estimated regression of the log difference of KFTX; $RESID_{\_RF}$: the residual of the regression of the log difference of FINANCIALS.

As we can find that all the tests in Table 31 point to the non-rejection of the normality assumption because the probabilities (Prob.) associated with the D, W^2, U^2, and A^2 tests are higher than the level of significance (0.05). Thus, we can conclude that the errors of the re-estimated comparative model which is the difference between the log-returns of KFTX and FINANCIALS, and the re-estimated regression of the log difference of KFTX as well as the residual of the regression of the log difference of FINANCIALS are normality distribution.

Annex B.2 Multicollinearity test

Multicollinearity is mostly a sample phenomenon in which two or more explanatory variables are highly linearly correlated in a multiple regression model. When the correlation between explanatory variables is strong, it is difficult to distinguish the influence of each explanatory variable on the dependent variable.

One of the most important indicators is the Variance Inflation Factor (VIF) and tolerance value, which are a quick measure of how much a variable is contributing to the standard error in the regression. In calculation, VIF is defined as the reciprocal of tolerance (TOL)[14], and the value of VIF starts from 1. It is well known that the more the VIF increases, the lower the reliability of the regression results. The acceptable levels of VIF have been various recommended and published in the literature. Most commonly, the maximum acceptable level of VIF has been suggested is a value of 10. If the value of VIF is greater than 10, indicates a high degree of correlation and is worthy of attention. Some researchers recommend using a

[14] The VIF is the inverse of the tolerance: $VIF = \frac{1}{TOL} = \frac{1}{1-R_j^2}$, where R_j^2 is the coefficient of determination from the regression of each X_j on the rest of independent variables.

more conservative level of 2.5 or higher.

Table 32 Tolerance and VIF value

Dependent Variable	**Variable**	**Collinearity Statistics**	
		Tolerance	**VIF**
△RKRF	C	NA	NA
	DLNNFP	0.7520	1.3298
	DLNSP500	0.8682	1.1518
	DLNT10Y2Y	0.8803	1.1360
	DLNLIBOR3M	0.7186	1.3916
	AR (1)	0.9344	1.0702
Dependent Variable	**Variable**	**Collinearity Statistics**	
		Tolerance	**VIF**
RK	C	NA	NA
	DLNNFP	0.7134	1.4017
	DLNSP500	0.8610	1.1615
	DLNT10Y2Y	0.8702	1.1491
	DLNLIBOR3M	0.6828	1.4646
	AR (1)	0.9286	1.0769
Dependent Variable	**Variable**	**Collinearity Statistics**	
		Tolerance	**VIF**
RF	C	NA	NA
	DLNNFP	0.9700	1.0310
	DLNSP500	0.9709	1.0299
	DLNT10Y2Y	0.9187	1.0885
	DLNLIBOR3M	0.9149	1.0930

△RKRF: the difference between the log-returns of KBW Nasdaq Financial Technology Index and the S&P 500 Financials Services Select Sector Index; RK: the log difference of KBW Nasdaq Financial Technology Index; RF: the log difference of S&P 500 Financials Services Select Sector Index.

Table 32 presents the values of VIF and TOL for each independent variable in the three regression models we established. As we can see that the values of VIF associated with every single one of the independent variables in the three models are close to 1 < 10, and all the values of TOL are more than 0.1, indicating that there is almost no correlation between the predictor variables. Therefore, we can conclude that no multicollinearity problems exist between the independent variables in the three regressions (the transformed model of the difference between the log-returns of KFTX and FINANCIALS, the transformed model of the log difference of KFTX as well as the model of FINANCIALS).

Annex B.3 Autocorrelation test

Another assumption of the linear regression model is no autocorrelation. Autocorrelation occurs when the residuals are not independent of each other. When the data exist substantial autocorrelation, the estimated variances for the coefficients are biased and the hypothesis testing is no longer valid.

Durbin-Watson (D-W) test and Breusch-Godfrey(B-G) LM test are common procedures to check the error's autocorrelation. The D-W test is only related to the first-order autocorrelation coefficient of residuals, AR (1), while the B-G LM test has none of these restrictions, and can be used to detect the correlation between the error terms in different periods. The null hypothesis of the B-G LM test is that there is no serial correlation of any orders. Besides, this test method can also be applied to test regression models including the case where the lag value of the dependent variable is used as the independent variable in the model representation.

As mentioned in Section 4, we found the error's first-order autocorrelation exists in the transformed model which is the difference between the log-returns of KFTX and FINANCIALS as well as the regression of the log return of KFTX in the first trial. After the CORC AR (1) procedure which is based on the generalized difference method, we correct the autocorrelation issues and the B-G LM test results for the transformed models and the model of FINANCIALS are presented as below:

Table 33 Breusch-Godfrey LM test

Breusch-Godfrey LM Test: The regression of the comparative model (re-estimate result) - Dependent variable: △RKRF			
F-statistic	0.0621	Prob. F (2,44)	0.9398
Obs*R-squared	0.1469	Prob. Chi-Square (2)	0.9292
Variable	Coefficient	t-Statistic	Probability
RESID (-1)	0.2248	0.1895	0.8506
RESID (-2)	0.0279	0.0621	0.9508
Breusch-Godfrey LM Test: The regression of KFTX (re-estimate result) - Dependent variable: RK			
F-statistic	0.9653	Prob. F (2,44)	0.3890
Obs*R-squared	2.1903	Prob. Chi-Square (2)	0.3345
Variable	Coefficient	t-Statistic	Probability
RESID (-1)	1.3025	1.2844	0.2059
RESID (-2)	0.5943	1.3892	0.1719
Breusch-Godfrey LM Test: The regression of FINANCIALS (RF) - Dependent variable: RF			
F-statistic	0.7964	Prob. F (2,44)	0.4573
Obs*R-squared	1.7817	Prob. Chi-Square (2)	0.4103
Variable	Coefficient	t-Statistic	Probability
RESID (-1)	0.1894	1.2487	0.2184
RESID (-2)	-0.0069	-0.0439	0.9652

△RKRF: the difference between the log-returns of the KBW Nasdaq Financial Technology Index and the S&P 500 Financials Services Select Sector Index; RK: the log difference of KBW Nasdaq Financial Technology Index; RF: the log difference of S&P 500 Financials Services Select Sector Index.

As we can see, we do not reject the null hypothesis of the B-G LM test in all of the above models. Because in the re-estimated comparative model, the probability associated with the observation R^2 (Obs*R-squared) (0.1469) is 0.9292 and the probability of the RESID (-1) is 0.8506, all higher than the 0.05 significance level. Thus, we do not reject the general null hypothesis and the null hypothesis (there is the autocorrelation of first order) of the RESID (-1) series, and we can assume the absence of autocorrelation in the residuals in the transformed model.

In the re-estimated regression of KFTX where the probability associated with the Obs*R-squared (2.1903) is 0.3345, and the probability of the RESID (-1) is 0.2059, both of them are higher than the level of significance (0.05). So, we accept the assumption of no autocorrelation for the general transformed model and the RESID (-1) series.

Regarding the model of FINANCIALS, as the D-W test is 1.6268[15], and the Durbin-Watson

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[15] See the original table with results in Annex A–Table 30.

Table[16] shows that for n=50, k=5 (including the intercept), the critical values are d_L=1.335 < 1.338877, d_U=1.771, the test is on the region Ⅱ, which is the inconclusive region, nothing can be concluded about the AR(1). We compute the B-G LM test for the regression of FINANCIALS, and the results in Table 34 show that the probability of the Obs*R-squared (1.7817) is 0.4103, and the probability of the RESID (-1) is 0.2184, higher than the significant level. Therefore, we can conclude the absence of autocorrelation in the residuals in the OLS model of FINANCIALS, as we don't reject the null in the D-W and B-G LM tests.

Annex B.4 Heteroskedasticity test

The heteroskedasticity test aims to examine whether the error's condition distribution, given the explanatory variables, has constant variance (homoskedasticity), which is one of the assumptions of the MLRM. If the error's variance is not constant, the errors are heteroskedasticity.

White (1980) proposed a direct test to detect the error's homoskedasticity, especially, it does not need a functional form for the heteroskedasticity structure, besides, and does not depend on the error's normally assumption, and the test is asymptotically valid.

We apply this widely used method, in which the null hypothesis is the error's variance is homoskedasticity, to detect if the errors are heteroskedasticity in our regression models, and the results are shown as follow:

[16] Evans (2014).

Table 34 Heteroskedasticity Test

White test: The regression of the comparative model (re-estimate result) - Dependent variable: △RKRF			
F-statistic	0.8413	Prob. F (21,29)	0.6548
Obs*R-squared	19.3072	Prob. Chi-Square (21)	0.5654
Scaled explained SS	13.6997	Prob. Chi-Square (21)	0.8821
White test: The regression of KFTX (re-estimate result) - Dependent variable: RK			
F-statistic	1.2536	Prob. F (21,29)	0.2821
Obs*R-squared	24.2671	Prob. Chi-Square (21)	0.2803
Scaled explained SS	15.9823	Prob. Chi-Square (21)	0.7706
White test: The regression of DLNFINANCIALS - Dependent variable: RF			
F-statistic	0.9208	Prob. F (14,36)	0.5463
Obs*R-squared	13.4468	Prob. Chi-Square (14)	0.4917
Scaled explained SS	21.2724	Prob. Chi-Square (14)	0.0949

△ RKRF: the difference between the log-returns of the KBW Nasdaq Financial Technology Index and the S&P 500 Financials Services Select Sector Index; RF: the log difference of KBW Nasdaq Financial Technology Index; RK: the log difference of S&P 500 Financials Services Select Sector Index.

On the above results, as the probabilities associated with the White test in both transformed models and the model of FINANCIALS is 0.5654, 0.2803, and 0.4917 respectively, are higher than the 0.05 significant level, we do not reject the null hypothesis. Thus, we can conclude that the errors are homoskedasticity in the re-estimated comparative model, and the re-estimated model of KFTX as well as the model of the log difference of FINANCIALS.

Since the errors of the re-estimated comparative model which is the difference between the log-returns of the KBW Nasdaq Financial Technology Index and the S&P 500 Financials Services Select Sector Index, and the re-estimated model of the KFTX, as well as the model of FINANCIALS, are normality, and there is no autocorrelation, and no heteroskedasticity, besides, the explanatory variables are not multicollinearities. Thus, the assumptions of the OLS method hold, and the OLS estimators are BLUE: Best Linear Unbiased Estimators. Moreover, the t-tests and F-test provide accurate results.

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