

# THE LEGAL ROLE OF FINTECH IN FINANCIAL INCLUSION IN CHINA

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## **Abstract**

*The purpose of technology is not to make finance better, but to make finance serve real life better. Fintech has grown much faster in China than in the United States. In China, this success has come not from an initial technology advantage, but from integration between finance and real-life needs. This experience has important implications for understanding financial innovations, and for the development of inclusive finance. China has experienced a financial technology boom (Fintech), enabling it to be a world leader of the field. China's decision makers and authorities are promoting a digital vision the aim of which is to foster financial inclusion. Using FinTech as a catalyst for financial inclusion can be an effective and less costly solution for China. This study examines the leading role of FinTech in the efforts of the Chinese authorities towards financial accessibility in China. Using time series econometrics over the 2010 to 2020 period, we show that FinTech promotes financial inclusion. More specifically, the results show that only the access dimension can be promoted using FinTech. However, for the usage dimension, FinTech does not have a positive effect. Such findings should further encourage Chinese authorities to invest in FinTech to help remove barriers to financial inclusion.*

**Keywords:** Legal Role, FinTech, Financial Inclusion, China, Mobile Payments, P2P Loan, Internet.

**JEL Codes :** O33; D14; G10; G21; G18

## **1. INTRODUCTION**

China has seen market-oriented reforms in the early 1980s, allowing it to generate significant economic growth of about 9.5% per year. China's economy is the largest Asian economy, and has become the second largest economy in the world behind the United States. Experts estimate that China is expected to become the world's leading economic power by 2025. In 2013, China is the world's largest trading nation, with exports of \$2.21 trillion and imports of \$1.95 trillion. However, the problem with China's rapid growth is the income inequality between rural and urban areas or between low and high income people. The Chinese authorities are aware that

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increasing the income of rural residents is the key point to reduce this gap. To this end, the Chinese government has to solve the problem of financial exclusion in rural areas because financial exclusion represents the main reason behind the income gap between urban and rural areas as indicated by Tan and Li, (2016). The problem of financial exclusion can let people in rural areas fall into a vicious poverty circle, suggesting that lack of access to financial services and financing can cause poverty. In other words, lack of money for rural areas in China represents an obstacle to develop chances to create start-ups, and access credits. The number of poor people in China without access to banking services is one of the largest in the world. Therefore, FinTech could be an opportunity or a tool to solve the problem of financial exclusion in rural China. Moreover, cell phones or smartphone services and internet use in China could play an important role in solving financial exclusion, as statistical data indicates that cell phone service access and internet coverage rates in China are 98%. Chinese people who have a cell phone represent 88% of the population (Shrader and Duflos, 2014). Then, Chinese authorities dispose of a great opportunity to narrow the income gap using financial technology.

The use of FinTech as a means to foster financial inclusion can be effective because these technologies can extend financial services to most of the population at lower costs. Financial technologies offer new opportunities, i.e., new financial products and services that can help foster financial inclusion, through customizing services to customers' needs and making these services more flexible and affordable to meet the needs of low-income people. Furthermore, the new services presented by FinTech can provide rural populations with better financial access opportunities, which leads to the development of rural businesses, such as small and medium enterprises, as well as important rural investments.

China has seen a great expansion trend and a rapid growth in the use of FinTech. Accordingly, the economic policy of the Chinese authorities is to promote an inclusive policy that seeks to integrate the entire eligible population in the creation of value and also integrate the entire population in the creation of wealth. This commands the Chinese government to put a strong emphasis and weight on the use of FinTech to achieve its goal. The support given to financial technologies and the use of internet and the adoption of the use of smart phones represent the main tools of the Chinese government to reach rural areas and the people excluded from the financial system.

Financial inclusion is an important goal for China, which is investing heavily to accelerate financial inclusion. This makes China the world leader.

For years now, a new component has been shaking up the rules dictated in the market of financial products and services. Blockchain, artificial intelligence, machine learning, and big data gave life to a new area of financial products and services. These new services have turned traditional financial products and services upside down, as FinTech focuses on decentralizing access to and use of financial services and supporting Internet as a catalyst for easy access to financial services.

FinTech has therefore redistributed power among the various market

stakeholders. Then, customers have become the focus of attention because of the new needs they express. Chinese policy makers are looking for reducing financial exclusion through the lowest possible costs and integrating a large population into the financial system.

It has become more over bearing than ever to pursue this objective, as financial inclusion can be seen as closely linked to the financial sector's development process. If financial inclusion means access to financial services, then these services should be closer to the population, offering deposit collection, payment processing, microfinance, insurance products, in other words, all the products and services that fuel investment, create jobs and stimulate growth. Bearing on these different proposals, we formulate our main research question as follows: Can FinTech foster financial inclusion in China?

Our main objective is to understand the nature of the relationship between FinTech and its various dimensions and financial inclusion in general in China. This objective is reformulated into the following sub-questions : Can FinTech support both dimensions of financial inclusion, i.e., access and usage? Is FinTech limited to improving only one dimension?

In this article, I first document the rapid growth of Fintech in China. Although the concepts and business models were usually initially born outside China, in terms of the number of customers and the amount served, China's Fintech coverage has been a lot higher than that of the United States in almost all areas, including payment, wealth management, financing, and others.

I then argue that China's success came not from initial technology advancement, but, enabled by technology, from a much better integration between finance and real-life scenarios, a phenomenon I call scenarization of finance. Scenarization promotes a virtuous circle among technology, finance, and real-life needs. If the concept of Fintech emphasizes the importance of technology enabling finance, then "finlife," emphasizing the importance of finance serving real life, seems more appropriate for Fintech's growth path. Put differently, the success of Fintech should start with technology, but end with trust and usage in real life.

Such analysis is not only important for understanding financial innovation, but also useful for the development of inclusive finance, given how rapidly consumers can obtain access to finance through new technology.

The rest of the article proceeds as follows. Section 2 documents the rapid growth of Fintech in China (litterature). Section 3 uses the case of Ant financial, the leading Fintech company in China, to explore why Fintech has grown so fast. Sections 4 discuss the concept of scenarization and its implications for financial inclusion. Section 5 discusses the implications for government policy and regulation.

The interest in addressing the topic of financial inclusion and FinTech can be explained by the fact that financial inclusion is now high on the agenda of policymakers, regulators, and development organizations around the world. Access to financial services is seen as a driver of growth and sustainable development. Since 2010, more than 55 countries have made commitments to financial inclusion and

more than 30 have already launched or are designing a national strategy for financial inclusion. The World Bank Group shows that the pace of reform has accelerated and the impact of reform increases when a country has a national strategy for financial inclusion. Financial technologies, or "FinTech," have made it easier to widen the access to financial services.

Then, this paper is structured as follows. The first section introduces the conceptual framework of this study, and reviews the literature on the concept of FinTech and financial inclusion. In the second section, a set of propositions will then be detailed, which will form our research hypotheses. In the third section, we present our empirical study that examines the relationship between financial inclusion and FinTech. Finally, we will discuss the relevance of the obtained results against the literature. Finally, the overall conclusion will focus on the contributions and limitations of the study, as well as on the future research perspectives.

## 2. LITERATURE REVIEW :

In this section, we present the methodology of our study used to examine the impact of financial technologies (FinTech) on financial services access (financial inclusion). Therefore, we review the research methods and techniques used to study this relationship. Many studies have sought to answer the question of how to foster financial inclusion, highlighting in the process the importance of financial inclusion as a research objective. Then, these studies correlate financial inclusion with other variables that can be a catalyst to foster financial inclusion. Examples of such a line of research include the correlation between mobile payments and internet lending to promote financial inclusion (Biyun al., 2017). In this study, the method used to examine the impact of mobile payments and internet lending on financial inclusion is the probit model. The latter is a binomial regression model, which also represents a special case of the generalized linear model. The probit model is used because the data are in a binary form (0 and 1). In this regard, to examine financial exclusion in rural areas, Wang (2007) used the probit model. Similarly, studying correlation between financial inclusion and internet and mobiles, Evans (2018) used panel econometrics on a sample of 44 countries observed between 2000 and 2016 found that use of internet and smartphones can help facilitate access to financial services.

Likewise, Allen et al, (2015), studying the impact of ownership and use of official accounts on financial inclusion, also used the binomial regression model to estimate data in a binary form (0 and 1). Similarly, Cephas Paa Kwasi et al, (2020) studied the impact of mobile payment transactions on accessibility in Sub-Saharan Africa using a multiple linear panel econometric regression method. In a similar way, Liu et al, (2020) examined digital financial inclusion and sustainable growth of small and micro enterprises in China following favorable digital financial inclusion initiatives, using a multiple linear regression. Additionally, Xiang et al, (2019) studied the effect of FinTech on sustainable growth in China using P2P data estimated by a panel econometric model with fixed effects.

Moreover, to study the present and future behavior of FinTech users or adoption of digital financial services, Johannes et al, (2019) used a probit model to estimate data in a binary form.

The unique demographics of FinTech in the MENA region also pose some challenges. For instance, as international firms outnumber regional or local firms, they often face a steep learning curve to understand how to conduct business in the region, as well as how to access the services and infrastructure they need in addition to navigating a fragmented regulatory environment. Therefore, regulators should be mindful of the increased barriers that non-local companies might face. As some countries have relatively small populations and internal markets do not see high levels of activity, the lack of harmonisation across the region might make it more difficult to scale and reach profitability (Kheira, 2021 ; Mueller and Piwovar, 2019). In addition, excessively stringent Fintech regulation might stifle growth, especially if one-size-fits-all solutions are adopted (World Bank, 2020a).

As discussed, FinTech has an important role to play in terms of financial inclusion in MENA with regards to servicing unbanked and displaced populations. As inclusion increases, however, ensuring that consumer financial literacy equally increases (as does regulatory capacity), may become essential to curb medium and long-term risks that would arise otherwise (Riley et al., 2020; Kheira, 2021).

In the same vein, the deployment of digital identity across the region could help address its financial inclusion issues.

In terms of long-term sustainability, investment in the underlying infrastructure for the FinTech market will become increasingly relevant. Apart from addressing the talent gap, robust risk management policies and adapting KYC and AML frameworks to the evolving practices might help the balancing act between fostering innovation while safeguarding consumers and financial stability (CGAP, 2020; World Bank, 2020a).

### 3. DATA AND METHODOLOGY

Several are the studies that examined financial inclusion and financial technologies, yet most of them have only focused on one dimension of FinTech, or measured financial inclusion in a wholistic manner. In this study, the objective is to check whether there is a relationship between financial inclusion and different dimensions of FinTech in a comprehensive way. To this end, we divide financial inclusion and FinTech into two dimensions. The first dimension is access to financial services and the FinTechs that promote that access. The second dimension is the use of those financial services and the FinTechs that promote that use. "Access" refers to the ability to use the services and products offered by formal financial institutions.

Determining levels of access may need identifying and determining potential barriers to opening and using a bank account. These include cost or physical proximity to bank service points (branches, ATMs, etc.). Access data can generally be obtained from information provided by financial institutions. "Usage" refers to the depth or breadth of use of financial services and products. To calculate the overall financial

inclusion indicator, we consider the total number of access points represented by the number of bank branches and the number of ATMs, which form the access dimension. For the usage dimension, we consider the number of deposit and credit accounts, since these are the two services that the customer uses to make transactions, and which can reveal the depth or breadth of usage. For FinTech, we chose the variables that represent the use of a financial service managed by innovative technologies such as BigData, AI, and Blockchain. These variables are described in Table 1 below. The variables include online financial services such as online payments, online shopping platforms, number of cell phones, number of mobile subscriptions, and use of Internet. The first step of our analysis is to use a principal component analysis (PCA). Generally, PCA is used to process, analyze or search for simultaneous connections between more than two variables and to provide synthesized information. The second step is to test the relationship between financial inclusion and FinTech empirically through a time series analysis.

**Table1 : Description of variables**

The variables	Definition	Sources
Financial Inclusion	Financial inclusion is the set of measures put in place to fight against banking and financial exclusion. It includes a whole range of financial and non-financial products and services made accessible to poor segments of population.	Global Findex : World Bank
Number of lenders on online peer-to-peer (P2P) lending platforms	The number of investors who invest in online lending through an online platform.	Statistia
Number of online peer-to-peer (P2P) lending platforms	An online P2P lending platform represents the online intermediary between lenders and borrowers without the intermediation of a bank	Statistia
Online payment use rate	The online payment rate represents the rate at which users go online to make payments	Statistia
Number of mobile payment transactions	Represents the number of payment transactions using a cell phone	Statistia

Number of internet users	The number of Internet users	Statistia
Internet user access rate	The rate of access to the Internet by users	Statistia
Number of Internet users by type of connection	The number of Internet users by each type of Internet	Statistia
Use rate of mobile Internet users	The rate of cell phone use for Internet access	Statistia
Number of mobile internet users	The number of Internet users via mobile	Statistia
Mobile Internet market volume	Internet market revenues	Statistia
Number of mobile subscriptions	The number of mobile network subscriptions	Statistia
Number of cell phone subscriptions per 100 inhabitants	Number of cell phone subscriptions per 100 inhabitants	Statistia
Online shopping rate	The rate of online shopping transactions	Statistia
Number of online payment users	the cumulative number of online payment users	Statistia
Inflation	loss of purchasing power, which translates into a general and lasting increase in prices. It must be distinguished from the increase in the cost of living.	International Monetary Fund
Real interest rate	the real interest rate is the nominal interest rate that must be adjusted for inflation and risk premium.	International Monetary Fund
School enrollment, primary	means the ratio of enrolled students of legal school age in the grade to the number of school-age children in that grade.	UNESCO's Institute of Statistics

Control of corruption	it indicates to what extent public authority is at the service of private interests and informs about the phenomena of "corruption" of the state by elites and private interests.	PRS group
Quality of regulations	reflects perception of the government's ability to effectively formulate and implement policies and regulations to foster private sector development.	The Worldwide Governance Indicators (WGI)

#### 4. EMPIRICAL ANALYSIS

Principal Component Analysis (PCA) is one of the most widely used methods of multivariate data analysis. It is used to explore multidimensional data sets made up of quantitative variables. Principal Component Analysis can be considered as a projection method that allows for displaying observations from the p-dimensional space of the p variables to a k-dimensional space ( $k < p$ ) such that a maximum of information is kept (information is measured here through the total variance of the scatterplot) on the first dimensions. It allows for reducing the number of variables and to make information less redundant.

##### 4.1. Principal component analysis of the general model

###### Step1 : Extraction of the main components of FinTech

Table 2 and the associated Figure 1 represent a mathematical object, eigenvalues. These are fortunately linked to a very simple concept: the quality of projection when we go from N dimensions (N being the number of variables, here 14) to a smaller number of dimensions. In our case, we see that the first eigenvalue is 12.149 and represents 86.78% of the variance. This means that if we represent the data on a single axis, then we will always have 86.78% of total variance preserved. Each eigenvalue has a corresponding factor. Each factor is in fact a linear combination of the starting variables. The factors are particularly uncorrelated. The eigenvalues and factors are sorted by decreasing order of represented variance. **In general, factor = PCA dimension = PCA axis.**

Ideally, the first two eigenvalues explain a high % of variance, so that the representation on the first two factor axes is of good quality. It is clear that information can be synthesized on the first two dimensions. These "useful" dimensions explain the totality of information of the starting variables.



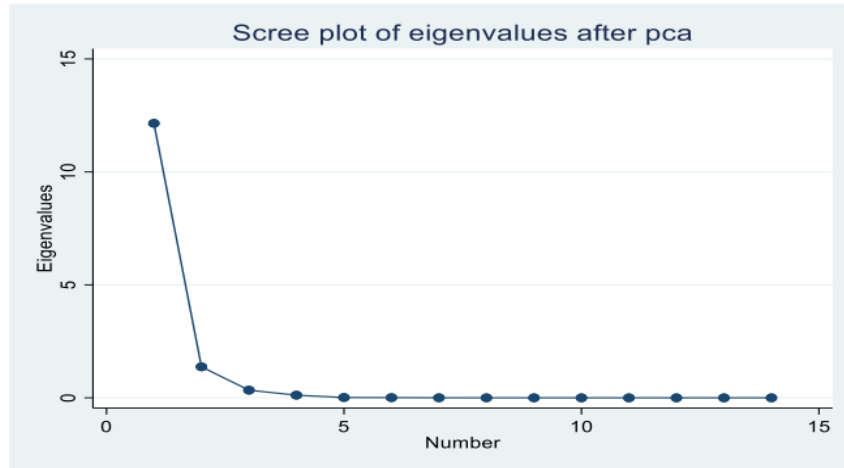
[Table 2]

Table2- Principal components and variance contribution rates (Model1)

Principal components / correlation Number of obs = 10 Number of comp.=9 Trace = 14 Rotation : ( unrotated = principal Rho = 1.0000			
Component	Eigenvalue	Difference	Cumulative Proportion
Comp1	12,1495	10,7776	0,8678
Comp2	1,37184	1,03422	0,0980
Comp3	0,337627	0,221059	0,0241
Comp4	0,116568	0,103425	0,0083
Comp5	0,0131435	0,00456637	0,0009
Comp6	0,00857714	0,00719479	0,0006
Comp7	0,00138235	0,000600108	0,0001
Comp8	0,000782242	0,000163101	0,0001
Comp9	0,000619141	0,000619141	0,0000
Comp10	0	0	0,0000
Comp11	0	0	0,0000
Comp12	0	0	0,0000
Comp13	0	0	0,0000
Comp14	0	0	0,0000

[Figure 1]

**Figure1-Screplot Of eigen values after PCA (Model1)**



**Step2: Extraction of the Eigen values of the principal components**

Eigen values of the principal components represent correlation between the variables and each component. This means the weight of each variable in each component, or the information contribution of each variable in each component to preserve information in each component (Table 2).

**[Table 3]**

**Table 3- Eigenvalues of the principal components (Model 1)**

Principal components (eigen values)									
Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7	Comp8	Comp9
NPPP	0.2263	0.4099	0.5971	-0.4663	0.3422	-0.0256	-0.2595	0.1002	0.0838
NPPL	0.1115	0.7702	-0.1095	0.5115	0.0152	0.2038	0.2209	0.0384	0.1288
TPPL	0.2842	-0.0052	0.1018	0.3045	0.0975	-0.6841	-0.0766	0.4469	0.1583
NTPM	0.2505	-0.3576	0.2575	0.5769	0.1839	0.0806	-0.3311	0.3491	0.0354
NI	0.2857	-0.0062	-0.1499	-0.0725	0.1113	-0.0902	0.2007	0.3165	-0.0494
TPI	0.2849	0.0017	-0.1890	-0.0920	0.1215	-0.1559	0.2560	0.2212	-0.0534
NUITC	0.2765	-0.2071	0.1629	-0.1421	-0.1880	0.0547	0.4978	0.1969	0.5213
TPIM	0.2806	0.1431	-0.1507	-0.1307	-0.5733	-0.3386	-0.2212	0.2660	-0.0288

NIM	0.2864	0.0210	-0.0704	-0.0751	-0.2240	-0.0075	-	0.264	-0.1989
							0.0264	2	
VMIM	0.2741	-0.1735	0.3576	0.0930	-0.1903	0.3545	0.2332	0.102	0.0135
								8	
NACM	0.2808	-0.1006	-0.2807	-0.0386	0.2686	0.1323	-	-	-0.1078
							0.1525	0.090	
								9	
NAM	0.2748	-0.0588	-0.4633	-0.1656	0.4067	0.1640	-	-	0.2736
							0.0789	0.043	
								9	
TPAL	0.2853	0.0570	-0.0922	-0.0337	-0.3446	0.4001	-	-	0.0859
							0.4639	0.424	
								0	
NUPL	0.2862	0.0018	0.1122	0.0079	0.0733	0.0558	0.2569	-	-0.7339
								0.371	
								4	

**Step3: Calculate the scores of the principal components**

Referring to the component scores calculated in Step 1, only the first 3 principal components were retained because the cumulative variance rate is greater than 80%. The results, reported in Table 4 below, show that FinTech loads heavily on the first principal component which explains 86% of information. FinTech loadings increased from -4.955 in 2010 to 5.027 in 2019. The second principal component explains 9.8% of information, which remains a low threshold to explain FinTech change. The third principal component explains 2.4 percent of information, which remains insufficient to explain variance in FinTech. This concludes that only the first principal component is retained to explain whether its variance can affect and promote financial inclusion in the overall model.

[Table 4]

Table 4- Scores of the retained principal components (Model 1)

Année	PC1	PC2	PC3
2010	-4.955324	-0.515487	0.8824475
2011	-4.044965	-0.5754514	0.2936319
2012	-2.950622	-0.5632319	-0.2406929
2013	-1.859625	-0.3395231	-0.80605
2014	-0.8893198	0.4855857	-1.057723
2015	0.6952839	2.274963	0.0558902
2016	1.803832	1.105657	0.2837809
2017	2.981503	0.6823043	0.5083913
2018	4.191807	-0.5866131	0.0713243
2019	5.027429	-1.968204	0.0089995

**4.2. Principal component analysis for the access model**

**Step1: Extraction of FinTech principal components**

Table 5 and Figure 2 show the eigenvalues for FinTech. We see that the first eigenvalue is 5.964 and represents 85.20% of the variance. This means that if we represent the data on a single axis, then we will always have 85.20% of total variance preserved.

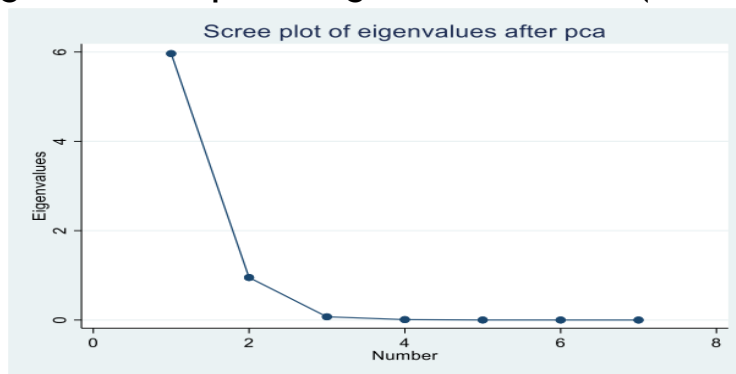
[Table 5]

Table 5- Principal components and variance contribution rates (Model 2)

Principal components/correlation Number of obs = 10				
Number of comp.= 7				
Trace = 7				
Rotation: (unrotated = principal) Rho = 1.0000				
Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	5.96424	5.01232	0.8520	0.8520
Comp2	.951922	.87946	0.1360	0.9880
Comp3	.0724617	.0626198	0.0104	0.9984
Comp4	.00984194	.0089856	0.0014	0.9998
Comp5	.000856339	.000196858	0.0001	0.9999
Comp6	.000659481	.000641583	0.0001	1.0000
Comp7	.0000178973	.	0.0000	1.0000

[Figure 2]

Figure 2: Scree plot of eignvalues after PCA (model 2)



**Step2: Extraction of the Eigen values of the principal components**

Table 6 reports the correlation between the variables and each component. This means the weight of each variable in each component, or the information contribution of each variable in each component to verify the preservation of information in each component.

[Table 6]

Table 6- Eigenvectors of the principal components (Modèle 2)

Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7
NPPL	0.1663	0.9359	0.0897	0.2684	0.0350	0.1213	0.0211
NUITC	0.3865	-0.2773	0.6937	0.2765	0.0608	0.4556	0.0692
NI	0.4092	-0.0278	0.0654	0.0892	-0.3739	-0.3547	-0.7442
TPI	0.4093	-0.0186	-0.0163	-0.0038	-0.5187	-0.3620	0.6570
TPIM	0.4035	0.1454	0.1458	-0.8418	0.2928	-0.0014	-0.0181
NACM	0.4047	-0.1327	-0.2488	0.3671	0.6906	-0.3723	0.0801
NAM	0.4016	-0.0857	-0.6504	0.0117	-0.1534	0.6182	-0.0493

**Step3: Calculate the scores of the main components**

Referring to the component scores (Table 7) calculated in step 1, we retained only the first 3 main components because the contribution rate of cumulative variance is higher than 80%. FinTech loads heavily on the first principal component which explains 85% of information. FinTech loadings increased from -3.932 in 2010 to 3.327 in 2019. The second principal component contributes 13.6% of information, which remains a low threshold to explain FinTech change. The third principal component explains 1% of information, which remains insufficient to explain variance in FinTech. This concludes that only the first principal component is retained to explain whether its variation can affect and promote financial inclusion in the overall model.

[Table 7]

Table 7-Scores of the retained principal components (Model 2)

Années	PC1	PC2	PC3
2010	-3,932512	-0,3514059	0,3951717
2011	-2,937863	-0,485949	0,0582897
2012	-1,926572	-0,5428683	-0,1789059
2013	-0,9008688	-0,3453879	-0,4175886
2014	-0,1610777	0,6031829	-0,3885816
2015	0,4726731	2,080936	-0,0287938
2016	1,193156	0,8384881	0,2709761
2017	1,944412	0,2587133	0,2408842
2018	2,921008	-0,6987814	-0,0053345
2019	3,327645	-1,356928	0,0538827

**4.3. Principal component analysis for the usage model**

**Step1: Extraction of FinTech principal components**

Table 7 and the associated Figure 3 indicate that the first eigenvalue is 6.329 and represents 90.43% of variance. This means that if we represent the data on a single axis, then we will always have 90.43% of total variance preserved. Each eigenvalue has a corresponding factor. Each factor is in fact a linear combination of the starting variables. Ideally, the first two eigenvalues explain a high % of variance, so that the representation on the first two factor axes is of good quality. It is clear that information can be synthesized on the first two dimensions. These "useful" dimensions explain the totality of information of the starting variables.

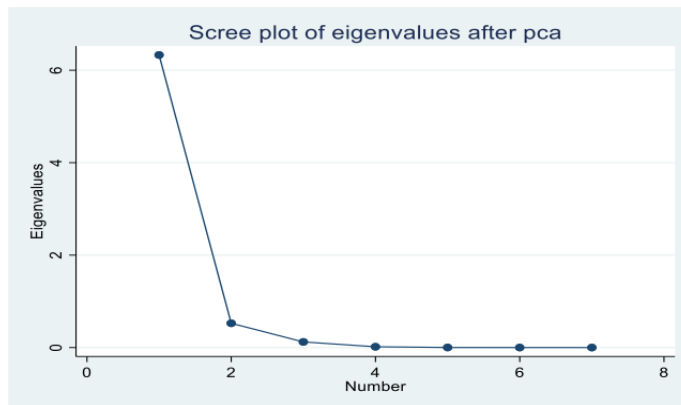
[Table 8]

Table 8. Principal components and variance contribution rates (Modèle 3)

Principal components/correlation Number of obs = 10 Number of comp. = 7 Trace = 7 Rotation: (unrotated = principal) Rho = 1.0000				
Component	Eigenvalue	Difference	Proportion	Cumulat
Comp1	6.32979	5.8034	0.9043	0.9043
Comp2	.526397	.40395	0.0752	0.9795
Comp3	.122448	.10471	0.0175	0.9969
Comp4	.0177376	.0156691	0.0025	0.9995
Comp5	.00206848	.001018	0.0003	0.9998
Comp6	.00105048	.000544644	0.0002	0.9999
Comp7	.00050584	.	0.0001	1.0000

[Figure 3]

Figure 3: Scree plot of eignvalues after PCA (model3)



**Step 2: Extraction of the eigen values of the principal components**

The Eigenvalues of the principal components (Table 9) represent the correlation between the variables and each component. This means the weight of each variable in each component, or the information contribution of each variable in each component to check preservation of information in each component.

[Table 9]

Table 9-Eigen values of the principal components (Model 3)

Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7
NPPP	0,3214	0,7770	0,4815	0,0516	0,1356	0,0819	0,1827
TPPL	0,3949	-0,0355	-0,1067	0,7790	-0,1621	-0,4075	-0,1793
NTPM	0,3556	-0,5825	0,4024	0,1735	0,3242	0,3388	0,3497
NIM	0,3925	0,0379	-0,4334	-0,1988	-0,4186	-0,0154	0,6646

VNIM	0,3877	-0,2173	0,3901	-0,5249	-0,2000	-0,5184	-0,2571
TPAL	0,3905	0,0807	-0,4919	-0,2032	0,7211	-0,1026	-0,1650
NUPL	0,3969	0,0235	-0,1128	-0,0631	-0,3391	0,6580	-0,5265

**Step3: Calculate the scores of the main components**

Referring to the component scores (Table 10) calculated in Step 1, only the first 3 principal components were retained because cumulative variance explained by these components is greater than 80%. The results show that FinTech loads heavily on the first principal component, which explains 90% of information. FinTech loadings increased from -3.088 in 2010 to 3.768 in 2019. The second principal component explains 7.5% of information, which is still a low threshold to account for FinTech change. The third principal component explains 1.7% of information, which remains insufficient to explain change in FinTech. This concludes that only the first principal component is retained to explain whether its variance can affect and promote financial inclusion in the overall model.

[Table 10]

**Table 10 :Scores of the retained principal components (Model 3)**

Années	PC1	PC2	PC3
2010	-3,088755	-0,2647278	0,5450326
2011	-2,785948	-0,2425939	0,306525
2012	-2,245223	-0,2137218	-0,0672662
2013	-1,721108	-0,1717991	-0,4366626
2014	-1,083511	-0,1189833	-0,6848723
2015	0,5254244	0,994095	0,0034083
2016	1,358955	0,7281457	0,0224615
2017	2,269235	0,8405564	0,1938628
2018	3,002066	-0,0367086	0,0291088
2019	3,768863	-1,514262	0,0884021

**4.4. Model and Data**

The principal component analysis (PCA) shows that FinTech has changed significantly from 2010 until 2020. This means that the use of FinTech is more favorable for individuals and businesses. However, the direct relationship between financial technologies and financial inclusion needs to be tested empirically. To this end, we use a time series analysis using FinTech data retained by the principal component analysis, preserving totality of information from the source data. After running the needed stationarity tests, we found that the series are non-stationary. The next stage is to test our models with the ARIMA process, "Autoregressive Integrated Moving Average", where (p,d,q) denote difference orders.

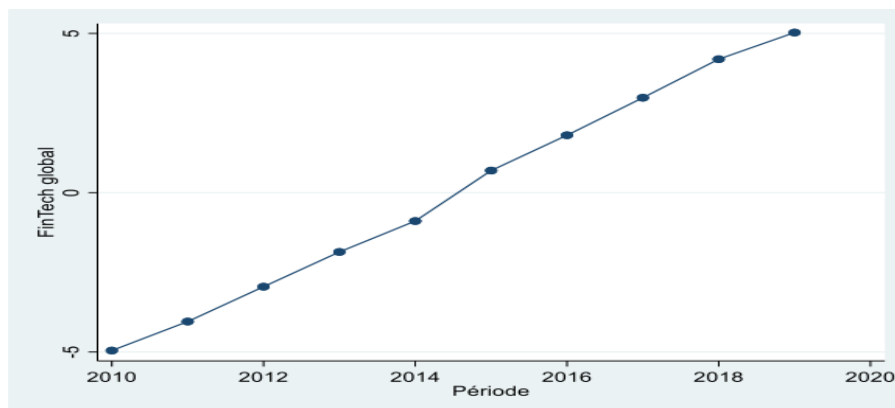
[Table 11]

Table 11- Descriptive statistics

Variable	Mean	Std.Dev.	Min	Max
IF global	82.94769	8.675035	72.73122	90.55736
IF access	9.647688	.7271693	8.731224	10.55736
IF usage	73.3	8.01457	64	80
FinTech global	-9.00e-08	3.485607	-4.955324	5.027429
FinTech access	6.00e-08	2.44218	-3.932512	3.327645
FinTech Usage	-1.60e-07	2.515908	-3.088755	3.768863
Inflation	2.589563	1.183596	1.437025	5.553897
Real interest rate	2.067063	2.232377	-1.402429	4.522308
Primary school enrollment	98.89972	1.813428	95.79643	101.9257
Control of corruption	-.3603748	.106999	-.5616429	-.2540594
Regulatory quality	-.2398621	.0461025	-.2894387	-.1476175

[Figure 4]

Figure 4: the evolution of financial inclusion between 2010 and 2019





**Econometric model**

To further examine the effect of financial technologies on financial inclusion, we constructed an econometric model as follows:

**Global econometric model :**

$$IF_t = \beta_0 + \beta_1 PC_1 + \beta_i controls_{it} + \epsilon_t$$

Where IF<sub>t</sub> indicates the level of financial inclusion in year t in China, B<sub>0</sub> is a constant, B<sub>1</sub> is the coefficient of the independent variable, PC<sub>1</sub> is the main independent variable that measures level of FinTech in China, B<sub>i</sub> indicates the coefficient vector of the control variables. ε<sub>t</sub> is the random error term.

With :  $X_t = \alpha + \beta_t + \epsilon_t$

- $t - X_{t-1} = \beta + \epsilon_t - \epsilon_{t-1}$

**H0:** FinTech promotes financial inclusion

**H1:** FinTech does not promote financial inclusion.

Thus, once the series are differentiated, the linear linear time dependence is eliminated and the difference is stationary. The econometric model for the usage dimension is as follows:

$$IF_t = \beta_0 + \beta_1 PC_1 + \beta_i Controls_{it} + \epsilon_t$$

**H0:** Usage dimension; FinTechs are driving the use of financial services.

**H1:** Use-size; FinTechs do not promote the use of financial services.

Where IF<sub>t</sub> indicates level of financial inclusion explained by the usage dimension, B<sub>0</sub> is a constant, B<sub>1</sub> is the coefficient of the independent variable, PC<sub>1</sub> is the main independent variable that measures level of FinTech usage dimension in China, B<sub>i</sub> indicates the coefficient vector of the control variables. ε<sub>t</sub> is the random error term.

$$IF_t = \beta_0 + \beta_1 PC_1 + \beta_i controls_{it} + \epsilon_t$$

**H0:** Access-size of FinTechs promotes access to financial services.

**H1:** Access dimension of FinTechs does not promote access to financial services.

Where IF<sub>t</sub> indicates level of financial inclusion explained by the access dimension, B<sub>0</sub> is a constant, B<sub>1</sub> is the coefficient of the independent variable, PC<sub>1</sub> is the main independent variable that measures level of access dimension of FinTechs in China, B<sub>i</sub> indicates the coefficient vector of the control variables. ε<sub>t</sub> is the random error term.

**Main variables and data description**

- **Dependent variable**

Financial Inclusion in China (FI) is the dependent variable. Our study considers two dimensions of financial inclusion. The first dimension is access to financial services which is measured by the number of bank branches and ATMs. The second dimension is the use of financial services which is measured by the total number of regulated deposit and credit accounts.

- **Independent variables**

The independent variables are the different dimensions of FinTech implemented in the financial market such as the number of online peer-to-peer (P2P) lending platforms, number of lenders on P2P platforms, online payment, mobile payment,

and FinTech tools that can help foster financial inclusion such as Internet, number of cell phone subscriptions, and mobile Internet market volume. PCA is used to calculate an overall score for FinTech score to replace and reduce the dimensions of the baseline variables. PCA was used as a proxy variable.

- **Control Variables**

This study aims to control for a range of variables that may affect the level of Financial Inclusion in China. In the literature, the omission of relevant variables in a regression model can lead to bias (Gujarati, 2003). To avoid this bias, the model includes other macroeconomic variables such as inflation (Cpi), primary school enrollment (Penr), interest rate (Intr), corruption (Cor), and regulatory quality (Regq).

**Empirical analysis**

**Unit root tests**

Following the previous literature, the present study uses unit root tests of time series on the independent variables, the dependent variable and the control variables to establish their unit root properties. The Augmented Dickey-Fuller test (ADF) and Phillips-Perron test (PP) are used.

- **Augmented Dickey-Fuller test**

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \delta_2 \Delta y_{t-2} + \dots$$

The Augmented Dickey-Fuller test allows for higher-order autoregressive processes by including  $\Delta y_{t-p}$  in the model. The null hypothesis for both tests is that the data are non-stationary. If we want to REJECT the null hypothesis for this test, then the p-value should be less than 0.05.

**Phillips-Perron test**

$$y_t = c + \delta t + \alpha y_{t-1} + e(t).$$

This test is a non-parametric adaptation of the Dickey and Fuller test. The null hypothesis of this test is the same like that of the DF test, the presence of a unit root. The results of these two stationarity tests indicate that financial inclusion is stationary in the first difference I(1), while the principal component that measures FinTech (PC1) is stationary in the second difference I(2), and the control variables are stationary but of different order I(0), I(1), I(2).

**Autocorrelation and partial autocorrelation functions**

To choose the orders of specification of the models we used the correlogram as a method of analysis. In the ARIMA model there are three specification orders to be determined (p,d,q). Where (p) indicates the autoregressive order, (d), integrated order, and (q), moving order. To determine the autoregressive order we used the partial autocorrelation function (ACF), for moving average order we used the autocorrelation function (ACF), and for the necessary minimum number of differences (d), we used the trend graph method (Lineplot) to distinguish the minimum number of differences necessary to make the series stationary. For the global model, ARIMA (0, 1, 0), the usage model, ARIMA (0, 1, 0) and the access model, ARIMA (0, 1, 0).

For the overall model (Model 1), estimation by ARIMA regression (Table 12) yielded the following results. Table 10 reports the statistical significance of the principal component variables and the control variables. For the first variable (PC1) which measures the overall level of Fin Tech in China, the results show that PC1 is significant ( $0.032 < 0.05$ ), and having a positive relationship with financial inclusion (0.0523). For the control variables, the results show that inflation, real interest rate, regulatory quality are not significant. On the other hand, primary enrollment rate and corruption control are significant respectively at the following calculated probabilities ( $0.000 < 0.05$ ) and ( $0.002 < 0.05$ ), but the primary enrollment rate has a negative relationship with financial inclusion since the coefficient of this relationship is negative (-4.570). On the other hand, corruption control has a positive relationship with financial inclusion (0.113). Bearing on these results, we can confirm that the basic assumption of this model is true, and FinTech can promote financial inclusion.

For the usage dimension model (Model2), estimation by ARIMA regression (Table 13) yielded the following results. Table 12 reports the statistical significance of the principal component variables and the control variables. For the first variable (PC1) which measures level of Fin Tech usage in China, the results show that PC1 is not significant ( $0.094 > 0.05$ ), with no positive relationship with financial inclusion (-0.0158). For the control variables, the results show that inflation, real interest rate, regulatory quality and corruption control are not significant. On the other hand, the primary enrollment rate is significant ( $0.000 < 0.05$ ), but the primary enrollment rate has a negative relationship with financial inclusion since the coefficient of this relationship is negative (-3.799). From these results, we can confirm that the basic assumption of this model is not retained, and FinTech cannot promote the use of financial services.

For the access dimension model (Model 3), estimation by ARIMA regression (Table 14) yielded the following results. Table 13 reports the statistical significance of the principal component variables and the control variables. For the first variable (PC1) which measures level of FinTech access in China, the results show that PC1 is significant ( $0.000 < 0.05$ ), having a positive relationship with financial inclusion (0.0320). For the control variables, the results show that inflation, real interest rate, and regulatory quality are not significant. On the other hand primary enrollment rate and corruption control are significant respectively at the following calculated probabilities ( $0.000 < 0.05$ ) and ( $0.002 < 0.05$ ). However, the primary enrollment rate has a negative relationship with financial inclusion since the coefficient of this relationship is negative (-1.555). Additionally, corruption control has a negative relationship with financial inclusion (-0.096). Bearing on these results, we can confirm that the basic assumption of this model is true, and FinTech can promote access to financial services.

[Table 12]

Table 12: ARIMA ESTIMATION (Model 1)

ARIMA regression						
Sample : 2011-2019			Numberofobs=9			
Loglikelihood = 37.54344			Waldchi2(6)=75.13			
			Prob>chi2=0.0000			
D.IF	Coef.	Std.Err.	z	P>z	[95%Conf.	Interval]
PC1						
D1.	.0523645	.0243996	2.15	0.032	.0045422	.1001869
inflation						
D1.	-.0338452	.0449518	-0.75	0.451	-.1219491	.0542588
Real interest rate						
D1.	-.0033941	.0103231	-0.33	0.742	-.0236271	.0168389
Primary school enrollment						
D1.	-4.570671	.6850343	-6.67	0.000	-5.913313	-3.228028
Control of Corruption						
D1.	.1134386	.0357393	3.17	0.002	.0433908	.1834864
Regulatory Quality						
D1.	.0197161	.0796665	0.25	0.805	-.1364273	.1758595
_cons	.0199331	.0030337	6.57	0.000	.0139872	.025879
/sigma	.0037334	.0032821	1.14	0.128	0	.0101662

[Table 13]

Tableau 13a- ARIMA ESTIMATION (Modèle 2)

Variable	Mean	Std. Dev.	Min	Max
IF global	82.94769	8.675035	72.73122	90.55736
IF access	9.647688	.7271693	8.731224	10.55736
IF usage	73.3	8.01457	64	80
FinTech global	-9.00e-08	3.485607	-4.955324	5.027429

FinTech access	6.00e-08	2.44218	-3.932512	3.327645
FinTech Usage	-1.60e-07	2.515908	-3.088755	3.768863
Inflation	2.589563	1.183596	1.437025	5.553897
Real interest rate	2.067063	2.232377	-1.402429	4.522308
Primary school enrollment	98.89972	1.813428	95.79643	101.9257
Control of Corruption	-.3603748	.106999	-.5616429	-.2540594
Regulatory Quality	-.2398621	.0461025	-.2894387	-.1476175

**Table 13b : ARIMA ESTIMATION (Model 2)**

ARIMA regression						
Sample:2011-2019						
Loglikelihood=32.79946						
Numberofobs=9						
Waldchi2(6)=66.86						
Prob>chi2=0.0000						
OPG						
D.IF	Coef.	Std.Err.	z	P>z	[95%Conf.	Interval]
D1.PC1	-.015837	.0094483	-1.68	0.094	-.0343554	.0026814
D1.Inflation	-.0248814	.018481	-1.35	0.178	-.0611036	.0113407
D1.Real interest rate	.0014155	.0122405	0.12	0.908	-.0225755	.0254065
D1. Primary school enrollment	-3.799102	.5960617	-6.37	0.000	-4.967361	-2.630843
D1.Control of Corruption	.1896718	.1938957	0.98	0.328	-.1903569	.5697004

D1.Regulatory Quality	.0109128	.0108928	1.93	0.054	-.0003401	.0429053
_cons	.0212828	.0110323	1.93	0.054	-.0003401	.0429057
/sigma	.0063245	.004337	1.46	0.072	0	.0148249

[Table 14]  
Table 14- ARIMA ESTIMATION (Model 3)

ARIMAregression						
Sample: 2011-2019 Number of obs = 9						
Wald chi2(6) = 169.61						
Log likelihood = 47.31503 Prob > chi2 = 0.0000						
OPG						
D.IF	Coef.	Std.Err.	z	P>z	[95%Conf.	Interval]
D1.PC1	.0320976	.0044962	7.14	0.000	.0232852	.04091
D1.inflation	-.003069	.0082371	-0.37	0.709	-.0192133	.0130753
D1.Real interest rate	.0009932	.0070339	0.14	0.888	-.0127929	.0147794
D1.Primary school enrollment	-1.55558	.2572496	-6.05	0.000	-2.05978	-1.051381
D1.Control of Corruption	-.0963327	.0314605	-3.06	0.002	-.1579941	-.0346712
D1.Regulatory Quality	-.0110956	.0427013	-0.26	0.795	-.0947887	.0725975
_cons	.0079094	.0019726	4.01	0.000	.0040432	.0117757
/sigma	.0012606	.000752	1.68	0.047	0	.0027345

Tableau 15 - ARIMA ESTIMATION (Modèle 3)

ARIMA regression	
Sample: 2011 - 2019 Number of obs = 9	
Wald chi2(6) = 169.61	
Log likelihood = 47.31503 Prob > chi2 = 0.0000	

OPG						
D1	Coef	Std. Err	Z	P	[95% Conf. Interval]	
D1.PC1	.0320976	.0044962	7.14	0.000	.0232852	.04091
D1.inflation	-.003069	.0082371	-0.37	0.709	-.0192133	.0130753
D1. Real interest rate	.0009932	.0070339	0.14	0.888	-.0127929	.0147794
D1. Primary school enrollment	-1.55558	.2572496	-6.05	0.000	-2.05978	-1.051381
D1.Control of Corruption	-.0963327	.0314605	-3.06	0.002	-.1579941	-.0346712
D1.Regulatory Quality	-.0110956	.0427013	-0.26	0.795	-.0947887	.0725975
_cons	.0079094	.0019726	4.01	0.000	.0040432	.0117757
/sigma	.0012606	.000752	1.68	0.047	0	.0027345

### 5. DISCUSSION AND RESULTS

Our main research question that this study tries to answer is: "Can FinTech foster financial inclusion in China? In a first stage, we focused on assessing whether there is a relationship between FinTech and financial inclusion in an aggregate way. The statistical results of the first model show that FinTech has a positive relationship with financial inclusion, i.e., as FinTech use increases, financial inclusion should be more favorable. This finding can be explained by the change in customer preferences, who prefer innovative financial products and services that are easier to access. Moreover, the low costs of FinTech services and products attracted a large group of customers, who are looking for innovative and affordable products. In the first model, no similar significant positive relationship with financial inclusion was found for the macroeconomic variables. Inflation and real interest rate are not significant, only primary school enrollment has a significant negative relationship with financial inclusion. This implies that macroeconomic factors do not play an important role in promoting financial inclusion. For the institutional variables, only control of corruption has a significant relationship with financial inclusion, while regulatory quality has not. This indicates that institutional factors such as control of corruption may play a role in increasing financial inclusion.

In a second stage, we focused on examining the different dimensions of financial inclusion, and the nature of the relationship of FinTech with these dimensions. The usage dimension is estimated by the second model and the access dimension is estimated by the third model. The usage model estimation showed no significant positive relationship between FinTech. This indicates that FinTech cannot promote

use of financial services. For the macroeconomic variables, such as inflation and real interest rate which are not significant, only the primary school enrollment rate has a significant negative relationship with the usage dimension. This implies that macroeconomic factors do not play an important role in driving the usage dimension. For the institutional variables, neither corruption control nor regulatory quality has a significant relationship with the usage dimension. This indicates that institutional factors do not play a role in increasing usage of financial services.

The relationship between FinTech and the usage dimension of financial inclusion can be explained by the barriers to using sophisticated financial products and services that require digital and financial knowledge. The lower the knowledge about financial products and concepts and risks, the higher the barrier to using FinTech. Thus, macroeconomic and institutional variables do not play an important role because the barrier is educational. The only significant variable is primary school enrollment but with a negative relationship with the usage dimension. This indicates that primary education level is not sufficient to use sophisticated financial products like FinTech. It also indicates a lack of customer competence and confidence to become more aware of financial risks and opportunities, make informed, reasoned choices, or take other effective initiatives to improve their financial well-being.

For the access dimension, which was estimated by the third model, a significant positive relationship was found between FinTech and the access dimension. This indicates that FinTech can promote access to financial products and services. For the macroeconomic variables, we found that inflation and real interest rate are not significant. On the other hand, the only significant variable is primary school enrollment but with a negative relationship with the access dimension. This indicates that macroeconomic variables do not play an important role in favoring the access dimension. For the institutional variables, only control of corruption has a negative significant relationship with the access dimension. This indicates that the institutional factor does not play a significant role in promoting access to financial services. The empirical results also show that FinTech can promote access to financial services by reducing costs, reducing geographical barriers, and also organizational barriers, as a result of the high use of innovative technologies. such as, blockchain, P2P technology, crypto currency and crowdfunding that are based on decentralized access.

The results of our study showed that FinTech can foster financial inclusion in general. However, from a dimensional perspective, we found that only the access dimension can be promoted through FinTech, as opposed to the usage dimension, which requires digital and financial literacy. This finding confirms previous studies and the literature on financial inclusion and FinTech:

Peterson. (2017), studying the impact of digital finance on financial inclusion and stability, found that the use of cell phones can improve financial inclusion. This confirms our finding that accelerating the adoption of cell phone use and similar devices can help reduce barriers to accessing financial services.

Olaniyi. (2018), who analyzed the relationship between internet, cell phone and



financial inclusion in Africa, found that the increasing adoption of internet-connected phones in Africa can have positive effects on financial inclusion. This also confirms our result and shows the importance of the internet as a factor in promoting access to financial services. For Morshadul. (2020), the regional development of China's inclusive finance can be achieved by financial technology. The relationship between FinTech services, such as Internet investment, Internet credit, Internet payments, and Internet insurance, can develop rural businesses, develop SMEs, and rural investment in China. Schumpeter. (1911) argued for innovation and technical progress and the "creative destruction" phenomenon. If we apply the Schumpeterian view for innovation on FinTech, obviously these innovations have destroyed the traditional financial services and created new more efficient and affordable ones, affecting thus financial inclusion as a positive externality.

## 6. GENERAL CONCLUSION

After shaking the daily financial services market, financial technology (FinTech) has helped improve financial inclusion. China is pursuing a policy to integrate millions of people into the mainstream financial system and reduce financial inequality. The role of technology in financial inclusion is almost certain, i.e., technological progress can improve access to financial services, including reducing costs and enabling services to be offered in areas where there are no bank branches, such as rural areas. The technological innovation that led to the emergence of FinTech start-ups offers several advantages, better knowledge of customers and their innovative needs, competition with traditional banks, positive externalities, low costs compared to traditional financial services, and a decentralized access.

In this regard, our study is articulated around two objectives. The first examines the relationship between financial inclusion and FinTech in general. The second focused on the two dimensions of financial inclusion, and examined which dimension can be fostered by financial technologies. To achieve these two objectives, the study used the following methods:

The first technique used was a principal component analysis (PCA), which is multidimensional descriptive methods under the factor analysis method. The purpose of using this method is to find out which variables correlate more with each other, and which do not correlate with each other.

The second technique is an ARIMA model, estimated by three models. The first model estimates financial inclusion and FinTech as a whole. The first model was then divided into two sub-models to examine which dimension can be favored by FinTech, the access or use dimension.

The results of our study found a strong support for adopting FinTech as a tool to foster overall financial inclusion. In contrast, our analysis of the access and use dimensions showed that FinTech can foster the access dimension as a result of the acceleration of adoption of internet and platform-based financial solutions. However, for the usage dimension, the results showed that FinTech cannot promote usage of financial services. The problem is that financial confidence and knowledge

are not developed enough, which represents a barrier between FinTech opportunities and financial inclusion. Then, robust financial inclusion requires a focus on fostering both the access and usage dimensions simultaneously.

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