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The Impacts of Economic and Political Drivers on the Performance of the Chinese Fintech Sector: The Mediating Role of Blockchain Developments

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Abstract

The emergence of finance technologies (fintech) has revolutionised traditional financial services and delivery processes, the advancement of blockchain technologies has aided the transition of fintech services with optimized efficiency and added values for modern customers. This study critically explored the impacts of macroeconomic environment factors and policy interventions in China on the developments of blockchain across the period of 2017 to 2021, examining how blockchain developments (BDI) mediate the relationship between economic driver influence (EDI), political driver influence (PDI) and Chinese fintech market performance (CFMP). This study contributed to literature gap and utilised empirical knowledge on the measurement of macroeconomic and political factors toward technological development, forming designated proxies and latent variables to offer new parameters to measure the influence of these factors in unified manners. This study measured economic driver influence under GDP per capita (GDP), gross national income (GNI), government borrowing and debt (GBD), gross domestic expenditure on R&D per capita (GERD) and labour cost index (LCI), political factor influence is measured under government funding (GF), pilot zones (PZ), incubators (IC), national champions (NC) and supportive policies by engaged province ratio (SP). Blockchain development is measured by the number of blockchain company registrations (BCR), blockchain patents (NBP), venture capital investment volume (VCI) and revenue of blockchain companies (RBC). The results reveal that both EDI and PDI have highly statistically significant relationships with BDI, positively impacting the growth of the overall Chinese fintech market sector and across 4 key fintech segments of alternative finance, digital assets/ investments and payments.

Keywords: *Blockchain technology, Chinese fintech, Finance innovation, Political drivers, Economic drivers.*

Introduction

Over the last few decades, the development of technology in the financial industry has undergone a significant transformation, disrupting and innovating traditional financial services and models. This has occurred within a fintech-dominated era, which has created both opportunities and threats for the financial services industry, according to Pollari (2016). The utilization of software, algorithms, and technological applications to enhance

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financial products, instruments, and tools outside the traditional financial services system, collectively known as fintech, has optimized traditional financial services in areas such as banking, insurance, investing, and trading. Scholars and practitioners have defined fintech as an innovative financial technology, this terminology has been used by Schueffel (2016), Nicoletti et al. (2017), Goldstein et al. (2019), and Thakor (2020).

According to Nicoletti et al (2017), the modern fintech industry has experienced three waves of evolution in which have engineered its conceptualization amongst academicians. During the late-19th to mid-20th century, fintech was commonly referred to as new technologies that sought to improve and automate the delivery, use and monitoring of financial services during an era of the first technological developments in finance (Nicoletti et al, 2017). In the 1950s, the world’s first credit card system was developed by IBM engineer Forrest Parry, referred by Karayew (2012) as a major breakthrough in the development of magnetic stripe card technologies that had paved key foundation for future fintech innovations in borrowing and payment services. During the second wave of fintech’s evolution between the mid-20th century to early 21st century, Nicoletti et al (2017) highlighted the key role of banks and financial institutions behind the accelerated development of financial technologies, as traditional financial services and financial related processes embarked a revolutionary shift from analog to digital. During the latter years of the 20th century, a series of disruptive fintech innovations took place and added new dimensions to traditional financial services, opening up new opportunities in areas of digital finance, wealth management and transaction systems (Nicoletti et al, 2017).

The current research consensus points to the ever-growing importance of financial technologies and the need for fintech developments, illustrating the apparent weaknesses in traditional financial systems and processes that require innovative technologies to optimize the efficiency of financial services, delivering cheaper and automated financial solutions to help both financial institutions and its customers via value-added financial processes/ service delivery. In recent years, increasing numbers of start-up projects and multinational firms have attempted to apply blockchain technologies in the financial services industry, striving to optimise business processes by effectively sharing data in a more transparent and secured manner (Ali et al, 2021). The application of blockchain technologies has replaced traditionally expensive and inefficient financial service intermediaries and processes likewise to fintech solutions. However, fintech has received widespread criticism in recent years due to data security issues, restricted user privacy compliance with government regulations, lack of existing technological infrastructure, established trust and low transparency/ visibility across financial service processes (Hwang et al, 2017). The benefits of blockchain technologies illustrate highly efficient solutions to optimise existing fintech systems and solutions, allowing the process of transactions in real time, lowering overall accounting costs associated with the reconciliation of ledgers, freeing up key resources, offer the capability to verify customers with built in cryptography protection, enhancing data security protection, reducing frauds and safer ways to conduct transactions with strong transparency (Fernandez-Vazquez et al, 2019).

China's national strategic plan, known as MIC 2025 (Made in China 2025), was introduced by the Chinese government in 2015. This plan aimed to make China a global leader in the technology and manufacturing sectors, with the goal of becoming an "innovation country" by 2020 and a global leader in innovation by 2030, according to Wubbeke et al. (2016). As a result, China has made significant progress in technological research and development, providing funding through industrial policy programs to support key technological markets, such as blockchain, artificial intelligence (AI), aerospace, semiconductors, biotech, and electric vehicles, and to encourage technological competitiveness against other countries, as highlighted by Huimin et al. (2018). The development of blockchain technology has received unparalleled support from the

Chinese government and is recognized as a strategic priority in the MIC 2025 plan. President Xi Jinping's 2019 speech at the CPC central committee political bureau on technological developments underscored the Chinese government's commitment to supporting and encouraging the development of blockchain technology. As a result, the Chinese government has established 15 pilot zones and 164 entities to incubate innovative blockchain technology applications, as reported by TOI News (2022). The number of newly registered enterprises in blockchain-related fields has more than doubled each year since the establishment of the blockchain pilot zones and blockchain incubation entities by the Chinese government. This significant growth in blockchain development in China, increasing by almost twenty-fold between 2014 and 2020, has been fostered by a combination of a supportive regulatory environment, aggressive investment from capital markets, and an accelerated shift towards blockchain adoption in the financial sectors. As a global leader in total finance users and market size, China’s fintech market has been benefited by innovative blockchain applications (Sun et al, 2022), resulting in blockchain adoption amongst its largest fintech unicorns including Ant Financial (Ant Group), Tencent, Lufax and Zhong An.

The purpose of this paper is to investigate the role of blockchain developments in China’s fintech market performance over the period 2017 to 2021, exploring what role political and economic drivers have contributed to this process. This paper takes a sample of China’s recent five years of fintech market and blockchain development data (2017-2021), emphasising on specifically chosen macroeconomic environment indicators and government interventions to comprehensively examine the role in which economic and political drivers have contributed to Chinese fintech market growth and further analyse the mediating role played by blockchain developments directly resulted from economic and political influence.

The novelty of this paper is that (1) the selection approach of economic and political indicators utilizes key measurement constructs from relevant empirical studies, overcoming the apparent gap in lack of unified parameters for measuring economic and political drivers on blockchain development that can be transferrable in future studies. (2) The measurement of the mediating role of blockchain developments on the Chinese fintech market from political and economic factors has not been performed in literature. (3) The performed analysis addresses five key Chinese fintech market segments including alternative financing, digital assets, digital investment, digital payment and neo-banking, exploring the Chinese fintech market as a whole and with specific focus on key market segments.

The rest of the paper consists of four parts. The “Literature review and research hypothesis” section introduces an empirical review of literature with formulation of research hypotheses. The “Empirical model and data” section details the design of research model, data sources and selection of indicators. The “Empirical analysis” section presents the results and findings from empirical evidence. The “Conclusions and recommendations” section summarises key findings and offer practical recommendations for Chinese policy makers.

Literature review and hypothesises development

The intertwining relationship between technology and macroeconomics is widely explored in empirical studies, as Von Tunzelmann (1995) argues that technological advancements are the foundations of economic growth, enabling more efficient production of more and better goods and services with enhanced economic productivity output. This is further illustrated in the Carlaw & Lipsey’s (2003) study where a two-way relationship is identified between economic growth and technological developments, as high economic growth would create a continuous flow of opportunities that are capitalized by technological innovations and subsequent technological developments would drive further economic growth. As for blockchain technology developments, Khalil et als' (2022) study on the Pakistani financial sector founded a positive relationship between business process innovation fostered by blockchain technology applications and overall performances of the financial sector, indicating the mediating role of blockchain technology development between economic growth and financial sector process innovation. Zhao (2019) also reinforced this relationship as sustainable economic growth is achieved by the establishment of trust mechanisms stimulated by blockchain technologies, as increased economic outputs are positively correlated to the increased values facilitated by blockchain technologies.

Several studies have attempted to quantify the macroeconomic environment in relation to technological developments, a study conducted by Welfens & Perret (2014) explored the relationship between the gross domestic product (GDP) per capita levels with developments of information & communication technologies. Welfens & Perret (2014) founded a 2-5% increase on GDP per capita amongst OECD countries when measuring the ICT investment to GDP ratio in real terms, highlighting the importance of the technological developments in ICT to contribute to GDP levels. In Hausmann & Dominguez's (2020) study, the relationship between economic growth measured in GDP per capita and technology is explored via the innovation complexity index, proposing that increase in real GDP would positively correlate to the investments in technological research & developments, as technological firms are more likely to have higher capital and higher-level skills labour to focus on technological developments. The intertwining relationship between economic productivity and technology development is widely recognized as the majority of existing studies focus on the impacts of technology development on economic growth, raising the research need to further understand the impacts of economic growth (measure in GDP per capita) on technological developments as suggested by Zagorchev et al (2011).

Another approach to measure economic factors that drive technological developments is shown in the study of Chong et al (2012), whereby the increase in gross national income levels is found to stimulate greater technological developments, especially in the digital economy where higher gross national income positively correlate to higher technology acceptance and usage. Mubarak et al (2020) further reinforced this relationship as higher gross national income levels is found to positively correlate to increased penetration of digital technologies amongst internet users and encourages investment and technology related research & development. A study conducted by Raghupathi & Raghupathi (2017) measured technological development innovation at country levels via economic indicators such as GDP, gross national income and labour costs, finding a positive relationship between economic growth via gross national income on higher research & development expenditures in private, technological sectors. Blien et al (2022) also utilised gross national income data across nine countries (Austria, Belgium, Germany, Finland, France, Italy, Netherlands, UK and US) from the World Bank to illustrate that increased economic inputs would enhance the demand for technological services and solutions, thus driving the demand for technological developments.

Cowling et al (2018) proposed the dilemma of innovation debts as high-tech companies and related developments are perceived to be more risky than conventional industries, suggesting the need for more consideration when designing loan contracts and provision of government loan guarantees. Subsequently, the debts and related costs for technological developments are recognized to have profound impacts on the rate of engagement in technological innovation activities, as shown in Anderson & Lavoie's (2004) study where the level of government borrowing and debt management initiatives are found to impact financial and technological innovations. Coccia's (2013) study also indicated that higher levels of government borrowing and debts (GBD) would help to simulate higher short term economic growth, especially in innovation driven technology sectors where governments can increase spending on technological research &

development without raising taxes. However, inappropriate management of government borrowing and debts could harm economic growth and investments in high-risk technological sectors as shown in the case of Nigeria (Adepoju et al, 2007), whereby spiraling out of control government debts would have adverse effects on all economic developments, especially expensive technological developments.

Falk (2007) proposed the relationship between research & development expenditure levels and the growth of high-tech sectors, adopting a dynamic empirical growth model using panel data for OECD countries between 1970 and 2004, finding a positive correlation between research & development expenditures (measured per capita) and the share of research & development investment in the high-tech sectors, as well as posing moderating effects on GDP per capita growth. Wang et al’s (2013) study also found a heterogenous effect on research & development expenditure and the growth of high-tech sectors, performing a quantile regression approach that shoed a positive correlation in research & development expenditure and the growth of high-tech industrial sectors. Tajaddini & Gholipour’s (2020) study also measured the effect of research & development expenditure per capita on the growth of innovation outputs in countries including Australia, Brazil, Canada, Chile, China, France, Germany, India, Italy, Japan, Singapore, Spain, Sweden, UK and the US, finding a positive correlation between R&D expenditure per capita and increased innovation outputs in technological patent applications and grants.

Labour costs measured by the labour cost index (LCI) is also widely used to explain technological development growth, especially in advanced technologies where innovation requires substantial labour efforts and high skilled labour (Adams, 2018). According to Adams’ (2018) systematic on labour market literature, a common theme is identified in empirical studies that recognizes the effects of technological advancement on reducing the need for routine mechanized/ low skilled work, proposing that innovation technological developments would decrease manual, unskilled jobs. Alternatively, there are insufficient studies contributed to the reverse effects of labour costs on technological developments according to Ozturk & Bicimveren (2018), representing a research gap for this study to address. Nonetheless, Ozturk & Bicimveren (2018) examined the relationship between labour costs and the level of investments in information and communication technologies across the G7 countries between 1990-2010, finding a negative and significant relationship where reduction of labour costs would result in the rise of investments in information and communication technologies. The findings of Ozturk & Bicimveren (2018) examined data from over a decade ago as this research will look to testify this hypothesis when applied to the developments of blockchain technologies. Therefore, based on the recognized importance of economic factors that influence blockchain developments and the overall impacts of blockchain developments on Chinese fintech sector performance, this paper proposes the following research hypotheses.

H1(a): Macroeconomic environment (economic drivers) has a positive effect on the shaping of political intervention/ decisions to support blockchain developments

H1(b): Macroeconomic environment (economic drivers) has a positive effect on blockchain development

blockchain developments in the Chinese fintech sector.

H1(c): Macroeconomic environment (economic drivers) has a positive effect on Chinese fintech sector market performance

H1(d): Macroeconomic environment (economic drivers) has a positive effect on Chinese fintech sector market performance mediated through political drivers

H1(e): Macroeconomic environment (economic drivers) has a positive effect on Chinese fintech sector market performance mediated through blockchain developments

H1(f): Macroeconomic environment (economic drivers) has a positive effect on Chinese fintech sector market performance mediated through political drivers and blockchain developments

The importance of political factors on the development of all forms of new technologies is widely recognized across the academic field (Doh & Kim, 2014; Pratchett, 1999; Kim et al, 2016). According to Kim et al (2016), government support is found to have a moderating role in the research & development of innovation service technology systems, positively influencing the attitudes of private sector investment and intention to engage in new technology fields. This is further echoed in the study of Salmenkaita & Salo (2002) as government intervention is found to have a positive relationship with private venture capital investment, supporting the commercialization and development of new technologies. Additionally, Salmenkaita & Salo (2002) also illustrated the importance of political intervention on new technologies as it would help to mitigate market and systemic failures, eliminating structural rigidities or respond to anticipatory myopia. The general research consensus supports the relationship between technology driven policies and the fostering of technological development through stimulating higher attention for economists, policy makers and practitioners, especially in the country context of China where state intervention is found to be the key driver for innovative technological developments (Lin & Luan, 2020; Wu et al, 2022).

According to Lin & Luan (2020), the development of advanced technologies in China is found to be affected by preferential policies and government funding, whereby increase in the volumes of government subsidiaries would directly increase innovation efficiency of new technologies and innovation performance. A study conducted by Hou et al (2018) explored the role of government support in the promotion and development of blockchain technology in the Chinese photovoltaic industry, finding that the policy environment is vital to blockchain technological developments as it would disrupt previous patterns where production, transportation distribution and sales processes are replaced with blockchain applied processes. Hou et al (2018) argued for the need of the Chinese government, industry associations and researchers to collaborate on designing favourable policies to support blockchain technology developments, providing structural guidance to eliminate unfavorable consequences from the disruptions caused on existing industry practices (pre-blockchain application), providing clarity on the nature of blockchain technology application best practices with designated industry standards and national standards related to blockchain technologies.

Numerous empirical studies have attempted to quantify the nature of political factors that influence the development of new technologies, Ye et al (2022) measured government intervention based on the design of various fiscal and financial policies to engage in technology related research & development, arguing for the need for industry specific measurement metrics to measure the levels of government intervention beyond the volume of government subsidies and tax incentives. This is further echoed in Guo et als' (2018) study with the findings that increasing fiscal support would help to motivate enterprises to stimulate higher investments of technological development related research & development activities. Another school of thought proposed the need to measure government support beyond conventional fiscal means, championed by Yu et al (2022) who argued the importance of practical support such as government established technological pilot zones that would help achieve an effective balance between regulation and blockchain technology innovation. Yu et al (2022) explored China's digital economy with the measurement of blockchain related pilot zones in selected Chinese cities from the fintech development plan issued by the People's Bank of China.

The measurement in the number of pilot zones established by the Chinese government and its relationship to the overall blockchain development in China is also used in the studies of Cai et al (2021); Zhang et al (2018) and Zhong et al (2022). The construction of China's cross border e-commerce (CBEC) comprehensive pilot zones is found to support the sustainable development of blockchain technologies, promoting sector growth through the concept of industry agglomeration as all blockchain related research & developments, key suppliers, investors and technologies are concentrated with close proximity (Zhong et al, 2022). Another approach to measure the practicality of government intervention on blockchain developments is shown in the studies of Liu (2018); Aysan et al (2019) and Lim et al (2019), measuring through the government sponsored incubators with a diverse set of metrics including the number of start-ups incubated, percentage of successful exists, financial stability of incubator, volume of investments attracted, funding and infrastructure supports. Lim et al (2019) also found a positive relationship between received assistance and mentorship from government incubators and the invested volumes of private investment funds into incubators, illustrating the influential role of government fiscal and practical support provided by the government on the overall developments of blockchain incubators.

The influential role of China's national champions in the development of new technologies and especially blockchain technologies is recognized amongst the studies of Wheeler (2020), Manuel et al (2019) and Arcesati et al (2020). According to Wilson (2012), China's national champions are defined as previously state-owned Chinese enterprises that have evolved into partially privatized multinational corporations with close connections to the state, retaining a central position in the priority of government policies as the activities of national champions would contribute to the advance of interests of the nation. China's national champions in the digital technology and fintech sectors including Baidu, Alibaba and Tencent are found to play a vital role in the design and implementation of new government policies for technological developments (Jia et al, 2018), leveraging the technological expertise, resources and competences of national champions to develop innovative blockchain solutions to expedite the growth technological sectors. The development of China's state backed blockchain ecosystem with the support of national champions is found to have contributed to the design and implementation of technological architectures (China Mobile), financial technology architectures (China UnionPay Corporation) and core software strategies (Beijing Red Date Technology) to achieve cost reductions, interoperability and improve technical literacy that aids the development of blockchain technology applications in China's fintech sector (Jia et al, 2018). Therefore, based on the recognized importance of political factors that influence blockchain developments and sector performance, this paper proposes the following research hypothesis.

H2(a): Political support (political drivers) has a positive effect on blockchain developments

H2(b): Political support (political drivers) has a positive effect on Chinese fintech market performance

H2(c): Political support (political drivers) has a positive effect on Chinese fintech market performance mediating through blockchain developments

H3: Blockchain development has a positive effect on the Chinese fintech market performance

Based on the research hypotheses formulated from relevant empirical literature knowledge, this paper assumes that economic driver influence (EDI) directly impacts the shaping of policies by the Chinese government measured under political driver influence (PDI), directly and indirectly impacting the level of developments on blockchain technologies. Higher levels of economic driver influence (EDI) and political driver influence (PDI) are assumed to aid the development of blockchain technologies, providing higher funding, incubating, capital investment and policy support to facilitate a wider range of opportunities for blockchain technology development in China. The realization of such opportunities can be expressed in the form of blockchain company registration rates, blockchain patents, amount of venture capital investment and the revenue of Chinese blockchain companies. The gains from blockchain development can lead to growth in Chinese fintech markets due to the increasing application of blockchain technologies in Chinese fintech firms. To sum up, Fig 1 presents the conceptual framework of the study.

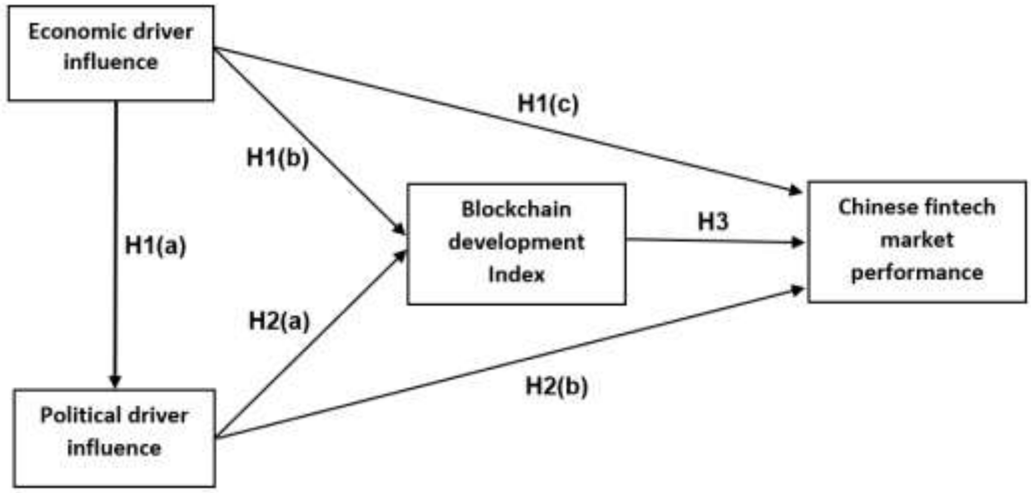

Fig.1 Proposed conceptual framework

First, we examine the effects of economic driver influence (EDI) on political driver influence (PDI), blockchain development index (BDI) and Chinese fintech market performance (CFMP). We then look at the effects of PDI on BDI and CFMP, followed by the effect of BDI on CFMP. Finally, the mediating effects of EDI on CFMP via PDI, EDI on CFMP via EDI, and EDI on CHMP via EDI and PDI are investigated.

Empirical model and data methodology

In order to examine the impact of blockchain developments on China's fintech market performance, this paper utilizes a variety of industry data reports including Statista, IMG, World Bank, Chinese blockchain patent report 2022, Chinese blockchain industry development report 2021-2022, Chinese fintech industry development report 2022, Ant-Financial group report 2021-2022 and Chinese government reports. The obtained secondary data sample covers the period 2017-2021 to offer the most up-to-date data from empirical research. To capture the impact of macroeconomic environment drivers and remove potential bias from Chinese regions that were not impacted by blockchain development related policies, this paper excludes the data samples in the Hong Kong Special Administrative Region, Macao Special Administrative Region and Taiwan. Chinese regions that have been affected by blockchain development policies documented in the MIC 2025 plan are selected, covering 29 major Chinese regions and provinces for analysis (see table 7 in Appendix). Empirical academic studies conducted on measuring macroeconomic environment influence and political intervention influence as aforementioned in the literature chapter uses a range of defined observed variables on empirical levels. However, these multifaceted and dynamic nature of macroeconomic, political intervention and blockchain developments require the design of latent constructs to via multiple observed indicators to increase its relevancy. Therefore, a range of latent variables comprised of empirically recognized indicators are used to serve the structural equation modelling (SEM) methodological approach for this study. According to Barrett (2007), SEM is more effective than multiple regression as it overcomes the limitations of examining a single relationship at a time, hence the SEM is developed to estimate a series of interrelated dependence relationships simultaneously under the designs of latent constructs. All latent constructs with observed indicators in accordance to representative codes are shown in table 1 below.

Table 1: List of observed and latent variables

Latent construct	Observed indicators	Abbreviation
Economic driver influence (EDI)	Gross domestic products per capita	GDP
	Gross national income	GNI
	Government borrowings & debts	GBD
	Gross expenditure on research & development	GERD
	Labour cost index	LCI
Political driver influence (PDI)	Amount of government funding	GF
	Number of established government-sponsored pilot zones	PZ
	Net volume of incubated project projects in government pilot zones	IC
	Net value of investments from Chinese national champions	NC
	Supportive policies in ratio of Chinese provinces engaged	SP
Blockchain development index (BDI)	Number of blockchain companies registered	BCR
	Number of applied new blockchain patents	NBP
	Amount of venture capital investment	VCI
	Revenue of blockchain companies in China	RBC
Chinese fintech market performance (CFMP)	Transaction volume of Chinese fintech market sector(s)	CFMP

Economic driver influence (EDI): The relationship between macroeconomic environment factors and the development of technologies is widely recognized amongst empirical literature. Numerous studies have attempted to measure the growth of technological sectors with generic macroeconomic indicators defined by the OECD to evaluate the macroeconomic environment that influences the performance of technological sectors, as this study selects five main economic drivers that have been recognized to technological developments. (1) The calculation of the sum of gross economic outputs per person is measured under GDP per capita as it is acknowledged to directly impact labour salaries, employment and the ultimate value of products/ services offered within the country's industry sectors (Welfens & Perret, 2014). (2) The total amount of money earned by a nation's total economic activities is measured under the gross national income (GNI), posing high correlation to the performance of key technological sectors (Chong et al, 2012). (3) The net amount between what the government spends and what it receives in taxes over a particular time period and the amount that the public sector owes its creditors under the government borrowing and debt volumes (DBD), as higher borrowing is found to divert money away from private sector investment (Cowling et al, 2018). (4) The total expenditure on research & development carried out in the nation per person is measured under the R&D expenditure per capita (GERD), as it is found to impact the stock of knowledge and the use of knowledge to devise new technological developments/ applications (Falk, 2017). (5) The average cost of labour per unit of output measured under the labour cost index (LCI), affecting the costs of technological developments due to the apparent cost impacts company pay for higher-level labour efforts (Adams, 2018). The measurement of Economic driver influence (PDI) uses data gathered from Chinese government, IMF and World Bank reports on China's macroeconomic environment between 2017-2021.

Political driver influence (PDI): Due to the subjectivity and high complexity of designing a criterion to determine influence of political and government interventions, Arts & Verschuren (1999) proposed a triangulation EAR instrument approach to measure political influence in (1) political players' own perception of their influence; (2) affected stakeholder's perceptions of the influence brought to bear; (3) researcher's analysis in the validity check on the basis of the indicators' goal achievement, intervention and anticipation. In application of Arts & Verschuren's (1999) triangulation EAR instrument approach, this study measures political driver influence (PDI) with objective indicators identified in empirical literature under five indicators. (1) The amount of government funding, grants and tax incentives designated to the development of blockchain technologies is measured in accordance to Ye et als' (2022) yearly total sum approach. (2) the numbers of established government sponsored pilot zones to support the research & development and innovative application of blockchain technologies in measured within an agglomerated environment setting according to Yu et al (2022). (3) The net volume of incubated blockchain projects and companies in government established pilot zones is measured as a proxy to illustrate the provided mentorship, assistance and practical support on blockchain technology developments, which are found to stimulate higher investments from private companies (Aysan et al, 2019). (4) The inclusion of Chinese national champions in the development of blockchain technology infrastructures and applications is measured via the net value of investments from Chinese national champions, representing the proxy to measure government supported state enterprise contribution to the design and implantation of key blockchain policies and plans (Wheeler, 2020). (5) The introduction of supportive policies that aid the development of blockchain technologies and applications with specialized privileges to stimulate private sector interests is measured under the ratio of Chinese provinces engaged in supportive blockchain development related policies. The measurement of Political driver influence (PDI) uses data gathered from Chinese government reports, Chinese blockchain patent report 2022, Chinese blockchain industry development report 2021-2022 and Ant-financial group report 2021-2022.

Blockchain development index (BDI): Due to the nascent nature of blockchain development studies, there is an apparent lack of unified approaches to measure the development of blockchain in country context, as numerous studies have attempted to measure its impacts (Loizou et al, 2019) or its performance in companies (Hong & Hales, 2021; Cao et al, 2022). Cao et al (2022) created a set of blockchain development indicators to investigate how the influence of blockchain development under a total factor productivity (TFP) model on listed blockchain companies. This study incorporates a similar approach when measuring blockchain developments across the overall Chinese fintech sector, utilizing the fundamental principle of TFP to compare total outputs relative to the total inputs used in production of the output. Therefore, in this paper a proxy is designed to measure the desired input indicator of the blockchain development index (BDI) under the amount of venture capital investment (VCI) injected into Chinese blockchain related companies between 2017-2021 as a means of measuring inputs into the sector. The desired output indicators are measured under the number of blockchain companies registered (BCR), the number of applied new blockchain patents (NBP) and the revenue of blockchain companies in China (RBC) between 2017-2021 by multiplying the base period from 2018, forming a proxy to measure the volumes of outputs from the sector relative to the total inputs over the defined period.

Chinese fintech market performance (CFMP): Empirical studies have attempted to measure fintech market performance under Tobin's q approach to gauge market performance by considering present profitability of fintech firms, as well as prospective growth in years to come to sum up total liabilities, market capitalization, minority and preferred equity over the value of total assets as shown in Dhiaf et als' (2022) study. However, the private and SMEs-dominated nature of the Chinese fintech sector raises apparent data accessibility challenges to access liabilities and equity related data. To overcome this, this study adopts key components from Chen et als' (2022) multidimensional attention to fintech (MAF) model, taking into account the total transaction volume of the Chinese fintech market and within specific fintech market segments (alternative financing, digital assets, digital investment, digital payment, neo-banking). In this paper, the Chinese fintech market performance (CHMP) is measured via SPSS software, in which the desired input indicator is Chinese fintech markets transaction volumes (in billion USD) between 2017-2021, as per the overall fintech market sector and across five key major Chinese fintech market segments. A correlation matrix of all measured latent constructs is shown in table 8 in Appendix.

The range of data used for empirical analysis differs across each measurement construct, involving large numbers and log transformation is used to make highly skewed distribution less skewed, enhancing the interpretability to meet the assumptions of inferential statistics (Changyong et al, 2014). A summary of descriptive statistics for all variables is presented in table 2.

Table 2: Summary of descriptive statistics

Variable	Observed values/ N	Mean	S.D	Min	Max	Skewness	Kurtosis	Shapiro-Wilk
GDP	100	4.01	0.06	3.95	4.10	0.80	2.00	0.96***
GNI	100	4.22	0.05	4.15	4.28	0.18	0.13	0.97***
GBD	100	1.78	0.06	1.71	1.85	0.41	-2.69	0.97***
GERD	100	2.27	0.15	2.12	2.44	0.27	-2.80	0.96***
LCI	100	2.11	0.02	2.09	2.14	-0.18	-0.64	0.97***
GF	100	11.15	16.30	1.00	39.60	1.99	4.00	0.98**
PZ	100	1.51	0.19	1.18	1.64	-1.89	3.71	0.96***
IC	100	1.37	0.51	0.48	1.78	-1.96	4.17	0.96***
NC	100	1.04	0.12	0.85	1.11	-1.46	1.40	0.96***
SP	100	1.17	0.45	0.60	1.72	-0.16	-1.71	0.98**
BCR	100	2.82	0.28	2.39	3.11	-0.96	0.86	0.97***
NBP	100	3.03	0.25	2.72	3.30	-0.41	-2.41	0.96***
VCI	100	5.09	4.68	0.28	11.06	0.08	-1.97	0.97***
RBC	100	2.30	1.94	0.46	5.27	0.99	0.18	0.97***
CFMP	100	0.62	0.35	0.25	1.15	0.78	-0.22	0.96***

*p<0.05, **p<0.01, ***p<0.001

Empirical analysis and findings

This chapter presents the empirical analysis and findings to fulfil research objectives (purposes) as prior mentioned in the introduction chapter. In order to examine the normality of latent variables, the skewness, kurtosis and Shapiro Wilk test values are tested. The skewness of the explanatory variable Chinese fintech market performance (CFMP) is 0.78 which demonstrates moderately positive skewed data patterns according to Groenveld et al’s (1984) moderate skewness between 0.5 and 1. The kurtosis is -0.22 which implies a platykurtic distribution as it is lower than 3, suggesting that the data set generally obeys a normal distribution with a lack of outliers and illustrate steady growth between 2017-2021. Similarly, the skewness of most variables is between 0.5 and 1 or -0.5 and -1, illustrating moderately skewed distributions, the variables GF, PZ, IC and NC have skewness less than -1 or greater than 1, suggesting a highly skewed data distribution. The kurtosis of all variables falls within the -7 to 7 range, as indicated by Hair et al (2010) to be considered acceptance and proves normal univariate distribution. The Shapiro-Wilk test W values all fall within the range between 0 and 1, the significance levels are greater than 0.05 and indicate strong normality as data do not significantly deviate from normal distributions. As the normality of latent variables are checked, validity and reliability testing is then performed prior conducting structural equation modelling (SEM) and multi group (SEM) to gain more in-depth understanding of Chinese fintech market performance impacts across five key market segments.

Validity and reliability

To examine the validity and reliability of the proposed conceptual framework for this study, factor loading is used to measure the variability among observed, correlated variables, this is measured under unstandardized and standardized factor loadings as Cudeck & O’dell (1994) considered these indices as the main statistical criteria for validity measurement. The reliability is checked through squared multiple correlations, considered by Kwan & Chan (2014) to be a useful tool to examine the coefficient of determination by measuring the proportion of the total variation explained by a statistical model. The results of the measurement model are shown in table 3, the standardized factor loadings column indicates that all variables have a standardized factor loading of above 0.88, illustrating high statistical significance in accordance to Phakiti’s (2018) rule of thumb where high factor loading is generally accepted at above 0.7 under the SEM approach. The reliability of all latent constructs is examined as the R2 (item reliability) measures the squared multiple correlations, all values are higher than the recommended level of 0.7 (Kwan & Chan, 2014), as the Cronbach’s Alpha values of all four latent constructs are also above the recommended level, measured at 0.93 (EDI) 0.91 (PDI) 0.88 (BDI) and 0.89 (CFMP) respectively and confirms high levels of internal consistency.

Table 3: Results of measurement model

Latent construct	**Observed indicators**	**Unstandardized factor loadings**	**Standardized factor loadings**	**Standard error**	**Z value**	**R^2 (item reliability)**
EDI	GDP	0.06	0.95***	0.01	0.06	0.93
	GNI	0.05	0.93***	0.01	0.05	0.92
	GBD	0.06	0.94***	0.01	0.06	0.94
	GERD	0.16	0.91***	0.02	0.15	0.88
	LCI	0.02	0.98***	0.01	0.02	0.96
PDI	GF	16	0.91***	0.07	1.30	0.87
	PZ	0.18	0.97***	0.01	0.19	0.95
	IC	0.5	0.92***	0.02	0.51	0.91
	NC	0.12	0.93***	0.04	0.12	0.91
	SP	0.44	0.92***	0.01	0.45	0.90
BDI	BCR	0.28	0.91***	0.01	0.28	0.88
	NBP	0.25	0.93***	0.04	0.25	0.88

	VCI	4.66	0.92***	0.02	1.68	0.90
	RBC	1.92	0.88***	0.01	1.94	0.87
CFMP	CFMP	0.35	1***	0.00	0.35	0.89

CFMP CFMP 0.35 1*** 0.00 0.35 0.89

*p<0.05, **p<0.01, ***p<0.001

Model fit: x2(100) = 280.3, AGFI = 0.98, CFI = 0.98, TLI = 0.95, RMSEA =0.048, SRMR = 0.071

The z value column illustrates the findings of convergent validity testing as the statistical significance of factor loadings are measured, it is apparent that all z value estimates fall within the recommended range of being lesser than 2 and higher than -2. The z value of all variables demonstrates apparent convergent validity of each construct, indicating one-dimensionality and they can be adequately explained by their respective latent constructs. To further assess discriminant validity and demonstrate that there are no or low correlation between measures of unrelated constructs, a confirmatory factor analysis (CFA) is performed to examine the fit between latent factors and their observed indicator variables (Brown, 2015). CFA testing is performed under a series of pairwise approaches, measuring one pair of constructs under non-constrained and constrained manners to eliminate the influence of construct pairs that pose significant values over non-significant pairs (Kline, 2015).

Structural equation model (SEM)

The validity and reliability of the measurement model have been tested and proven, allowing the proceeding to the SEM approach to measure multivariate causal relationships through testing direct and indirect effects of pre-assumed causal relationships formulated in research hypotheses. This section discusses the estimations of construct parameters, model fit indices and the testing of research hypothesis from the structural equation modeling method (SEM). The performed SEM incorporated the measurements factor loadings and regression coefficients between variable relationships as indicated in their designated paths as shown in Fig.2. The standardized factor loadings of all fifteen variables satisfy Phakiti's (2018) acceptance level of 0.7 and are thus statistically significant. The overall structural model demonstrates a strong fit in accordance to the chi square x2 value of 406.3, as the ratio of x2 fits well with the degree of freedom (280.3/100 = 2.8), the value of 2.8 is lesser than the acceptance level of 3 according to Bollen & Long (1993) hence representing a strong fit.

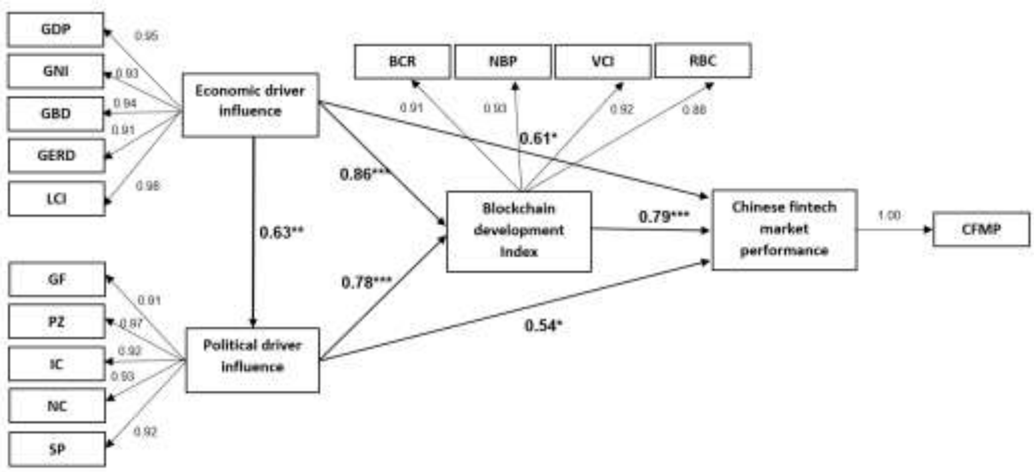

Fig.2 Structural equation model (SEM) results

*p<0.05, **p<0.01, ***p<0.001

Model fit: x2(100) = 280.3, AGFI = 0.98, CFI = 0.98, TLI = 0.95, RMSEA =0.048, SRMR = 0.071

The fitness of the structural model is tested by other indices including the adjusted goodness of fit (AGOF) that measures the fit between a hypothesized model and the observed covariance matrix (Xie & Zhu, 2019), the score of 0.98 indicates that the structural model is able to accurately predict 98% of both variances and co-variances. The comparative fit index (CIF) is used to examine the discrepancy between the data and the hypothesized model, adjusting for sample size as the value of 0.98 indicates as strong fit given its closeness to 1 (Bentler, 1990). The Tucker-Lewis index (TFI) is used to measure the relative reduction in misfit per degree of freedom, a score of 0.95 satisfies the recommended acceptance level of higher than 0.9 proposed by Marsh et al (1988) and indicates an acceptable fit. The root mean square error of approximation (RMSEA) is used for adjusting the sample size where chi-square statistics were used, the score of 0.048 falls within Kim et als' (2016) acceptance level where RMSEA values lesser than 0.05 is generally regarded as good fit. The standardized root mean squared residual (SRMR) is used to measure the average of standardized residuals between the observed and hypothesized covariance, the value of 0.071 falls under the rule of thumb proposed by Shi et al (2018) where values under 0.08 are generally accepted as having strong fits, as a value of zero indicates perfect fit.

The strong fit of the proposed structural equation model as reflected by the variety of aforementioned model fit index testing illustrate reliability and validity for examining hypothesized relationships between the pre-assumed latent constructs. The standardized estimates of the latent variable relationships from research hypotheses are shown in table 4. The calculated statistical significance of the regression coefficients between chosen variable relationships suggest that H1a, H1b, H1c, H1d, H1e, H2a, H2b, H2c and H3 are all accepted due to its recognized statistical significance. The H1b, H1e, H2a, H2c and H3 hypotheses demonstrate highly statistically significant standard estimates, indicating that economic driver influence is found to have highly positive effect on blockchain developments, this effect on blockchain development is found to have a mediating effect on the performance of Chinese fintech markets. Political driver influence is also found to have highly positive effect on blockchain developments, of which the effect on blockchain development also illustrate strong mediating effect on the performance of Chinese fintech markets. The relationship between blockchain development and the performance of Chinese fintech markets is found to be highly significant. Economic driver influence positively affects political driver influence, blockchain developments and Chinese fintech market performance. However, the mediation effect of via the combination of political driver influence and blockchain developments are found to be insignificant. To further investigate the impacts of economic driver influence and political influence on Chinese fintech market performance mediating by stimulated blockchain developments, further investigations toward five key Chinese fintech markets under a multi-group structural equation modelling is performed in the next section.

Table 4: Results of SEM hypothesis testing

Hypotheses	**Regression path**	**Standard estimates**	**Standard error**	**Critical ratio**	**Results**
H1a	EDI > PDI	0.63**	0.09	7	Accepted
H1b	EDI > BDI	0.86***	0.12	7.17	Accepted
H1c	EDI > CFMP	0.61*	0.11	5.55	Accepted
H1d	EDI > PDI > CFMP	0.61*	0.13	4.69	Accepted
H1e	EDI > BDI >	0.84***	0.32	0.84	Accepted

	CFMP				
H1f	EDI > PDI > BDI > CFMP	0.31	0.37	2.45	Rejected
H2a	PDI > BDI	0.78***	0.18	2.62	Accepted
H2b	PDI > CFMP	0.54*	0.22	4.33	Accepted
H2c	PDI > BDI > CFMP	0.77***	0.13	5.92	Accepted
H3	BDI > CFMP	0.79***	0.17	4.65	Accepted

*p<0.05, **p<0.01, ***p<0.001

Multi-group SEM model (MGSEM)

To further examine the model fit of the proposed structural equation model (SEM) for different segments of Chinese fintech markets, Chen et als' (2022) multidimensional attention to fintech (MAF) model is adopted to breakdown the general Chinese fintech industry into more specific and key emerging segments of alternative financing (AF), digital assets (DA), digital investment (DI), digital payment (DP) and neo-banking (NB). This enables the testing of EDI, PDI and BDI effects on different Chinese fintech market segments, anticipating potential variations in impacted effects. Therefore, the sample of 100 Chinese fintech market data is broken down into five groups including alternative financing (N=20), digital assets (N=20), digital investment (N=20), digital payment (N=20) and neo-banking (N=20), measuring their quarterly transaction value between 2017 and 2021 to illustrate the changes in the performances of these sectors. The performed multi-group analysis compares the regression coefficient across each assessed groups, measuring with the same constraints used in previous model fit index testing parameters in comparison to different parameters across groups as shown in table 5 below.

Table 5: Results of model fit index testing for invariance

Models	**X^2**	**df**	**CFI**	**AGFI**	**RMSEA**	**SRMR**
MG: Configural (x^2=163.71)	/	/	/	/	/	/
MG – MG2: Equal loadings	8.12	4.6	0.023	0.005	0.031	0.11
MG – MG3: Equal intercepts	21.32	5.1	0.017	0.007	0.028	0.13

The MGSEM results demonstrate strong model fit as the ratio of x2, the degrees of freedom, CFI, AGFI, RMSEA and SRMR model fit indexes have all remained within the acceptance levels, as there are no statistically significant differences between the configural, equal intercepts and equal factor loading models, illustrating metric invariance to facilitate substantiate multi-group comparisons of factor variances and covariances. Given the established metric invariance, the regression coefficients across all Chinese fintech market segment groups can be compared as shown in table 6. The regression coefficient of the MGSEM analysis indicate similar results to the overall Chinese fintech market, as economic driver influence (EDI) is found to have high statistical significance with blockchain development impacts (BDI) and the mediating of these impacts to positively influence the performance of the alternative financing, digital assets, digital investments and digital payments sector. Although a positively significant relationship is also found in neo-banking, the direct effects of EDI on BDI and the mediating effect of BDI on fintech market performance is relatively lower than the other four fintech market segments.

Table 6: Comparing MGSEM regression coefficients

	Alternative financing (AF)		**Digital assets (DA)**		**Digital investments (DI)**		**Digital payment (DP)**		**Neo-banking (NB)**	
Regression paths	**SE**	**CR**	**SE**	**CR**	**SE**	**CR**	**SE**	**CR**	**SE**	**CR**
EDI > PDI	0.63**	6.8	0.61**	7.1	0.55**	7.6	0.62**	6.74	0.41*	6.77
EDI > BDI	0.87***	7.13	0.88***	7.32	0.73***	7.72	0.87***	7.11	0.69**	6.34
EDI > CFMP	0.63*	5.31	0.60*	5.63	0.51*	5.83	0.65*	5.29	0.51*	5.35
EDI > PDI > CFMP	0.52*	4.41	0.59*	4.81	0.50*	4.92	0.51*	4.38	0.51*	4.36
EDI > BDI > CFMP	0.83***	0.99	0.80***	0.91	0.77***	1.31	0.77***	0.98	0.67**	0.67
EDI > PDI > BDI > CFMP	0.21	2.31	0.28	2.21	0.19	2.1	0.32	2.56	0.14	2.73
PDI > BDI	0.82***	2.5	0.81***	2.41	0.76***	2.89	0.79***	2.31	0.63**	2.53
PDI > CFMP	0.56*	4.02	0.51*	4.11	0.41*	4.32	0.41*	3.98	0.47*	4.27
PDI > BDI > CFMP	0.77***	5.32	0.79***	5.66	0.75***	5.87	0.73***	5.34	0.62**	5.59
BDI > CFMP	0.83***	4.4	0.81***	4.7	0.73***	4.91	0.78***	4.32	0.78***	4.43

SE = Standardized estimates, CR = critical ratio

The positive impacts of political driver influence (PDI) on blockchain development (BDI) and the mediating role of these impacts on fintech market performance are found to also have highly statistically significant relationships across the AF, DA, DI and DP fintech sectors. Similarly, despite a positive significance established between PDI and BDI, EDI on CFMP via BDI, the strength of the regression coefficient is substantially lower than the other four Chinese fintech market segments, indicating that neo-banking market performance is lesser driven by economic, political driver influences and blockchain developments. The positive relationship between blockchain development (BDI) and fintech market performance (CFMP) remains highly statistically significant across all five key Chinese fintech market segments, illustrating the apparent impacts that blockchain development has on the performance of all Chinese fintech markets. Additionally, the effects of EDI on CFMP mediated by a combination of PDI and BDI are found to be insignificant across all five key fintech market segments.

Discussion and conclusion

This study critically examined the relationships among macroeconomic environment drivers, political interventions, developments of blockchain technology and their effects on the performance of the Chinese fintech market. The findings of this study confirm that improvements in macroeconomic environment conditions and supportive government interventions would help to stimulate better developments in blockchain technologies, ultimately improving the performance of the Chinese fintech market which has increased its adoption of blockchain technologies in recent years (Zhong et al, 2022). The study revealed that improvements in macroeconomic environment conditions measured under the latent construct of economic driver influence (EDI) has a significant positive effect on blockchain developments, reinforcing the arguments of Welfens & Perret (2014), Zagorchey et al (2011), Chong et al (2012), Mubarak et al (2020) and Raghupathi & Raghupathi (2017) where a range of macroeconomic environment indicators have been used to study its impacts on technological developments. The findings of this study contributed to the identified literature gap where inadequate studies have attempted to explore the relationship between macroeconomic environment factors and the development of blockchain technologies.

The influence of supportive political interventions is also found to have significant positive effect on blockchain development (BDI) measured under political driver influence (PDI), the identified relationship also reinforced the arguments of Ye et al (2022), Guo et al, 2018), Yu et al (2022), Cai et al (2011), Zhang et al (2018) and Zhong et al (2022) that attempted to quantify the nature of political factors to measure its influence on the development of new technologies. The findings of this study focused specifically on a range of constructs relevant to blockchain specific government interventions, combining the approaches used by Liu (2018), Aysan et al (2019) and Lim et al (2019) to offer a new latent construct design in measuring political intervention impacts on blockchain developments. Additionally, the findings indicate that supportive political intervention especially in the amount of funding given, number of established pilot zones to stimulate blockchain developments and blockchain-friendly policies have inevitably promoted greater blockchain developments across the 29 regions and provinces incorporated in analysis. The role of blockchain developments caused by both economic driver influence (EDI) and political driver influence (PDI) is found to positively mediate the relationship on Chinese fintech market performance, as improvements in macroeconomic environment conditions and increasing political support have contributed to higher levels of blockchain developments, ultimately generating positive impacts on Chinese fintech market performance which adds to the identified research gap and offers new insights to both the academic and practitioner fields.

The extension to multi-group analysis revealed that the four key Chinese fintech market segments of alternative financing (AF), digital assets (DA), digital investments (DI) and digital payment (DP) demonstrate similar statistically significant relationships with economic driver influence (EDI), political driver influence (PDI) and blockchain development (BDI), suggesting that all four segments are positively effected by these latent variables. However, the Chinese fintech market segment of neo-banking demonstrated relatively weaker relationships with the aforementioned latent variables, potentially due to the nascent nature of the segment that has only received increasing popularity in recent years or that blockchain technologies have yet to be optimally applied in this fintech market segment, raising the need for future studies to explore further. The findings of this study is consistent with the majority of existing macroeconomic, policy and technological development literature, highlighting the influential role of macroeconomic environment factors and political intervention on the development of technologies, and its application in market practices to optimise performance levels. This study contributed to the identified gap in literature where inadequate studies have attempted to explore Chinese specific macroeconomic and political factors on the rapidly emerging field of blockchain technologies, contributing with the design of new parameters for measuring economic and political drivers on blockchain development that can offer valuable foundation in future studies. The findings on the mediating role of blockchain developments on the overall Chinese fintech market segment and within its five key segments contributed with new insights to recognize its importance to the blockchain applications of future fintech operations in China.

List of abbreviations

BCR	Number of blockchain companies registered
BDI	Blockchain development index
CFMP	Chinese fintech market performance
EDI	Economic driver influence
GBD	Government borrowings & debts
GDP	Gross domestic products per capita
GERD	Gross expenditure on research & development
GF	Amount of government funding
GNI	Gross national income
IC	Net volume of incubated project projects in government pilot zones
LCI	Labour cost index
NBP	Number of applied new blockchain patents
NC	Net value of investments from Chinese national champions
PDI	Political driver influence
PZ	Number of established government-sponsored pilot zones
RBC	Revenue of blockchain companies in China
SP	Supportive policies in ratio of Chinese provinces engaged
VCI	Amount of venture capital investment

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