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THE IMPLICATIONS OF FINTECH FOR TRADITIONAL BANKING AND REGIONAL ECONOMIC DEVELOPMENT IN CHINA

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Abstract

Over the past decade, the emergence of FinTech has reshaped the landscape of the financial sector worldwide. Although there are several alternative approaches to defining FinTech, a worldwide and generally accepted definition, as well as a unified, standard, and comprehensive index, is still absent. Due to data limitations, its potential effects are still far from clear. This thesis attempts to contribute to the literature by analyzing the effect and implications of FinTech for traditional banking and regional economic development in China. The general conclusion highlights the positive impacts of FinTech on both bank diversification and economic development. However, the magnitude of the positive connections strongly depends on different bank tiers and regional economic development levels.

I would like to dedicate this thesis to my parents, to my husband L Changyang and our son Leon, and also to my academic mentors: Emili Tortosa-Ausina and Jesús Peiró-Palomino, to whom I am deeply grateful for their patience and help.

Contents

List of Tables

List of Figures

Chapter 1

Introduction

1.1. The emergence of FinTch

In the past decade, digitalization has strongly affected many industries including the financial sector, which is reflected by the emergence of ”FinTech”. Since 2010, FinTech has become a highly discussed word in both technological and financial areas. It is characterized by new technologies of artificial intelligence, cloud computing, blockchain, and big data. Its rapid growth has reshaped the traditional financial sector by, for instance, changing the way of providing financial products and services and the nature of competition in the financial sector.

In the big picture of the global FinTech market, the US has been in the leading position, accounting for 57% in 2018. KPMG (2020) points out that, U.S.$ 59.8 billion was invested in FinTech across M&A, venture capital (VC) and private equity (PE) in the US in 2019, which sets a new annual record. The FinTech industry of China is also amongst the top leaders in terms of market volume, growth rate, garnering increasing international following and innovation capabilities (Xiang et al., 2017). Although its financial market was regarded undeveloped, China has already become home to some big fintechs in the world, such as Alibaba, which started as an e-commerce firm and is now one of the largest fintechs around the world (Kumar, 2014). On the European FinTech landscape, total investment in FinTech in 2017 is around $4.7 billion and is expected to keep raising (Miteva, 2018). Much of FinTech in Europe is focused on the UK, and is mainly based internally with limited cross-border flows (Vives, 2017). Alongside with the UK, Germany is an important FinTech market in Europe as well. It has a healthy FinTech investment environment and FinTech ecosystem, which can be demonstrated by the growing deal flow, the increasing deal size and the expanding investment volumes (EY, 2017). In the first three quarters of 2018, the value of FinTech investment in Germany has reached $665.3 million, which is 62.3% higher than 2017’s total (Fintechglobal, 2018). The largest FinTech deal in 2018 in Germany with $160 million was raised by

N26, which is a Berlin-based mobile bank.

Financial innovation began in the late 1950s and early 1960s with the rise of credit cards, and then followed by the development of debit cards, automated teller machines (ATMs) and telephone banking in the 1970s and 1980s (Dermine et al., 2016). It is, however, more difficult to establish when FinTech started, due to the absence of a worldwide and generally accepted definition (Zhang, 2017). This issue is critical, since otherwise, we cannot easily assess its relationship to phenomena such as bank diversification and economic development, the cases we are dealing with in this thesis. Several alternative approaches exist to define, all sharing the same underpinnings: the combination of technology and finance in order to provide new financial products and services, offering a different way for customers to operate with them.

The Financial Stability Board (FSB, 2017) defined FinTech as "technologically enabled financial innovation" that could result in new business models, applications, processes, or products with an associated material effect on financial markets and institutions, and the provision of financial services. Han (2016) points out that FinTech is simply a combination of the financial industry and advanced technologies—i.e. Internet technology. From a more in-depth understanding, FinTech allows advanced technology and internet companies to provide low-entrance standard financial services with the help of the internet, cloud services and big data. Li (2016) describes FinTech as a business model that makes use of advanced technologies to offer financial services more efficiently, and to drive future development of the financial industry.

The Basel Committee on Banking Supervision (BCBS) classifies FinTech activities into the following four categories: (i) payment, clearing and settlement services; (ii) credit, deposit and capital raising services; (iii) investment management services; and (iv) market support services (BCBS, 2018) (see Table 1.1).

Table 1.1: FinTech services

Payments, clearing and settlement		**Credit, deposit and capital rising**	**Investment management**	**Market support**
Retail	Wholesale	Lending marketplace	Robo-advice	Portal and data aggregator
Mobile wallets	Foreign exchange wholesale	Crowdfunding	E-trading	Cloud computing
Peer-to-peer transfers	Digital exchange platform	Mobile banks	Copy-trading	Distributed ledger technology
Digital currencies		Credit scoring	High-frequency trading	Data applications

The first three categories of FinTech services are closely related to traditional banking, which could result in a more significant impact on the industry. The BCBS report shows that payment, clearing and settlement services are the major services provided by FinTech firms, followed by credit, deposit and capital raising. Although market support services are not typical financial services or technologies, they are commonly regarded as third-party services aimed at financial institutions. In this sense, the Financial Stability Board (FSB, 2017) points to three common drivers of FinTech. From the demand side, increasing expectations of customers for more convenient financial services with lower costs promote FinTech development. From the supply side, developing technologies (e.g. big data, cloud computing and mobile technologies), and improving financial regulation, are the factors underlying the development of FinTech.

1.2. FinTech development in China

FinTech in China targets the "small and micro" level, constantly innovating credits by using big data mining to greatly reduce information asymmetry and financing costs of small and micro firms (Yun and Ruibo, 2014). Factors driving the rapid growth of FinTech include support from the high-speed development of information technology, increasing real economy and the demand for diversified financial services, insufficient serviceability of the traditional financial industry, changing consumer behavior, and regulatory arbitrage of fintechs. The number of mobile netizens in China hit 817 million in 2018, which accounts for 58.7% of the country's total population and represents a 17.6% increase on figures for the same period in 2016. As Xiang et al. (2017) point out, the continuously expanding scale of mobile users demonstrates the rapid spread of network connections and smart technologies, and the enormous market demand to encourage financial inclusion and to serve the real economy.

Following Cheng and Qu (2020) and Shim and Shin (2016), we divide the development of China's FinTech industry into the following four phases.

Problematization (before 2003): The financial industry in China before 2003 faced significant problems in the context of the state-owned banking system, for instance, commerce-related fraud and insufficient financial infrastructure. Government interventions and direct control of finance-related activities and business operations were commonplaces.

Internet finance (2003–2009): The stage between 2003 and 2009 is regarded as the infancy of Internet finance. In 2003, *Alibaba* started Taobao, its online customer-to-customer (C2C) marketplace, providing payment solutions in the same way as eBay, with which it entered into direct competition. In 2005, *Alibaba* introduced *Alipay*, an online escrow payment system, which led to great success in e-commerce transactions (Wang, 2014). Traditional financial institutions applied internet technologies to carry our electronification and office automation. During this stage, the Chinese government tried to modernize the payment system, and some related policies were released to facilitate its development and maintain financial stability.

Mobilization (2010–2015): In the development stage from 2010 to 2013, although a series of regulations were introduced to limit online payment services, mobile phone payment evolved and more Chinese internet firms were spurred by Alibaba's success to enter the emerging FinTech arena. Meanwhile, to achieve the ultimate goal of "full banking service coverage", the government started to work on financial inclusion and diversify financial products and services in order to greatly improve financial accessibility in rural areas and for small-to-medium businesses (Sparreboom and Duflos, 2012). Since 2014, China's FinTech industry has entered its mature stage. Internet-based private banking began to gain ground on online or mobile payment, which presented a serious challenge to the traditional financial industry. According to the PBOC (2015), five private banks, including two internet-based banks, were licensed in 2014, and approval was granted for 13 privately-controlled financial leasing companies, consumer finance companies and finance companies affiliated with corporate groups in the same year.

FinTech (after 2015): At this stage, finance is combined with emerging technologies, such as artificial intelligence, big data, cloud computing and blockchain. Emerging technologies encourage traditional banks to optimize their business models and improve their efficiency. According to Vives (2017), under the impact of rapid FinTech development, traditional financial institutions can either partially or totally partner with fintechs, or fight against them. In China, state-owned banks, for instance, the Industrial and Commercial Bank of China (ICBC), prefer to have their own internet financial strategies (Chen et al., 2017). Whereas some national shareholding commercial banks and city commercial banks, such as China CITIC Bank and Beijing Bank, have established strategic partnerships with Baidu[1] and Tencent.

1.2.1. Measurement of FinTech in China

As indicated above, FinTech is still absent from a unified, standard and comprehensive index. In previous empirical studies, factors (e.g., related to bank patents, third-party payment scale, number of banks' external FinTech competitors, and Internet-payment to online-banking transaction ratio), are used to proxy for FinTech-related activities (Guo and Shen, 2016; Li et al., 2017; Phan et al., 2020). However, the indicators are informative, they do not fully reflect all the possible array of FinTech activities. Focusing on the Chinese context, there are three popular approaches to measuring FinTech activities. The

[1]Baidu is one of the tech giants in China, specialising in AI, and internet-related services and products.

first one is to build a FinTech index by text mining to measure FinTech development (see, for instance, Hou et al., 2016; Dong et al., 2020; Cheng and Qu, 2020, among others). To this end, several scholars have relied on the Baidu search index, an Internet data mining and analyzing tool widely used in China (Dong et al., 2020). The second one uses the digital financial inclusion index of China compiled by the Digital Finance Center of Peking University (see, for instance, Fu and Huang, 2018; Qiu et al., 2018; Deng et al., 2021). The third approach is to construct a business-based FinTech index (Lee et al., 2021). Lee et al. (2021) collected enterprise-level data on the total number of FinTech companies, the total registered capital, the total number of financing events and the total amount of financing during the period of 2003–2017 to represent FinTech development in their study.

The second measurement – i.e. the Peking University Digital Financial Inclusion Index, is used in this thesis to reflect FinTech development in China. This index uses the massive database of Ant Financial's[2] trading accounts to report the degree of FinTech development in Chinese regions from multiple perspectives (Guo et al., 2020). Three main principles have been followed in the index construction. First, both breadth and depth have been taken into account. In order to comprehensively and accurately reflect the substance and features of FinTech development, it is important to consider not only the population and region covered by FinTech, but also its usage depth. Second, both vertical and horizontal comparability has been considered. FinTech development is a dynamic process, which is changing with the growth of the financial system and economic society. In addition, due to gaps in endowment, levels and structures of economic development, policies and institutions, different regions may deliver different FinTech performances. Thus, comparability across years (vertical) and across regions (horizontal) should be ensured in the design and construction of the index. The third principle is to reflect the multilevel nature and diversity of financial services. With the continuous innovation and evolution of financial services, an indicator system not only includes banking services (mainly credit), but also includes payment, investment, insurance, monetary funds, and credit investigation, among other services is required to holistically depict FinTech.

Based on the principles described above, the Peking University index captures three main individual dimensions of FinTech development, namely coverage breadth, usage depth and digitization. Table 1.2 presents the specific indicators of the index. The calculation method is first to nondimensionalize the 33 specific indicators by adopting the logarithmic efficacy function method. The formula is as follows:

[2]Ant Financial is one of the most powerful FinTech companies in China. The widely used third-party payment application *Alipay* and the world leading money market fund *Yu'e Bao* are owned by Ant Financial.

Table 1.2: Specific indicators for the Peking University digital financial inclusion index

Level 1 Dimension	Level 2 dimension		Indicator
Coverage breadth	Account average rate		Number of Alipay accounts owned by per 10,000 people
			Proportion of Alipay users who have bank cards bound to their Alipay accounts
			Average number of bank cards bound to each Alipay account
Usage depth	Payment		Number of payments per capita
			Amount of payments per capita
			Proportion of number of high frequency active users (50 times or more each year) to number of users with frequency of once or more each year
	Money funds		Number of Yu'ebao purchases per capita
			Amount of Yu'ebao purchases per capita
			Number of people who have purchased Yu'ebao per 10,000 Alipay users
	Credit	Individual User	Number of users with an Internet loan for consumption per 10,000 adult Alipay users
			Number of loans per capita
			Total amount of loan per capita
		Small & micro business	Number of users with an Internet loan for small & micro business per 10,000 adult Alipay users
			Number of loans per small & micro business Average amount of loan among small & micro business
	Insurance		Number of insured users per 10,000 Alipay users
			Number of insurance policies per capita
			Average insurance amount per capita
	Investment		Number of people engaged in Internet investment and money management per 10,000 Alipay users
			Number of investments per capita
			Average investment amount per capita
	Credit investigation		Number of credit investigations by natural persons per capita
			Number of users with access to credit-based livelihood services (including finance, accommodation, mobility, social contact, etc.) per 10,000 Alipay users
Digitization	Mobility		Proportion of number of mobile payments
			Proportion of total amount of mobile payments
	Affordability		Average loan interest rate for small & micro businesses
			Average loan interest rate for individuals
	Credit		Proportion of number of Ant Check Later payments
			Proportion of total amount Ant Check Later payment
			Proportion of number of "Zhima Credit as deposit" cases (to number of full deposit cases)
			Proportion of total amount of "Zhima Credit as deposit" (to amount of full-deposit)
	Convenience		Proportion of number of QR code payments by users
			Proportion of As above, please clarify with "Average amount" or "total amount". of QR code payment by users

Source: Guo, F., Wang, J., Wang, F., Kong, T., Zhang, X., and Cheng, Z. (2019). Measuring the development of digital financial inclusion in China: Index compilation and spatial characteristics. *Institute of Digital Finance, Peking University*

$$d = \frac{logx - logx^{'}}{logx^{h} - logx^{'}} \times 100 \quad (1.1)$$

for positive indicators, the 95% quantile of the actual indicator value in each region in 2011 is taken as the upper limit x^h, and the 5% quantile as the lower limit $x^{'}$; for negative indicators, the 5% quantile is x^h, and the 95% quantile is $x^{'}$. In addition, the value is winsorized beyond the limits in order to smooth the indicator and avoid the occurrence of extreme values.

The second step is to determine weight by combing both subjective weighting and objective weighting. Table 1.3 shows the decision matrix, which is based on the relative importance of the three dimensions. As for the six dimensions under "Usage depth", the complexity, risk and popularity of financial services are chosen as criteria (Table 1.4). The lower the complexity/risk, or the higher the popularity, the lower the weight, and vice versa. The weight of the four dimensions under "Digitization" is decided upon the influence on real life and the level of service maturity. The decision matrix of digitalization is shown in Table 1.5. The weight vectors corresponding to three individual dimensions shown in Table 1.6 are obtained by normalizing the maximum eigenvalue of the decision matrix passed the consistency check .

Table 1.3: Decision matrix of the Digital Financial Inclusion Index

	Coverage breadth	Usage depth	Digitization
Coverage breadth	1	2	3
Usage depth	1/2	1	2
Digitization	1/3	1/2	1

Table 1.4: Decision matrix of usage depth

	Payment	Monetary fund	Credit investigation	Insurance	Investment	Credit
Payment	1	1/2	1/3	1/4	1/5	1/6
Monetary fund	2	1	1/2	1/3	1/4	1/5
Credit investment	3	2	1	1/2	1/3	1/4
Insurance	4	3	2	1	1/2	1/3
Investment	5	4	3	2	1	1/2
Credit	6	5	4	3	2	1

Table 1.5: Decision matrix of digitization

	Credit	Convenience	Affordability	Mobility
Credit	1	1/2	1/3	1/4
Convenience	2	1	1/2	1/3
Affordability	3	2	1	1/2
Mobility	4	3	2	1

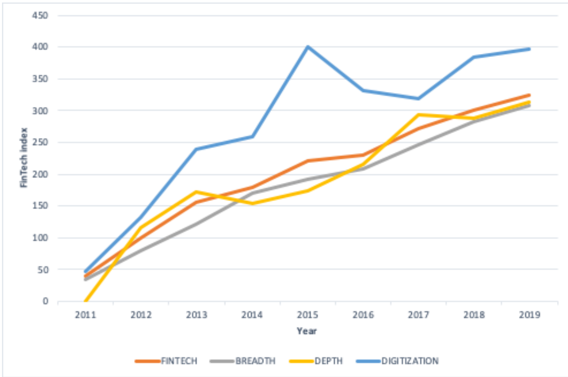
Table 1.6: Weight vectors of the Digital Financial Inclusion Index's three dimensions

Level 1 dimension	Level 2 dimension
Coverage breadth (54%)	
Usage depth (29.7%)	Payment (4.3%), monetary fund (6.4%), credit investigation (10.0%), insurance (16%), investment (25.0%), credit (38.3%)
Digitization (16.3%)	Credit (9.5%), convenience (16.0%), affordability (24.8%), mobility (49.7%)

The final step is to synthesise the index by using the weighted arithmetic mean (Guo et al., 2019). A bottom-up layer-by-layer sequence is followed for the synthesis. It means that the indicators on each hierarchy are firstly computed and then weight and unit the indicators into the overall index. Particularly, considering the different start times of the six financial services under "Usage depth", they are included by the time sequence. In addition, weighting normalization is used to ensure index stability.

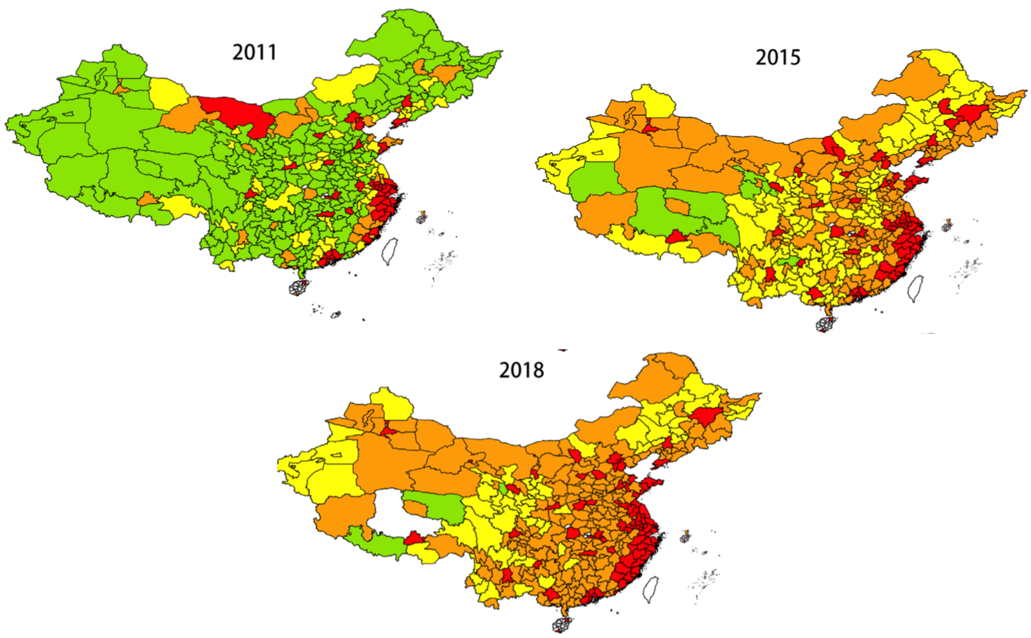
Figures 1.1 and 1.2 provide more features of the index. Figure 1.1 intuitively presents the leapfrog development of FinTech, as well as its three main dimensions, during 2011-2018. FinTech and its three dimensions have fluctuated, but have developed at a fast pace overall since 2011. The growth of $DIGITIZATION$ level is the most rapid between 2011 and 2015, followed by $BREADTH$ and $DEPTH$, and reached its peak in 2015. Since 2015, as the FinTech index reached a certain level in terms of $DIGITIZATION$, $DEPTH$ development has accelerated and become an important driver of FinTech growth nationwide. While it has experienced a slight decline in 2018 due to the downward trend of monetary funds and investment under the impact of policy constraints and other factors (Guo et al., 2019). Figure 1.2 presents relative city rankings of the digital financial inclusion index in 2011, 2015 and 2018. It shows spatial distribution changes of the index over the three periods. It can be seen that, in 2011, the gap in FinTech development is large among cities. The first echelon was concentrated in some big cities such as Shanghai, and most cities were in the fourth echelon; the first echelon expanded to southeast coastal cities and central cities at regional level in 2015, while the second and third echelons developed; and in 2018, the majority of the cities were in the first and second echelons, which implies that the regional gap of FinTech development had narrowed.

Figure 1.1: FinTech growth in China



Notes: This figure takes the mean value of FinTech index, which is compile by Peking University, at provincial level.

Figure 1.2: Relative rankings of cities in terms of overall index



Source: Guo, F., Wang, J., Wang, F., Kong, T., Zhang, X., and Cheng, Z. (2019). Measuring the development of digital financial inclusion in China: Index compilation and spatial characteristics. *Institute of Digital Finance, Peking University*

Note: By taking the highest–level index of the year as the benchmark, cities in red are the first echelon with an index higher than 80% of the benchmark index; cities in orange are the second echelon (70%–80%); cities in yellow are the third echelon (60%–70%); cities with an index lower than 60% are the fourth echelon in green. Taiwan, Hong kong, Macao and some other cities are in white due to lack of data.

1.3. Traditional banking in disruptive times

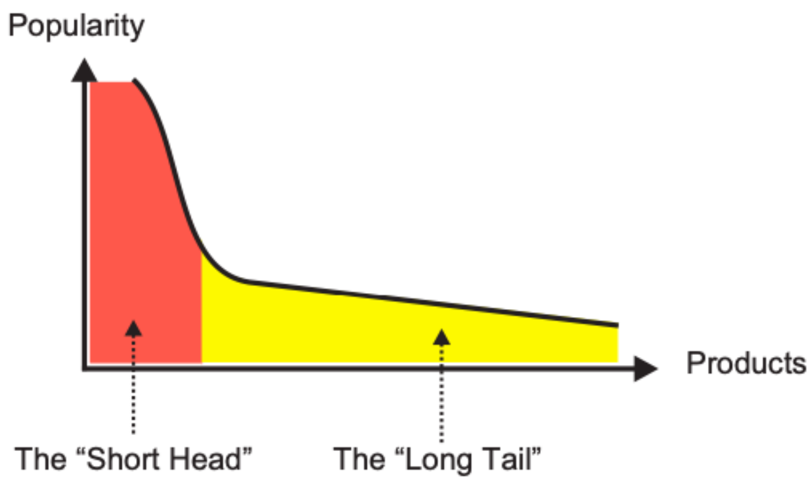
1.3.1. FinTech and traditional banks: theoretical background

The banking sector is undergoing unparalleled changes in the context of digital transformation. This section discusses the mechanisms linking FinTech and traditional banks from a theoretical perspective. The long tail theory, the Coase theorem, and the industry convergence theory are three main theories adopted to explain the development of FinTech and its effects on traditional banks. The long tail theory explains FinTech's variant and its future development; the Coase theorem explains how FinTech might affect traditional commercial banking; finally, according to the industry convergence theory (Pietronudo et al., 2022), FinTech encourages traditional banks to transform and provide innovative products and services in order to meet new customers' needs.

Specifically, the long tail theory (Figure 1.3) came into its own with the development of the internet, cloud computing services, big data and artificial intelligence. It was first raised by Chris Anderson in 2004 to describe the phenomenon that various niche products represent great future opportunities for businesses, having the potential to increase their share of total sales in disruptive times (Anderson, 2006). Prior to the "Long Tail" concept, the Pareto Principle (also known as the 80/20 rule) is commonly used by economists to explain the pattern of sales concentration (Brynjolfsson et al., 2011). It means that 80% of sales are generated by 20% of brands or products in the market. There exists another interpretation that 80% of the market is taken by 20% of the customers. The new internet-based business model is difficult to be explained by the Pareto Principle. Then the long tail concept emerges, and Anderson uses it to explain the business model of Apple, Amazon and Yahoo (Anderson, 2006). In the financial industry, traditional commercial banks preferred to provide lending services to large firms rather than SMEs in the tail. However, recent technological innovation reduces transaction costs and information asymmetry in areas such as micro-credit and mobile payments, and has enabled some financial institutions to deal with their long-tail customers in a rapid and low-cost way (Dai and Taube, 2019). Therefore, compared to the head market, the long-tail FinTech market shows greater competitive advantages.

The Coase theorem is regarded as a significant foundation for modern economics. It was originally discussed by Ronald Coase in his paper *The Nature of the Firm*, in 1937 (Coase, 1937). Roughly, the theorem states that when transaction costs are sufficiently low or negligible, bargaining will generate a Pareto-efficient outcome, which is unaffected by the initial allocation of property (Coase, 1960). Transaction costs are often referred to as information-seeking costs, bargaining costs, monitoring costs and law enforcement costs (Iman et al., 2018). However, the application of the Coase theorem is criticized by some economists who point out that real-world transaction costs are rarely

Figure 1.3: The long tail theory



Source: Anderson, C. (2006).The long tail: Why the future of business is selling more for less. Hyperion.

zero or sufficiently low to enable efficient bargaining. In this sense, the development of FinTech is in accordance with Coase's theorem since financial transaction costs tend to be greatly reduced with the rapid growth of technological innovation. This might, in turn, dramatically increase the efficiency of financial markets, resulting in a declining importance for banks as financial intermediaries.

The industry convergence theory has emerged with a focus on information technology and communications (Yoffie, 1996; Lei, 2000; Stieglitz, 2003; Weaver, 2007). It is described as the blurring of boundaries between two or more different industries by combining technology, scientific knowledge and markets, which play an increasingly crucial role in shaping industries and markets (Curran et al., 2010; Kim et al., 2015). The development of the internet, big data applications and telecommunications encourage the transformation of traditional industries, including the financial sector. Financial firms not only speed up the pace of their technological innovation, but also integrate product or service features from other markets to expand the scope of their products or services, which is linked to eventual industry convergence (Kim et al., 2015).

Several observers, such as Carney (2017) and Harrist (2017), have welcome the emergence of FinTech, claiming that it could radically transform financial services through more convenient, more secure, and cheaper transactions (Chen et al., 2019). Drasch et al. (2018) argue FinTech has a strong effect on the banking industry, providing both opportunities for and threats to banks. From the positive perspective, operation efficiency created by contestability in the FinTech context contributes not only to stabilizing financial institutions' business models, but also to the whole financial system and the real economy (Brock, 1983). Weller et al. (2013) point out that greater institutional diversity and decentralization in the financial system can be one way to better manage macroeconomic risks. From the micro aspect, big data and other technologies-based credit systems can reduce transaction risk (Dynan et al., 2006), and cloud computing-based applications can smooth banks' operations, improve internal management efficiency, and expand organizational scale (IMF, 2017). Related to this, in his study Philippon (2016) identifies a potentially positive impact on financial stability through increased competition in the financial industry caused by FinTech's development. In addition, Jagtiani and John (2018) find that FinTech growth has penetrated areas that are underserved by traditional banks, and plays an increasing role in shaping the relationship between finance and banking.

However, as mentioned above, the market share of traditional banks is diminishing due to the increased activities of FinTech shadow banks. Buchak et al. (2018) report that, due to the increased regulatory burden and disruptive technologies, shadow bank market share nearly doubled from 30% in 2007 to 50% in 2015 in the U.S. credit market. FSB recognizes that FinTech presents some threats, which it divides into two categories: micro-financial risks and macro-financial risks (FSB, 2017) (see Table 1.7). Micro-financial risks are linked to the vulnerabilities of individual companies, sectors, or financial market infrastructures under shocks. Macro-financial risks refer to system-wide threats to the financial system which could result in financial instability. In addition, Stulz (2019) finds that innovation and diversification in traditional commercial banks are less profitable. Considering the difficulty of managing highly diversified, but heavily regulated traditional banks effectively, as well as the potential obvious operational costs, banks could opt to specialize in times of rapid change.

The Economist Intelligence Unit's 2015 Telstra report (EIU, 2015) highlights the crucial role of cooperation between banks and FinTech in fostering innovation. In this vein, Drasch et al. (2018) find that banks prefer to cooperate with fintechs as service providers to avoid expensive integration efforts, although fintechs might be unwilling to sell their innovations. In order to win the competition, banks not only have to deal with challenges from potential disruptors, but more importantly, also collaborate with tech firms (Hung and Luo, 2016). According to Jagtiani and John (2018), FinTech platforms, such as LendingClub, have higher market shares in areas with fewer bank branches, and a more challenging environment. In light of the declining number of bank branches, FinTech may have an important role to play in filling the financial services gap in areas with fewer bank branches–the so-called banking deserts (Hegerty, 2016). However, to date, the negative aspects of the cooperation between banks and fintechs have not been examined so intensely.

1.3.2. Specialization and diversification in banking

The connection between FinTech and bank diversification strategy is one of the focuses of this thesis. The literature on bank diversification can be reviewed from a variety of

Table 1.7: Micro- and macro-financial risks

Micro-financial risks		Macro-financial risks	
Risks	**Impacts on financial stability**	**Risks**	**Impacts on financial stability**
Maturity mismatch	Create rollover risk	Contagion	Leads to general loss of confidence in financial institutions
Liquidity mismatch	Results in operational risk, disrupting markets		
Leverage	Difficult to stand losses from any market, credit or other risks with higher leverage	Procyclicality	Exacerbated degree and impact of fluctuation in economic growth and market price over the short and/or long term
Governance/ process control	Risk of direct disruption in providing financial services or infrastructure		
Cyber risk	More cyber attacks in financial activities	Excess volatility	Adverse outcomes caused by the overreaction of the financial system to news
Third-party reliance	Increasing systemic risk		
Legal/regulatory risk	Damaged confidence in the system with regulatory arbitrages	Systemic importance	Risk amplified by systematically important institutions through moral hazard
Business risk of financial market infrastructure(FMI)	Leads to financial services' withdrawal and impaired functions		

angles. An important strand evaluates the benefits of bank diversification related to the reduction of costs, raising profits and increasing stability (see, for instance, Boyd and Prescott, 1986; Hughes et al., 1999; Cerasi and Daltung, 2000; Stein, 2002; Elsas et al., 2010, among others). According to Boyd and Prescott (1986), under intermediation theories, diversification gives banks credibility as screeners or monitors of borrowers with lower costs. Cerasi and Daltung (2000) provide an additional explanation for why it is beneficial to diversify products and services, namely, that bank diversification could increase the incentives of bank owners to monitor lenders. According to Stein (2002), diversification has positive effects on banks through economies of scope. Elsas et al. (2010) use a comprehensive framework to investigate the direct and indirect effects of diversification on banking firms, and find that diversification is positively related to bank profitability. From the risk perspective, Hughes et al. (1999) examine how consolidation affects the risk of insolvency and point out that the risk of bank insolvency declines through diversifying the coverage of industries, categories of loans and maturity, and geographic area.

However, Morgan and Samolyk (2003) suggest that, depending on preferences, diversification could lead to an increase in risk. Berger and Ofek (1996), Servaes (1996) and Denis et al. (1997) indicate that it is beneficial for banks to concentrate on specialized products with management expertise, and to leave diversification to investors themselves. According to Lang and Stulz (1994), Berger and Ofek (1995), Boyd et al. (1998) and Park (2000), diversification in the banking industry is linked to an increasing risk of insolvency owing to the conflicts of interest between managers and shareholders, as well as between managers and debt holders. Santomero and Eckles (2000) also argue that, since a bad outcome in any single activity may affect the whole business line and its core franchise, bank diversification could result increase in the instability of a firm.

De Jonghe (2010) points to other risky implications, finding that revenue diversification will increase the systematic risk of banking firms, implying that the stock prices of diversified banks are more sensitive to market fluctuations than those of focused banks. Related to this, in their study on Taiwan Tsai et al. (2015) conclude that bank diversification does not have advantages during a recession. Therefore, the evidence suggests that there is no consensus as to the positive or negative effect of specialization and diversification on different aspects of banks' activities and risk.

Few studies have explored the specific determinants of diversification—particularly in developing countries. One of the few studies, which also evaluates the Chinese context as we do, is the one by Meng et al. (2018), who examine the underlying factors of bank income diversification during the 2003–2010 period. They find that income diversification is linked to banks' managerial capabilities: insolvency risks, asset scale, cost, capital position and ownership structure. External factors, banking assets to gross domestic product and lower interest spread result in higher bank diversification levels. Other relevant studies are, for instance, Ammar and Boughrara (2019), who consider a dynamic nonlinear panel data model to empirically explore the drivers of bank diversification in the Middle East and North Africa (MENA) region. Their results indicate that market share and bank-specific characteristics play a major role in affecting the bank diversification decision for the sample areas, while financial development does not encourage traditional banks to diversify. Other studies focusing on developing countries are, for instance, Duho et al. (2020), who employ panel corrected standard error ordinary least squares, fixed effects and system generalized methods of moments to investigate the determinants of bank diversification in Ghana; their results show that bank diversification decisions are affected by risk profiles and risk portfolios.

Overall, most existing studies focus on the effect of diversification on banks, while less attention has been paid to the determinants of diversification. Considering the rapid expansion of the newly emerging FinTech industry in the financial market, this thesis has attempted to explore its effect on bank diversification strategies.

1.4. FinTech and economic development

Schumpeter (1911) made the first contribution to the connection between finance and economic performance, and introduced the paramount role of entrepreneurss and innovations in the process of economic growth. Some researchers hold the same view and believe that the implications of finance for economic development are significant, by influencing investment decisions, saving rates, technological innovations and then growth for longer periods (Gurley and Shaw, 1955; Goldsmith, 1969; McKinnon, 1973). It is sharply argued by Robinson (1952), Solow (1956) and Lucas (1988) that the effect of finance is overemphasized, which merely responds to economic growth in the long run. Following the pioneering seminal work by King and Levine (1993a), more studies between the 1990s and the financial crisis that erupted in 2008 have illustrated the importance of financial development for economic growth. Beck et al. (2000) use two econometric techniques to empirically examine the relationship between financial intermediary development and the sources of growth, which include private saving rates, capital accumulation, and productivity growth. They find a robust and positive connection between financial intermediary development and both real per capita GDP growth and total factor productivity growth. Levine (2005) theoretically and empirically reviewed the link between financial development and economic growth, and indicates strong positive effects of an effective financial system on economic growth for longer periods. Ang (2008) provides a survey of the progress in the literature on the finance-economic growth nexus, and points out ample cross-country evidence of the positive role of finance on growth.

However, after the occurrence of the financial crisis, the potential cost associated with unsustainable financial development has been highlighted. Rousseau and Wachtel (2011) question the importance of the finance-growth nexus and indicate that the incidence of the financial crisis is related to the declining impact of financial deepening on economic growth. Law and Singh (2014) use an innovative dynamic panel threshold method to explore the relationship between finance and growth for 87 developed and developing countries. They indicate that financial development positively affects growth only up to a certain threshold, beyond which it affects growth adversely. Such an inverted U-shaped relationship has also been confirmed by Arcand et al. (2015) that too much modern finance no longer has positive effects on economic growth. Breitenlechner et al. (2015) investigate the finance-growth nexus during periods of the systematic banking crisis and find that, while there exist positive and non-linear effects of financial development on economic growth in non-crisis times, oversized financial sector results in worse economic outcomes during the crisis. Bijlsma et al. (2018) point out an overall positive but decreasing impact of financial development on economic growth by performing a meta-analysis.

Despite more than twenty years of study, no empirical consensus on the finance-growth nexus has been reached to date yet. The emergence of FinTech, representing a new form of financial development, provides unprecedented opportunities and challenges to the traditional financial sector globally. While few literature has examined the direct effect of FinTech on economic development in particular due to the data limitation. Zhang et al. (2018) investigate the FinTech-disparity relation and FinTech's effects on inclusive finance and inclusive growth in China. They find that FinTech narrows the gap between urban and rural areas in China by promoting entrepreneurial activity for rural residents. Demir et al. (2022) examine the interrelationship between FinTech, financial inclusion and income inequality for a panel of 140 countries by invoking quantile regression and provide new evidence that FinTech reduces income inequality indirectly through financial inclusion. In the study of Muganyi et al. (2022), the impact of FinTech on financial development during the period 2011-2018 in China is investigated by employing a two-stage least squares instrumental variable regression. The results show that there exists a positive causal relationship between FinTech and different aspects of financial development, such as in terms of access (loans), depth (deposits), and savings with financial institutions. Given the scarcity of evidence on this issue, more studies should be conducted on the link between FinTech and economic development.

In the context of China, the mainstream view is that financial development strongly supports economic development in China. For instance, an earlier relevant study from Tan (1999) empirically investigates the relationship between the development of the financial industry (from two perspectives, namely the development of financial intermediaries and the stock market) and economic growth in China during the period of 1993–1998. He finds that financial development promotes economic development overall in China. Specifically, the financial intermediaries-economic growth nexus and the financial intermediaries-stock market development nexus are significant and positive, while the effect of stock market development on economic growth is not significantly negative. Some others (see, for instance, Cao and Wu, 2002; Meng, 2003; Zhan, 2003, among others) conduct a Granger causality test on Financial development and economic growth in China, and indicate that financial development accelerates economic growth. Zhao and Xue (2004) apply the revised Greenwood-Jovanovic (1990) model to explore the connection between financial development and economic growth and find that the credit market in China has a significant and positive impact on economic growth, while the stock market does not. Lu (2012) theoretically and empirically investigates the nexus of financial development and economic growth by using provincial panel data, and demonstrates that financial development facilitates economic development in China.

However, this positive effect is argued by some researchers (see, for instance, Han, 2001; Zhang et al., 2009, among others) that the influence of financial development on economic development is limited. Han (2001) suggests that advances in technologies and policy innovation, rather than financial development, are the key factors determining economic growth in China. Zhang et al. (2009) use the threshold regression technique to examine the relationship between financial development and economic growth with a panel of 28 provinces in China during the period of 1978–2003. The empirical results support a non-linear relationship and indicate that the effect of financial development on economic growth varies across different development levels. It means that financial development promotes economic growth in regions with high economic development levels, while it hinders economic growth in regions with low economic development levels and cannot explain economic growth in regions with medium economic development levels.

Considering the vast land area of China, there are significant differences in regional finance and economic development. Recent relevant studies extend the focus to regional level. For instance, Yin and Li (2012) confirm the different impacts of financial development on economic growth across regions in China, which is less significant in provinces in the Eastern region than provinces in the Western and Central regions. They further explore the mechanism underlying the nexus of financial development and economic development, and find that financial development has contributed to promoting entrepreneurial activity by offering financial support, which drives economic growth in China. Wang (2015) reports a positive causal financial development-economic growth nexus in the Eastern region of China, while financial development and economic growth inhibit mutually in the Western region. Shi et al. (2019) investigate the relationship between financial development and economic growth, as well as the heterogeneity across regions, before and after the financial crisis with provincial panel data during the period 1998-2016. They find that financial development promotes economic growth overall in China, while the impact of financial development is more significant in less developed regions, indicating more substantial margin effects of an improved financial environment. In addition, some researchers take an individual province as an example to explore the link between financial development and economic growth in detail. Guo et al. (2013) empirically analyze the effect of regional financial development on economic growth in Gansu province ranging from 1978 to 2010 and report a significant and positive relationship between expanding financial development scale and economic growth in Gansu province. Feng et al. (2013) provide evidence of the influence of financial development on economic growth in Beijing. They find that the development of the financial industry in Beijing strongly promotes economic growth, while the effects of the banking industry, stock market and insurance market on economic growth are different. The banking industry has the most significant effect.

1.5. Aims of the thesis

This thesis has been organized into five chapters. **Chapter 1** is the introduction. It provides a general overview of the emergence of FinTech, particularly in the context of China. Considering the absence of a standard and unified definition and/or index of FinTech, which is critical in examining its link to phenomena, we discuss different definitions and the three main approaches more commonly used to measure FinTech development in China. In addition, an overview of the research on the mechanisms linking FinTech and traditional banks, as well as FinTech and economic development, has been provided in this chapter.

In **Chapter 2**, we examine the effects of bank diversification and specialization strategies in China between 2008-2019. Although the connection between bank diversification and costs and benefits has been well discussed in the financial literature, no consensus has been reached as to what these are (Moudud-Ul-Huq et al., 2018). The empirical focus of previous literature is mainly on the developed markets, particularly the US and Europe (see, for instance, Lepetit et al., 2004; DeYoung et al., 2004; Stiroh, 2004a; Stiroh and Rumble, 2006; Mercieca et al., 2007; Chiorazzo et al., 2008; Goddard et al., 2008; Lepetit et al., 2008; Stiroh, 2012; Saghi-Zedek, 2016, among others), while less evidence has been documented in developing markets such as the banking sector in China. Berger et al. (2010) is one of the few exceptions, which analyzes the impact of diversification versus focus on bank performance in China between 1996-2006. This chapter is an extension of Berger et al.'s work, to explore the possibly changing relationship between bank diversification and performance during a particularly turbulent period for macroeconomics (the impact of the 2007/08 international financial crisis) as well as other reasons related to innovation in the industry—such as the rise of FinTech.

We take into account measures of diversification from both the two main perspectives, namely, income-based indicators and asset-based indicators. In the case of income-based indicators, we consider further categories—the non-interest income ratio, the Herfindahl-Hirschman index, and the entropy index. In addition, we evaluate the impact of the different indicators considered on measures of risk and profitability, and whether this impact varies depending on the type of bank—state-owned banks, national shareholding commercial banks, and city commercial banks. We argue that the links can be too intricate to be captured by linear models and, complementing the previous literature, evaluate them considering semiparametric specifications.

Chapter 3 provides evidence of the influence of FinTech on the diversification decisions of traditional banks in China during the period 2012-2018. Some previous literature generally believes the positive effect of FinTech (see, for instance Philippon, 2016; FSB, 2017; Drasch et al., 2018, among others). However, other observers, such as (FSB,

2017) and Stulz (2019), recognize threats with the emergence of FinTech. This chapter attempts to answer the following three questions: Does FinTech development affect bank diversification in China? What are the differential effects of FinTech on three different bank tiers? Which type of Banks are more affected by FinTech? Due to the unavailability of a direct FinTech index, the digital financial inclusion index compiled by the Digital Finance Center of Peking University, which is the most comprehensive measure reflecting the financial innovation level in China (Guo et al., 2019), is employed to measure FinTech.

Our application in this chapter is relatively innovative from a methodological point of view, by using instrumental quantile regression which has only been considered in the work by Demir et al. (2022) up to now, but not to investigate the varying impact of FinTech development across different quantiles on bank diversification. Quantile regression has the advantage of providing a more complete picture by taking into account the diversification level of each bank. The issue of endogeneity in the quantile regression framework is dealt with following Harding and Lamarche (2009), allowing for fixed effects as introduced in Koenker (2004) and instrumental variables in the presence of endogeneity as developed in Chernozhukov and Hansen (2008).

Chapter 4 focuses on the impact of FinTech from a macro perspective. In this chapter, we empirically examine the nexus between FinTech and economic development for a panel of 31 provinces in mainland China during the period of 2012-2019. The evidence of three FinTech dimensions' effects, namely coverage breadth, usage depth and digitization level, on economic development are also provided. There is a large literature evaluating the links between financial development and economic growth, which dates back to early studies by Schumpeter (1911) and Robinson (1952). Although the direction of causality represents a not-entirely solved issue, the mechanisms are now relatively well understood. FinTech, as the recent wave of innovations in financial technology, represents a new form of financial development for which, up to now, there is little evidence of its impact on economic growth and development. Few exceptions exist, such as Demir et al. (2022), who evaluate the implications of FinTech for inequality, or Muganyi et al. (2022), who analyze its impact on financial development. However, the evidence as to the direct impact of FinTech on economic growth and development is still scarce in particular due to data limitation.

In order to deal with the endogeneity of financial development, we use an instrumental regression approach. The analysis is carried out by using instrumental variable ordinary least squares at the first stage to estimate the average effect of FinTech and its three main dimensions on economic development at regional and provincial levels. Henderson et al. (2013) point out that, while on average the impact of financial development on growth has increased over time, it varies across countries at different growth levels. As mentioned above, quantile regression has the advantage of providing relevant information as to the varying effects across different quantiles. Therefore, we use instrumental quantile regression with fixed effects as our second-stage approach to investigate the influence of FinTech in Chinese provinces at different development levels.

Chapter 6 concludes and provides some policy implications and ideas for future research lines. Overall, this thesis mainly aims to contribute to the previous literature by providing empirical evidence on the impact of FinTech from both micro and macro aspects, namely the impact on the traditional banking sector and economic development, in China.

Chapter 2

Bank diversification and focus in disruptive times: China, 2008–2019

2.1. Introduction

Over the past few decades, the banking industry landscape has been radically reshaped by the emergence of new products, evolving demands for banking services, technological changes and new market developments (Beck et al., 2016). Although the reshape has intensified more recently, since as early as the beginning of the 1970s, banking firms have been tending to provide a more diversified bundle of products and services—i.e. a combination of traditional and nontraditional activities (DeYoung and Torna, 2013). Prior to the financial crisis, the financial innovation and liberalization trends in many banking markets, particularly in developed countries, encouraged banks to pursue operational diversification (Kim et al., 2019). In this sense, Stiroh (2012) points out that, particularly after the financial crisis, diversification with greater scale and scope was expected to reduce risk and insulate firms from macroeconomic or financial market shocks.

In more recent years, certain tendencies in the industry have meant bank diversification is growing in importance and attracting even more attention. Due to the general fall in interest rates across the world today (Ulate, 2020), banks' net interest income and bank margins have been declining significantly which, in turn, has pushed banks to diversify their products and services to generate more income. According to the KPMG report on mainland China banking (KPMG, 2017a), the declining interest rate makes banks adjust their strategies to increase non-interest income, and results in tougher competitive conditions. As Kamani (2019) indicates, financial deregulation and increasing competitive pressures on earnings have urged banking firms to focus more tightly on nontraditional activities (DeYoung and Torna, 2013), such as commission-paying services and off-balance sheet activities (Lozano-Vivas and Pasiouras, 2014) and, as a result, banking systems have been restructured and are now characterized by the emergence of universal banks with size and activity diversification. These trends have accelerated recently, due to the newly emerging, and potentially disruptive, financial technologies, which have been expanding rapidly in financial markets across the World, while their potential effects are still far from clear (Navaretti et al., 2017; Beck, 2020; Boot et al., 2021). Therefore, questions related to whether banking firms benefit from either specialization (focus) or diversification in disruptive times are relevant from multiple points of view—for scholars, policy-makers, regulators and practitioners alike.

Although the likely costs and benefits associated with banking firms' diversification strategies has been a long-standing debate in the financial literature, up to now, no consensus has been reached as to what these are (Moudud-Ul-Huq et al., 2018). One stream in the banking literature suggests that, as banks increase their leverage levels, they should diversify across products, markets and sectors, to reduce their risks (Stiroh, 2004a). In this regard, Baele et al. (2007) find a strong positive relationship between bank diversification and franchise value, and an opposite link between diversification and bank-specific risk. In contrast, proponents of specialization argue that bank diversification could result in increasing instability (Santomero and Eckles, 2000), insolvency risk (Park, 2000) and systematic risk (De Jonghe, 2010). However, the links could be more intricate since, as indicated by Kim et al. (2019), the relationship between diversification and bank stability is U-shaped, with diversification increasing bank financial stability, but excessive diversification having negative effects.

In this study, we focus on the case of the China and its banking sector which, in the specific issue of bank focus and diversification, is relevant for multiple reasons. First, the existing analyses on this issue mainly deal with US and European financial institutions (see, for instance Lepetit et al., 2004; DeYoung et al., 2004; Stiroh, 2004a; Stiroh and Rumble, 2006; Mercieca et al., 2007; Chiorazzo et al., 2008; Goddard et al., 2008; Lepetit et al., 2008; Stiroh, 2012; Saghi-Zedek, 2016, among others), while there is much less empirical evidence documented on banking diversification in emerging markets. Second, as the largest emerging and transition economy, China has a changing environment in which banks have increasing flexibility to decide which business strategy to follow: specialization or diversification—in its different variants. Considering the country's huge impact on the global economy, it is meaningful to explore the relationship between diversification strategies and bank profitability/risk there. Third, China's financial technologies have been growing rapidly, and the country has emerged as a leading FinTech center (EY, 2016). Diversification may have more marked effects on bank profitability/risk in this highly disruptive context.

We examine the effect of diversification on bank profitability/risk using data on 19 listed Chinese commercial banks during the period 2008–2019. The empirical analysis is conducted on the entire sample, as well as three sub-samples of state-owned banks, national shareholding commercial banks and city commercial banks, to explore the effect more specifically. The results suggest that there is a non-linear relationship between diversification and bank profitability/risk during the sample period in China. On the whole, Chinese banks benefit more robustly from income diversification than asset diversification. The analysis and comparison of three different tiers of banks indicate that state-owned banks have a higher tolerance for income diversification, and obtain more benefits than shareholding national commercial banks and city commercial banks. Low-level asset diversification is suggested as an optimal strategy for all tiers of banks in China.

In light of these findings, our study contributes to the existing literature from three perspectives. First, it fills the gap in the existing literature on the links between bank diversification and profitability/risk by presenting and discussing evidence for a major emerging country: China. In contrast to the few previous contributions on China, we examine the effect of diversification for three tiers of Chinese banks—state-owned banks, national shareholding commercial banks and city commercial banks. Second, most previous studies have only considered one indicator to measure bank diversification of income or assets, disregarding the possibility of evaluating bank diversification from both income and asset perspectives, and using several diversification indicators. Instead, we include four different diversification measures in the models and, following Laeven and Levine (2007)Edirisuriya et al. (2015) and Moudud-Ul-Huq et al. (2018), we differentiate between income and asset diversification to comprehensively analyze the effect of bank diversification on profitability/risk. Third, we use semiparametric-partial linear regression (PLR) with fixed effects for the first time in investigating the diversification effect on bank profitability/risk. Some previous literature (Berger et al., 2010; Gambacorta et al., 2014) suggests there may be a non-linear relationship between diversification and bank profitability/risk. In addition, as Baltagi et al. (2002) indicate, PLR with fixed effects performs better for an unclear relationship between two variables than the fixed effects model, and partially avoids the curse of dimensionality problems inherent to fully nonparametric models. Hence, considering our sample size, PLR with fixed effects might be a more appropriate technique than both parametric and fully nonparametric alternatives.

The remainder of this article is structured as follows. We provide a brief overview of the Chinese banking industry in Section 2.2. Section 2.3 describes different approaches to measuring bank diversification from both income and asset perspectives. Section 2.4 explains the research design, including data, variables and methodology. Section 2.5 reports the empirical results and Section 2.6 concludes.

2.2. A brief overview of Chinese banking industry

Prior to the 1990s, Chinese banks were limited to granting loans only to designated sectors or customers, which resulted in fewer opportunities to diversify their product mixes. For instance, the Big Four state-owned banks at that time in China (i.e. Bank of China, Industrial and Commercial Bank of China, Agricultural Bank of China and China Construction Bank), were required by policy makers to provide the majority of their loans to foreign trade and exchange, manufacturing and commercial lending, agriculture, and construction.

These strict restrictions started to be loosened in the mid-1990s, specifically with the enacting of the 1995 Commercial Banking Law of China. It officially classified the state-owned banks as commercial banks, and allowed them to diversify into market-based commercial businesses (Berger et al., 2009). In this respect, Yuan (2006) points out that, within commercial business, Chinese banks relied heavily on net interest income activities, with fee-based activities accounting for only 10% of their total revenues—on average. This reflected a mature lending business and, simultaneously, a more immature cash management and treasury business. At the same time, although some new foreign banks were entering the market, the operational and geographical restrictions for foreign banks were not eased until China joined the WTO in December 2001.

In recent years, there is more freedom in the Chinese banking industry in terms of takeovers and M&As, operation, and geographical scope. Not only have several new regulations been enacted, but also some existing laws (for instance the Commercial Banking Law of China) have been modified to align with the WTO agreement (Berger et al., 2009). Geographic expansion restrictions on foreign banks in China were relaxed, allowing higher levels of geographical diversification for domestic banks as well. Compared to other commercial banks and city commercial banks, the Big Five[1] are the largest beneficiaries of geographical diversification, as they have branches in almost every corner of urban and rural China. Moreover, some Chinese banks have expanded into foreign markets, although under certain strict restrictions, considering the potential risks of the big difference between the Chinese banks and banks in developed countries. Therefore, in the current context of higher flexibility and deregulatory trends in the Chinese banking industry, banks have more options to choose between specialized and diversified business strategies under the WTO agreement.

As mentioned in the introduction, interest rates have been declining steadily over the last few years, in most banking industries across the world. In the specific case of China, the People's Bank of China (PBOC) reduced interest rates five times in 2015, which resulted in a declining net interest income for Chinese banks (KPMG, 2017a). Figure

[1] Bank of Communication (BOCOM) has been classified as a state-owned bank since 2006.

2.1 shows the share of non-interest income (defined as non-interest income to operating revenue) for five Chinese state-owned banks from 2007 to 2018. It can be seen that, although the scale of non-interest income for the Big Five experienced some fluctuations, the trend was one of overall growth over that period. This has been reflected in the steady development of nontraditional activities in the Chinese banking industry. In this regard, Li and Zhang (2013) show how Chinese banks have been shifting from traditional activities towards a more diversified income structure. Table 2.1 reports income structure in terms of interest income and non-interest income for Chinese banks, along with the activities corresponding to each income category.

Related to this, Navaretti et al. (2017) indicate that the emergence of FinTech contributes to intensifying competition in the Chinese banking industry and financial system in general. Banks attract an increasing number of clients by offering financial services—for instance third-party payments—with lower costs and, in general, higher efficiency levels. As in any leading FinTech context, the Chinese banking industry, especially its traditional activity of issuing loans and attract deposits, is confronted with major challenges. In response, and related to the aims of our paper, Chinese traditional banks are impelled to provide their customers with a more diversified and innovative product mix to meet the new demands, in order to remain competitive.

2.3. Different measures of bank diversification

According to the literature, and as indicated in previous paragraphs, there are two categories of diversification measures for banks, namely, income-based and asset-based indicators. The former measures diversification across different revenue sources, whereas the latter measures it across various types of assets (see, for instance Laeven and Levine, 2007; Baele et al., 2007; Armstrong et al., 2014; Edirisuriya et al., 2015; Moudud-Ul-Huq et al., 2018).

2.3.1. Income-based indicators

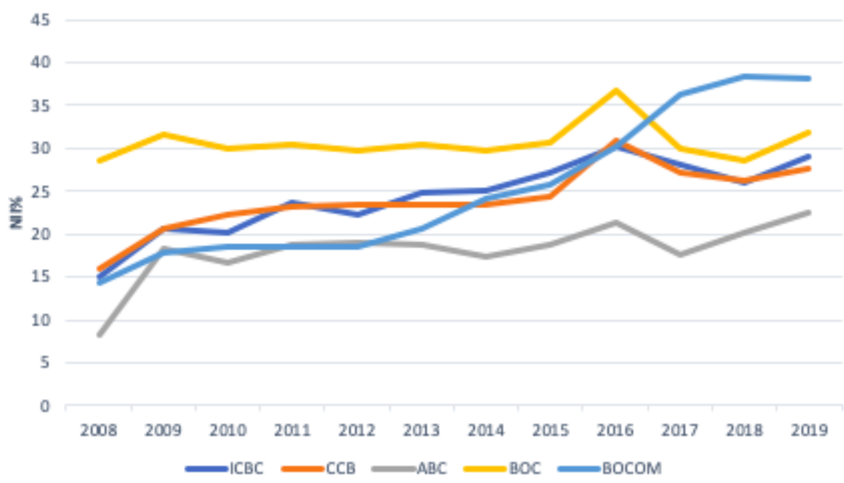
The income-based diversification indicators mainly include the following three measures:

Non-interest income ratio (NII): this is our first income-based diversification indicator, which we define as:

$$NII = \frac{\text{Non-interest Income}}{\text{Total Operating Income}} \tag{2.1}$$

or, alternatively,

Figure 2.1: Non-interest income share of Big Five



Source: Wind database

Note: the Big Five are the Industrial and Commercial Bank of China (ICBC), China Construction Banks (CCB), Agriculture Bank of China (ABC), Bank of China (BOC), Bank of Communication (BOCOM).

Table 2.1: Income structure of Chinese banks

	Income classification	**Corresponding activities**
Interest income	Interest rate spread	Interest rate spread between loan and deposit
	Interest received from investment	Bond investment interest received Interest income from central bank bill
	Interbank business	Interbank lending interest income
	Deposit in the central bank	Interest income from deposit in the central bank
Non-interest income	Income from fees and commissions	Clearing and settlement Bank card service Consultancy and advisory service Online banking service Bank guarantee business Trust business and others
	Investment income	Dividend earned Income from financial derivatives investment Bid-ask spread of bond and others
	Income from changes in fair value	Financial instruments measured at fair value through profit and loss Income from the change in fair value of any financial instrument
	Foreign exchange gains	Income caused by converting from a foreign currency to Chinese currency
	Other income	Property; sale and lease equipment; others.

$$NII = 1 - \frac{\text{Net Interest Income} - \text{Other Operating Income}}{\text{Total Operating Income}} \tag{2.2}$$

It takes values between 0 and 1, with values closer to 1 indicating higher degrees of diversification.

Interest income mainly derives from banks' traditional activities of providing loans and deposit services. Therefore, the amount of non-interest income could intuitively indicate a bank's diversification level. DeYoung and Rice (2004), Stiroh (2006), Stiroh and Rumble (2006), Laeven and Levine (2007), Armstrong et al. (2014) and Yanlei (2018) use this indicator to reflect banks' income portfolio diversification.

Revenue Herfindahl-Hirschman Index: the revenue Herfindahl-Hirschman Index (HHI) is the second income-based approach to indicate the degree of diversification. It is calculated as:

$$HHI = \sum_{i=1}^{n} P_i^2 \tag{2.3}$$

where n indicates the number of all bank businesses, and P_i denotes the share of one specific income source of total revenue.

It is commonly used in the study of bank diversification, and measures the revenue diversification level by calculating the share corresponding to each specific line of bank business. Considering the limited information available on the types of income generated by different business activities, a broad revenue HHI is usually used to indicate diversification (Baele et al., 2007). It categorizes bank income as net interest income and non-interest income. The lower the HHI index, the greater the diversification level in terms of a bank's revenues.

In some studies (see, for instance Acharya et al., 2006; Stiroh and Rumble, 2006; Elsas et al., 2010), the adjusted HHI is preferred for measuring income diversification:

$$HHI_a = 1 - \sum_{i=1}^{n} P_i^2 \tag{2.4}$$

where n indicates the number of all bank business, and P_i denotes the proportion of one specific income source in total revenue.

The conception of this measure is to subtract the sum of squared revenue shares from the unity, so that HHI_a increases when revenue diversification is higher. When a bank has several products and services, with a highly diversified revenue composition, the sum of squared revenue shares is small and the HHI_a is high. In contrast, when HHI_a declines, the bank becomes more *focused*, with a lower degree of income diversification. In addition, HHI_a takes values between 0 and 0.5, where 0 indicates an extremely specialized level (only one source of revenues), and 0.5 indicates a fully diversified bank from a revenue perspective.

Entropy Index: the Entropy Index is widely applied in finance and economics. It was originally developed in the field of physics and was first introduced in economics in the 1960s (Gulko, 1999), particularly in studies designed to evaluate inequalities. In the 1990s, significant contributions applying the entropy index in finance were made by Stutzer (1996) and Avellaneda (1998). In this line, Tabak et al. (2011) pointed out that the Shannon entropy is an effective approach to measure diversification, an approach also adopted by Li and Li (2014) and Ceptureanu et al. (2017). This entropy can be defined as:

$$\text{Entropy}_i = \sum_{i=1}^{n} P_i \times \log\left(\frac{1}{P_i}\right) = -\sum_{i=1}^{n} P_i \ln P_i \tag{2.5}$$

where n indicates the number of all bank business, P_i denotes the share of one specific revenue source in total revenue. The higher the diversification, the higher the entropy index.

2.3.2. Asset-based indicators

The loan-to-asset ratio (LAR), defined as total loans to total assets, and/or the ratio of non-interest bearing assets to total assets ($NIBATA$) is the most commonly used asset-based diversification indicator (see, for instance Baele et al., 2007; Edirisuriya et al., 2015; Moudud-Ul-Huq et al., 2018). The equations of both ratios are written below:

Loan-to-asset-ratio:

$$LAR = \frac{\text{Total Loans}}{\text{Total Assets}} \tag{2.6}$$

Non-interest bearing assets to total assets:

$$NIBATA = \frac{\text{Non-interest Bearing Assets}}{\text{Total Assets}} = \frac{\text{Total Assets} - \text{Loans}}{\text{Total Assets}} \tag{2.7}$$

Lower values of loan-to-asset ratio (LAR) or higher values of non-interest bearing assets to total assets ($NIBATA$) reflect higher diversification from a bank's assets perspective.

Diversity measures: an alternative asset-based indicator was proposed by Laeven and Levine (2007), and is used in the study of Armstrong et al. (2014). It is defined as:

$$DIV_A = 1 - \left|\frac{\text{Net loans} - \text{Other Earning Assets}}{\text{Total Earning Assets}}\right| \tag{2.8}$$

If the value is equal to 0, the bank is fully specialized, or focused; if the value is equal to 1, it means that the bank's assets are fully diversified. However, this variable relies on the assumption that the optimal diversification mix is constituted by an equal division between non-lending and lending activities (Baele et al., 2007).

In this study, we follow previous approaches to examine the effects of diversification on bank performance from *both* income and asset perspectives. In order to obtain more robust results, we will consider more than one diversification measure, from both perspectives, rather than confining the results to just one measure from each. This *dual* approach will provide us with a richer and more precise evaluation of the links between diversification and bank performance.

2.4. Research design

2.4.1. Hypotheses development

According to the modern portfolio theory, diversification could increase bank income and reduce risks. However, some literature argues that diversification has a negative impact on bank profitability/risk. There is therefore no consensus on either the sign or the nature of the effect. For instance, Elsas et al. (2010) suggest there is a potential non-linear relationship between bank diversification and profitability/risk, considering the multiple countervailing effect. Li and Li (2014) report that Chinese commercial banks are facing problems of declining capital adequacy ratio, fluctuating intermediary business income, and increasing correlation between interest income and non-interest income, which are caused by low-level product innovation and banks' cross-selling strategies. This might give rise to a non-linear effect of diversification on Chinese bank profitability/risk. In this line, Berger et al. (2010) point out that bank performance (in terms of profitability) and bank risk should be studied jointly to provide a more comprehensive understanding of the intricate effects of banks' diversification strategies. Against this background, we test the following hypothesis in this study:

Hypothesis 1 *There is a non-linear relationship between bank diversification and profitability/risk.*

On the one hand, it is important for banks to adopt an appropriate level of diversification if they are to achieve sustainable growth (Jiang and Han, 2018). A higher level of diversification across various financial products, as well as geographic diversification, does not per se imply better performance. On the other hand, by considering three different categories of Chinese commercial banks, namely state-owned banks, joint-stock banks and city commercial banks, we can examine whether diversification affects them differently.

Hypothesis 2 *Diversification has positive effects on bank profitability.*

Diversification would be beneficial from economies of scope. Both internal or cost economies of scope in joint production and marketing, and external or revenue economies of scope in consumption, expand the non-interest income of commercial banks (Klein and Saidenberg, 2000). Under the former, banks offer a wide range of products and services by implementing cross-selling strategies or developing new products. The latter can be defined as comprehensive banking, so that banks raise their profitability via mergers or holding other financial institutions to develop various businesses.

Hypothesis 3 *Diversification may have dual effects on bank risks.*

Different operating strategies, serving markets and FinTech opportunities are elements of diversification effects that differ enormously across various banks (Stiroh, 2004b). For banks at the mature stage of their business cycle, such as the Big Five banks in China, diversification strategies can help to diversify risk, whereas for relatively small banks—e.g., city commercial banks—high diversification levels might contribute to diversify resources rather than risk, ultimately resulting in a negative effect on banks. Lepetit et al. (2008) indicate that small banks' shift to nontraditional activities increases bank risk.

2.4.2. Model specification and methodology

According to the modern portfolio theory, profitability and risk are two important indicators in explaining performance. Some studies (see, for instance Berger et al., 2010; Li and Li, 2014) explore the relationship between bank performance and diversification by using bank profitability and risk jointly to indicate bank performance. Therefore, we follow these studies to consider profitability and risk as dependent variables.

The following models for profitability and risk are estimated to test the hypotheses above:

$$PROFITABILITY_{it} = \alpha_i + \beta_1 SIZE_{it} + \beta_2 LDR_{it} + \beta_3 CAR_{it} + \beta_4 ER_{it} + \beta_5 gM2_{it} + \\ + \beta_6 gGDP_{it} + F(DIV_{it-1}) + \mu_{it} \tag{2.9}$$

$$RISK_{it} = \alpha_i + \beta_1 SIZE_{it} + \beta_2 LDR_{it} + \beta_3 CAR_{it} + \beta_4 ER_{it} + \beta_5 gM2_{it} + \beta_6 gGDP_{it} + \\ + F(DIV_{it-1}) + \mu_{it} \tag{2.10}$$

where i indicates the cross-section dimension (i.e., bank), t denotes the time dimension, α_i denotes the fixed effect, $SIZE$ is bank size, LDR is loan-deposit ratio, CAR is capital adequacy ratio, ER is equity ratio, $gM2$ is $M2$ growth rate, $gGDP$ is GDP growth rate, DIV is the diversification indicator, and μ_{it} is the error term. Considering the potential endogeneity issue, DIV uses one year lagged value.

Both return on assets (ROA) and return on equity (ROE) are relevant to obtain a clear picture of corporate performance in banking. Considering the effect of banks' high leverage ratio on their ROE, which might lead to potentially contaminated results (Saghi-Zedek, 2016), we use ROA to measure bank profitability. We eliminate the impact of tax policies on banks by computing ROA as income before taxes as a share of total assets (rather than net income to total assets).

Risk is another dependent variable. The Basel Committee on Banking Supervision (BSBC) categorizes bank risks into operational risk, credit risk, liquidity risk and market risk. Credit risk is the main risk in most banks (Quang and Gan, 2019). Hence, the non-performing loan ratio (NPL), which reflects the credit risk of banks (Jiang and Han, 2018), is used to measure the risk of each bank; we define it as the ratio of non-performing loans to total loans.

In order to empirically validate or refute our hypotheses, we specify a semiparametric-partial linear regression (PLR) with fixed effects that models the relationship between diversification and bank profitability or risk. Our specification adopts the following general form:

$$y_{it} = X_{it}\beta + f(fin_{it}) + \alpha_i + \mu_{it}, \tag{2.11}$$

where $i = 1, \ldots, N, t = 1, \ldots, T$, X_{it} refers to the control variables, fin_{it} indicates the nonparametric component, α_i indicates the fixed effect, μ_{it} is the error term.

Semiparametric-partial linear regression, based on smoothing splines, was first used by Engle et al. (1986) to explore the relation between weather and electricity sales, but has been successfully extended to many other research areas.[2] As a hybrid between parametric and nonparametric regression, PLR accommodates data linear transformations easily and, therefore, provides a convenient framework to accurately capture the non-linear relationship between dependent and independent variables. Yatchew (1998) points out that limited economic theories could imply difficulties in finding specific functional forms when exploring the relationship between dependent and independent variables, so more flexible forms might be more appropriate. Therefore, compared to linear regression models such as OLS, PLR can constitute a better fit for intricate relationships between dependent and independent variables than fully parametric alternatives.

Another flexible alternative is provided by nonparametric regression (Li and Racine, 2007), which shares some of the underpinnings of semiparametric-partial linear regression, with the advantage of being even more flexible. However, it requires large data

[2] For instance, Tripathi (1997) analyzes firms' profitability by using PLR.

sets to obtain a meaningful model structure and estimates, and can also be affected by the curse of dimensionality (Härdle et al., 2012). In sum, despite being more flexible, nonparametric regression is not free from disadvantages and we therefore adopt a semiparametric specification.

Although semiparametric-partial linear regression is well established in the academic field, less attention has been paid to consistent estimation of PLR with fixed effects. It builds up asymptotic normality for the finite dimensional parameter of interest in the model and consistency for the nonparametric object by taking the first difference to eliminate the fixed effects and using the series method (Su and Ullah, 2006). PLR with fixed effects overcomes some drawbacks caused by the kernel approach of PLR, for instance related to the curse of dimensionality, although it is also subject to some problems such as non-estimated slope parameter (Baltagi et al., 2002). To date, these methods have only been used remotely for analyzing diversification vs. specialization (see Tortosa-Ausina, 2003).

2.4.3. Variables and measures

In both models (2.9) and (2.10), DIV is the explanatory variable for bank diversification, which is the non-linear and nonparametric component in the models. According to Benitez et al. (2016), endogeneity in the nonparametric part will generate incorrect results. Thus, one year lagged value of DIV is taken into account in the model. In addition, Newey et al. (1999) and Ahamada and Flachaire (2010) point out that, more control variables in the model could ensure exogeneity of the nonparametric part. Therefore, bank-level variables of bank size ($SIZE$), loan-deposit ratio (LDR), capital adequacy ratio (CAR) and equity ratio (ER), as well as macroeconomic-level factors of M2 growth rates ($gM2$) and GDP growth rates ($gGDP$), are considered as control variables in the models, for the reason explained below. In turn α_i indicates the fixed effect which might include factors (related to organizational and governance structure, for instance) and tax policy.

Explanatory variables

As explanatory variables, and as discussed in Section 2.3, we consider both income-based and asset-based indicators to measure the effect of diversification on bank performance. Four different measures belonging to these two categories of indicators are examined here, in order to explain the effects of diversification more comprehensively.

Regarding the income diversification measures, and according to what was defined in Section 2.3, they are defined as:

(1) The ratio of non-interest income to total operating income (NII).

(2) The adjusted-HHI, which is calculated as:

$$HHI_a = 1 - (P_1^2 + P_2^2) \tag{2.12}$$

where: P_1 indicates the share of net interest income, and P_2 denotes the share of non-interest income.

(3) The Shannon entropy (Entropy)

As for the asset-based indicator, following Edirisuriya et al. (2015) and Moudud-Ul-Huq et al. (2018), the ratio of non-interest bearing assets to total assets ($NIBATA$) is applied to examine bank diversification in assets.

Control variables

As indicated above, we will consider bank-specific and macroeconomic determinants as control variables in the models. From the micro perspective, the literature suggests controlling for the effect of bank size, asset structure, capital structure and capital adequacy on bank performance (see, for instance Chen et al., 2013; Li and Li, 2014).

According to Stiroh (2004a), Stiroh and Rumble (2006), Behr et al. (2007) and Chiorazzo et al. (2008), bank size affects bank returns and risk. Specifically, following Smirlock (1985), Akhavein et al. (1997), Demirgüç-Kunt and Huizinga (1999) and Goddard et al. (2004), size is closely and positively related to bank profitability. Regarding the links between bank size and risk, several authors (Saunders et al., 1990; Chen et al., 1998; Megginson, 2005) have found negative links. Berger et al. (1987) also found scale inefficiencies play a role, especially for large banks. Therefore, bank size is included as a control variable in the models.

Asset structure refers to the distribution of various categories of the firm's assets, which can to some extent affect its performance. Loans, as the largest asset type of most banks, is used in some diversification studies (DeYoung and Roland, 2001; Stiroh and Rumble, 2006) to explore the degree to which banks are dependent on traditional business. The loan-deposit ratio is included to examine the effects of asset structure on performance.

As firms with a high leverage ratio, the effect of bank capital structure on bank performance cannot be overlooked, especially for banks in developing countries. Sufian (2009) indicates that strong capital structure not only better ensures safety for depositors during macroeconomic fluctuation periods, but also strengthens banks' capacity to cope with financial crises. The variable of shareholder equity ratio is included in the models to examine the effect of bank capitalization. In turn, capital adequacy reflects the inner strength of a bank, especially against risk (Sangmi and Nazir, 2010), and is considered in the model as an important indicator of bank performance.

At the macro level, there is a close relationship between bank risk and macroeconomic factors—for instance, monetary policy and GDP growth (Buch et al., 2010). The GDP is expected to affect the supply and demand of banking services (Sufian and Noor Mohamad Noor, 2012). Armstrong et al. (2014) include $gGDP$ as a control variable in their model to explore the effect of financial institutions' diversification on valuation. M2 growth rate is another macroeconomic indicator included in the models, which reflects money supply. Mamatzakis and Remoundos (2003) report significant effects of money supply on bank profitability. Table 2.2 lists all variables in the models and their definitions.

Table 2.2: Summary of variables

Category	Variable	Definition
Dependent	Profitability	ROA: Income before tax/Total assets
	Risk	NPL: Non-performing loans/Total loans
Independent	Diversification (DIV)	Income-based and asset-based diversification
Controls	Bank size ($SIZE$)	Natural logarithm of total assets in real terms (CNY)
	Loan-deposit ratio (LDR)	Total loans/Total deposits
	Equity ratio (ER)	Shareholder's equity/Total assets
	Capital adequacy ratio (CAR)	Capital/Risk-weighted assets
	GDP growth rates ($gGDP$)	Annual growth rates of GDP (%)
	$M2$ growth rates ($gM2$)	Annual growth rates of $M2$ (%)

2.4.4. Data

Sample and data

The sample data are for 19 Chinese banks listed on the Shanghai and Shenzhen Stock Exchange for the years 2008 to 2019, broken down as follows: 5 state-owned banks (Bank of China, Industrial and Commercial Bank of China, Agricultural Bank of China, China Construction Bank, and Bank of Communications), 7 national shareholding commercial banks (China CITIC Bank, China Merchants Bank, China Minsheng Bank, Hua Xia Bank, Industrial Bank, Ping An Bank and Shanghai Pudong Development Bank), which are known as the "second-tier" Chinese domestic banks, and 7 city commercial banks (Bank of Beijing, Bank of Changsha, Bank of Jiangsu, Bank of Nanjing, Bank of Ningbo, Bank of Zhengzhou and Jiangsu Zhangjiagang Rural Commercial Bank). The data for specific banks are based on the yearly financial data reported in the balance sheet, profit and loss statement, and profitability report. They are mainly collected from the Wind database (the biggest financial database for China). Some missing and/or questionable values are collected and/or double checked from other official sources, such as each bank's official annual report. Macroeconomic data (M2 and GDP growth rates) are taken from the World Bank [3] . Panel data are used to assess the potential effects of diversification on traditional commercial banks.

Descriptive statistics

Table 2.3 reports summary statistics for the sample, including mean, standard deviation, minimum, maximum, and median for profitability (ROA), non-performing loans (NPL), size ($SIZE$), capital adequacy ratio (CAR), loan-to-deposits ratio (LDR), equity ratio (ER), M2 growth rate ($gM2$), and GDP growth rate ($gGDP$), as well as the four diversification measures selected. This information is reported for the full sample as well as the sub-samples of state-owned banks, national shareholding commercial banks and city commercial banks, for the 2008–2019 period. The table shows a large gap between maximum and minimum ROA (2.20% and 0.17%, respectively) for the full sample, indicating large profitability differences across banks. More specifically, the average profitability for state-owned banks is about 1.36%, which is higher than the average for the full sample (ROA =1.26%). For their part, both national shareholding commercial banks and city commercial banks have lower average ROA (1.20% and 1.23%, respectively) than the full sample. In the case of risk, state-owned banks in the sample have higher values for non-performing loans (NPL, about 1.50%) than the full sample (whose average NPL =1.26%). In contrast, lower risk can be found for national shareholding commercial banks and city commercial banks, with lower values for non-performing loans (NPL, on average, 1.20% and 1.15%, respectively). In addition, the maximum NPL value for the sub-sample of state-owned banks is 4.32%, implying potential excessive default risk for some state-owned banks.

As for the control variables, state-owned banks have a higher average for the capital adequacy ratio (CAR, 13.64%) compared to national shareholding commercial banks and city commercial banks, implying higher risk aversion for state-owned banks. Meanwhile, there is a large difference between minimum and maximum for the loan-to-deposits ratio (LDR), which refers to the banks' asset structure, when considering the full sample, but this difference is small within each sub-sample. This suggests that there is convergence of business models and revenue structure within types of banks, but not among different types of banks—i.e., among-group differences widen whereas within-group differences diminish (Correa and Goldberg, 2020). In addition, national shareholding commercial banks have a relative lower average for the equity ratio (ER = 6.09%) compared with the other two bank types.

Regarding the explanatory variables for income diversification—considering the non-interest income ratio (NII), the adjusted Herfindahl-Hirschman index (HHI_a) and the

[3]Source:https://data.worldbank.org/indicator/FM.LBL.BMNY.ZG?locations=CN&view=chart; https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG?locations=CN&view=chart

Table 2.3: Summary descriptive statistics

This table reports summary descriptive statistics for all variables on average over the period 2008–2019. ROA is return on assets ratio, NPL is non-performing loan ratio, $SIZE$ is bank size (as a natural logarithm of total assets in ten thousands CNY in real terms), LDR is loan-deposit ratio, CAR is capital adequacy ratio, ER is equity ratio, $gM2$ is $M2$ growth rate, $gGDP$ is GDP growth rate, NNI is non-interest income ratio, HHI_a is adjusted HHI, and $NIBATA$ is the ratio of non-interest bearing assets to total assets. All data are deflated by GDP deflator. Further details provided in Table 2.2.

	ROA (%)	NPL(%)	$SIZE$	CAR(%)	LDR(%)	ER(%)	$gM2$(%)	$gGDP$(%)	NII	HHI_a	$Entropy$	$NIBATA$
						Full sample						
# obs.	228	228	228	228	228	228	228	228	228	228	228	228
Mean	1.2564	1.2593	19.0822	12.7671	70.4056	6.5091	13.9617	7.9224	0.1968	0.2983	0.4671	0.5284
Standard deviation	0.2933	0.5224	1.7028	1.8977	12.1923	1.3385	5.6675	1.4538	0.0952	0.1077	0.1318	0.0771
Minimum	0.1671	0.3800	14.8022	8.5800	43.2000	3.1847	8.0000	5.9000	-0.0159	0.0000	0.0000	0.3869
Maximum	2.2033	4.3200	21.8255	24.1200	113.0500	12.1076	29.7400	10.6360	0.5109	0.4998	0.6929	0.7144
Median	1.2670	1.2200	19.2985	12.4050	70.6650	6.4170	13.2000	7.5345	0.1846	0.3011	0.4783	0.5191
						State-owned banks						
# obs.	60	60	60	60	60	60	60	60	60	60	60	60
Mean	1.3635	1.4982	20.9720	13.6443	68.5660	6.9479	13.9617	7.9224	0.2306	0.3463	0.5273	0.4910
Standard deviation	0.2568	0.5713	0.5522	1.5760	8.7958	1.1172	5.7027	1.4628	0.0663	0.0710	0.0823	0.0346
Minimum	0.7463	0.8500	19.4059	9.4100	49.5000	3.8606	8.0000	5.9000	0.0821	0.1508	0.2839	0.4245
Maximum	1.8213	4.3200	21.8255	17.5200	90.4000	8.9407	29.7400	10.6360	0.3844	0.4733	0.6662	0.5702
Median	1.3570	1.4550	21.0543	13.6450	70.2900	6.9614	13.2000	7.5345	0.2331	0.3576	0.5430	0.4871
						National shareholding commercial banks						
# obs.	84	84	84	84	84	84	84	84	84	84	84	84
Mean	1.2018	1.1954	19.4741	11.6749	78.6441	6.0913	13.9617	7.9224	0.2184	0.3208	0.4943	0.4981
Standard deviation	0.2832	0.4798	0.6678	1.3455	11.0397	1.2132	5.6890	1.4593	0.1020	0.1087	0.1288	0.0666
Minimum	0.1671	0.3800	17.6751	8.5800	61.9500	3.1847	8.0000	5.9000	0.0548	0.1037	0.2125	0.3869
Maximum	1.7715	2.1400	20.4245	15.6800	113.0500	8.9161	29.7400	10.6360	0.5109	0.4998	0.6929	0.6745
Median	1.1637	1.1650	19.5465	11.4950	74.5343	6.0995	13.2000	7.5345	0.2138	0.3361	0.5189	0.4967
						City commercial banks						
# obs.	84	84	84	84	84	84	84	84	84	84	84	84
Mean	1.2346	1.1525	17.3404	13.2327	63.4811	6.6136	13.9617	7.9224	0.1511	0.2415	0.3968	0.5855
Standard deviation	0.3105	0.4766	1.2083	2.0713	10.4890	1.4879	5.6890	1.4593	0.0885	0.1042	0.1331	0.0756
Minimum	0.7248	0.4400	14.8022	9.8600	43.2000	3.4406	8.0000	5.9000	-0.0159	0.0000	0.0000	0.4233
Maximum	2.2033	3.0800	19.4276	24.1200	94.5900	12.1076	29.7400	10.6360	0.4743	0.4987	0.6918	0.7144
Median	1.2366	1.0400	17.5042	12.9000	64.4500	6.3336	13.2000	7.5345	0.1281	0.2234	0.3828	0.5837

Shannon entropy—there are large differences in the range for the full sample. This might be suggesting various income diversification strategies for different banks. Meanwhile, both state-owned banks and national shareholding commercial banks have higher average income diversification levels compared to the full sample average. As for asset-based indicators, sample city commercial banks have higher average non-interest bearing assets to total assets ($NIBATA = 0.59$), not only than the entire sample average ($NIBATA = 0.53$), but also compared to both state-owned banks and national shareholding commercial banks with average non-interest bearing assets to total assets of 0.49 and 0.50, respectively. This might be suggesting that both state-owned and national shareholding banks are more income diversified, while city commercial banks have more asset-diversified portfolios.

2.5. Results

2.5.1. Semiparametric-linear regression (PLR) with fixed effects: full sample

In using the partially linear panel date model with fixed effects for the entire sample, we consider the bank-specific and macroeconomic control variables as the linear and parametric components, whereas diversification indicators are the non-linear and non-parametric components. In addition, in order to better compare the different models, we conduct ordinary least squares (OLS) regressions and fixed effects (FE) regressions for the entire sample of banks, including the control variables. We chose the Herfindahl-Hirschman index (HHI_a) diversification indicator in both OLS and FE models. Table 2.4 presents the regression results, in which Model (1) and Model (2) indicate the OLS regressions and the FE regressions, respectively; Models (3)–(6) indicate the PLR regression results of models with non-interest income ratio (NII), revenue Herfindahl-Hirschman index (HHI_a), Entropy ($Entropy$)and non-interest bearing assets to total assets ($NIBATA$), respectively.

As for the linear and parametric part, and as shown in Table 2.4 (profitability), $SIZE$ has a significant (10%) and negative effect on profitability (ROA), consistent with previous findings in the literature (e.g., Berger et al., 1987). The positive coefficient of $SIZE$ in Model (1) might be caused by missing fixed effects. Loan-to-deposit ratio (LDR) is significantly (1%) and negatively related to bank profitability (ROA), which is in line with what Huang and Pan (2016) found. ER is significantly and positively related to profitability (ROA), with a 1% significance level. It is in accordance with the findings of positive relationship between bank capitalization and profitability from García-Herrero et al. (2009); Sufian (2009); Tan and Floros (2012), among others.

Table 2.4 also reports results for risk models, for which half control variables are significant and negative in explaining non-performing loans (NPL)—that are bank size

Table 2.4: Effect of diversification on profitability (ROA) and risk (NPL), linear component, full sample

This table reports the regression results corresponding to the linear part of Equation (2.11) in which the dependent variable is profitability (ROA). $SIZE$ is bank size (as a natural logarithm of total assets in ten thousands CNY in real terms), LDR is loan-deposit ratio, CAR is capital adequacy ratio, ER is equity ratio, $gM2$ is $M2$ growth rate, $gGDP$ is GDP growth rate, and HHI_a is adjusted HHI. Model (1) indicates the OLS regressions; Model (2) indicates the FE regressions; Models (3)–(6) indicate the PLR regression results of models with NII, HHI_a, $Entropy$ and $NIBATA$, respectively. t-statistics in parentheses, and *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

	Dependent variable: ROA						Dependent variable: NPL					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
HHI_a	−0.2850	−0.4740					1.0460*	1.7250***				
	(−1.10)	(−1.53)					(1.40)	(3.30)				
$SIZE$	0.0500***	−0.0672	−0.1290*	−0.1280*	−0.1280*	−0.1360**	0.0292	-0.3870***	−0.568***	−0.5670***	−0.5650***	−0.5590***
	(2.47)	(−0.95)	(−2.10)	(−2.08)	(−2.07)	(−2.36)	(0.51)	(−3.25)	(−4.42)	(−4.42)	(−4.41)	(−4.10)
CAR	0.0026	−0.0100	−0.0092	−0.0092	−0.0089	−0.0039	−0.0591	−0.0896	−0.0261	−0.0261	−0.0255	−0.0239
	(0.16)	(-0.57)	(-1.20)	(-1.21)	(1.14)	(−0.46)	(−1.29)	(−1.53)	(−1.49)	(−1.49)	(−1.47)	(−1.59)
LDR	−0.0081**	−0.0122***	−0.0096***	−0.0096***	−0.0096***	−0.0097***	−0.0055	0.0031	0.0013	0.0013	0.0013	0.0010
	(−2.68)	(−4.04)	(−3.10)	(−3.10)	(−3.08)	(−3.65)	(−0.72)	(0.59)	(0.36)	(0.37)	(0.36)	(0.26)
ER	0.0970***	0.1140***	0.0751***	0.0753***	0.0754***	0.0841***	0.1050*	0.1220*	0.0117	0.0115	0.0118	0.0236
	(3.31)	(3.44)	(6.38)	(6.41)	(6.36)	(5.52)	(1.95)	(1.93)	(0.57)	(0.56)	(0.58)	(1.10)
$gM2$	−0.0014	−0.0053	−0.0065*	−0.0064*	−0.0064*	−0.0055	0.0022	−0.0067	−0.0168***	−0.0167***	−0.0167***	−0.0161***
	(−0.50)	(−1.37)	(−1.90)	(−1.88)	(−1.87)	(−1.72)	(0.78)	(−1.30)	(−5.43)	(−5.45)	(−5.50)	(−4.75)
$gGDP$	0.0800***	0.0319	−0.0184	−0.0184	−0.0180	−0.0149	−0.0447	−0.1230***	−0.1400***	−0.1390***	−0.1390***	−0.1350***
	(4.38)	(1.17)	(−1.64)	(−1.64)	(−1.58)	(−1.22)	(−1.49)	(−4.81)	(−7.31)	(−7.33)	(−7.33)	(−6.45)

($SIZE$), M2 growth ($gM2$) and GDP growth ($gGDP$). Specifically, larger banks have lower risk compared to small banks, which is in accordance with the results from Saunders et al. (1990), Chen et al. (1998), and Megginson (2005). The negative effect of $gGDP$ on bank risk is in line with the findings from Geng et al. (2016). In addition, the negative coefficient found for $gM2$ suggests that tighter monetary policies might have contributed to straining risk-related issues for our sample of listed banks in China during the period analyzed.

Figure 2.2 shows the nonparametric sections of the models for the full sample of banks, for the 2008–2019 period. Results are robust to the different diversification indicators used. The nonparametric estimation is conducted using B-splines, which is frequently used to model a non-linear predictive relationship between X and Y, and greatly contributes to explaining the results (Newson, 2012). The dashed area in all the subfigures reports 95% confidence intervals. In addition, Petersen (2009) suggests using clustered standard errors when a fixed firm effect exists in both the independent variable and the residual, otherwise the OLS standard errors underestimate the true standard errors. Therefore, the standard error is clustered in this study to ensure unbiased estimates. The subfigures in Figure 2.2 show there is a convoluted non-linear relationship between diversification and bank performance that any linear model would fit with more difficulties.

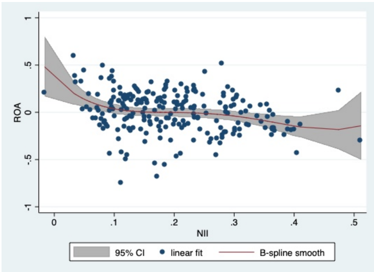
The three upper panels in Figure 2.2 show the effect of the different measures of bank income diversification (NII, HHI_a and $Entropy$). As indicated in Section 2.4, diversification is expected to affect bank profitability positively. However, a joint analysis of Figures 2.2.a, 2.2.c and 2.2.e would suggest that, after controlling for bank-specific and macroeconomic factors, when a bank's income is highly diversified, profitability declines. This finding agrees with results reported in Berger et al. (2010), which indicate that diversified Chinese banks are associated with lower profitability (ROA), on average, and higher costs. The increasing managing costs generated by implementing a high level of income diversification strategy might be the potential reason for the declining profitability. However, our result differs from Li and Zhang's (2013) findings that raising non-interest income leads to diversification benefits in the Chinese banking industry.

Regarding the risk perspective, Figures 2.2.b, 2.2.d and 2.2.f show that a high level of income diversification contributes to an overall increase in bank risk. Meanwhile, for less diversified banks (i.e. ¡0.1), the diversification strategy is beneficial in that it reduces risk. This result is in line with the relationship between diversification and bank risk found by Li and Zhang (2013), namely that increasing reliance on non-interest income may lead to higher risks for Chinese banks.

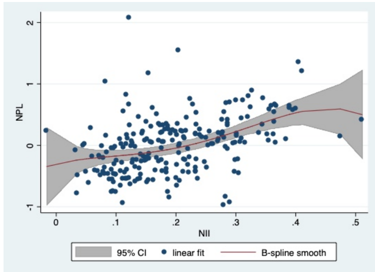
The lower panel in Figure 2.2 presents the relationship between diversification and

Figure 2.2: Impact of income diversification on profitability (ROA) and risk (NPL), full sample

NII

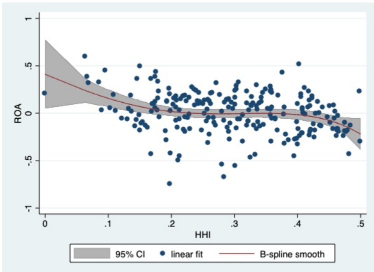


(a) ROA

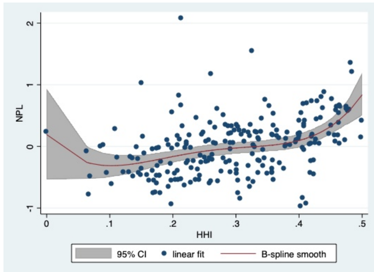


(b) NPL

HHI_a

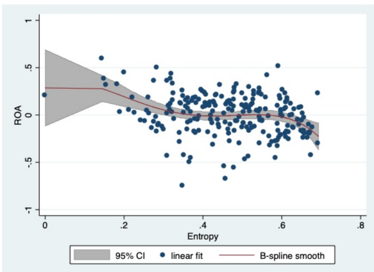


(c) ROA

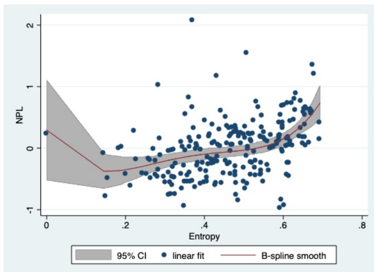


(d) NPL

Entropy

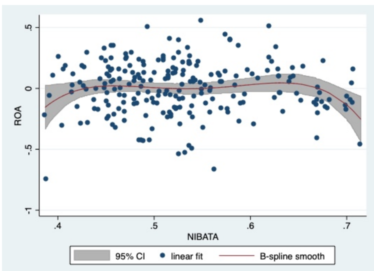


(e) ROA

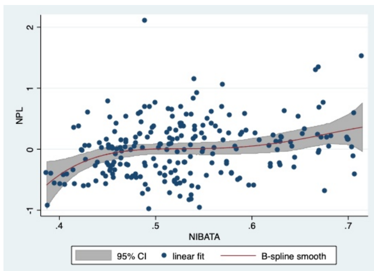


(f) NPL

$NIBATA$



(g) ROA



(h) NPL

Note: ROA is return on assets ratio, NPL is non-performing loan ratio, NII is non-interest income ratio, HHI_a is the adjusted Hirschman-Herfindahl Index (HHI), and $NIBATA$ is the ratio of non-interest bearing assets to total assets.

bank performance from the asset perspective. In general, asset diversification has an non-significant effect on both profitability and risk (panels 2.2.g and 2.2.h, respectively). Only when diversification is sufficiently low (i.e. under 0.45) do both profitability and risk increase; or when diversification is extremely high (i.e. above 0.65), profitability declines slightly. This differs from the situation of traditional banks in some other Asian countries (i.e. Indonesia, Malaysia, and Pakistan) reported by Chen et al. (2018). They find that asset diversification has negative effects on the profitability of traditional banks in those countries, but could lead to an increase of cost efficiency.

2.5.2. Semiparametric-partial linear regression (PLR) with fixed effects for sub-samples

The full sample is divided into three sub-samples of state-owned banks, national shareholding commercial banks and city commercial banks in order to better explore and compare the effect of income and asset diversification on the different types of banks in China.

Tables 2.5–2.7 present the regression results of the linear and parametric part for all bank types during the period 2008–2019. Models (1)–(4) here indicate semiparametric models with diversification indicators NII, HHI_a, Entropy and $NIBATA$, respectively. Table 2.5 shows that, for income indicators, bank size ($SIZE$), M2 growth ($gM2$) and GDP growth ($gGDP$) have significant and negative effects on profitability for state-owned banks. In model (4) with the assets indicator, only M2 growth ($gM2$) affects profitability significantly, 5%. As for risk, only equity ratio (ER) is significantly and positively linked to NPL for both income and assets indicators. Bank size ($SIZE$) and GDP growth ($gGDP$) have significant and negative effects on bank risk at the 1% significance level from assets perspective.

Regarding national shareholding commercial banks (Table 2.6), loan-deposit ratio, equity ratio and M2 growth have significant effects on profitability. Specifically, for both income and assets indicators, loan-deposit ratio affects profitability negatively, while the equity ratio effect is positive. The negative effect of the loan-to-deposits ratio on profitability may indicate that an overreliance on traditional activities reduces profitability for national shareholding commercial banks. M2 growth affects profitability significantly and negatively only for income indicators. In the risk models, both LDR and $gGDP$ have significant effects on non-performing loans (NPL); LDR affects NPL positively, while $gGDP$ affects NPL negatively. As shown in the panel of city commercial banks (Table 2.7), which are considered as the "third-tier" of banks in China, most control variables have significant (albeit both LDR and ER only at 1% significance level) and negative effects on profitability, except for the capital adequacy ratio and GDP growth, with non-performing loans being significantly and negatively affected by size, M2 growth and GDP growth.

Table 2.5: Effect of diversification on profitability (ROA) and risk (NPL), linear component, state-owned banks

This table reports the regression results corresponding to the linear part of Equation (2.11) in which the dependent variable is profitability (ROA). $SIZE$ is bank size (as natural logarithm of total assets in ten thousands CNY in real terms), LDR is loan-deposit ratio, CAR is capital adequacy ratio, ER is equity ratio, $gM2$ is $M2$ growth rate, and $gGDP$ is GDP growth rate. Models (1)–(4) indicate semiparametric models with diversification indicators NII, HHI_a, $Entropy$ and $NIBATA$, respectively. t-statistics in parentheses, and *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

	Dependent variable: ROA				Dependent variable: NPL			
	Model (1)	Model (2)	Model (3)	Model (4)	Model (1)	Model (2)	Model (3)	Model (4)
$SIZE$	−0.6400***	−0.6400***	−0.6330***	−0.0251	−0.7690	−0.7780	−0.7720	−2.3380***
	(−3.44)	(−3.43)	(−3.14)	(−0.16)	(−1.46)	(−1.47)	(−1.46)	(−5.60)
CAR	−0.0120	−0.0131	−0.0118	0.0025	−0.0793	−0.0745	−0.0813	−0.1080
	(−0.53)	(−0.58)	(−0.53)	(0.10)	(−1.24)	(−1.16)	(−1.28)	(−1.62)
LDR	0.0034	0.0035	0.0034	0.0027	−0.0114	−0.0116	−0.0114	−0.0093
	(1.18)	(1.20)	(1.18)	(0.79)	(−1.39)	(−1.41)	(−1.38)	(−1.00)
ER	0.0142	0.0163	0.0142	0.0121	0.3550**	0.3470**	0.3610**	0.3680**
	(0.28)	(0.32)	(0.28)	(0.21)	(2.43)	(2.38)	(2.48)	(2.32)
$gM2$	−0.0136***	−0.0139***	−0.0135***	−0.0076**	0.0018	0.0027	0.0014	−0.0106
	(−3,72)	(−3.76)	(−3.70)	(−2.22)	(0.17)	(0.25)	(0.13)	(−1.14)
$gGDP$	−0.0543**	−0.0536**	−0.0537**	0.0151	−0.0245	−0.0278	−0.0225	−0.2040***
	(−2.20)	(−2.17)	(−2.19)	(0.64)	(−0.35)	(−0.40)	(−0.32)	(−3.18)

Table 2.6: Effect of diversification on profitability (ROA) and risk (NPL), linear component, national shareholding commercial banks

This table reports the regression results corresponding to the linear part of Equation (2.11) in which the dependent variable is profitability (ROA). $SIZE$ is bank size (as natural logarithm of total assets in ten thousands CNY in real terms), LDR is loan-deposit ratio, CAR is capital adequacy ratio, ER is equity ratio, $gM2$ is $M2$ growth rate, and $gGDP$ is GDP growth rate. Models (1)–(4) indicate semiparametric models with diversification indicators NII, HHI_a, $Entropy$ and $NIBATA$, respectively. t-statistics in parentheses, and *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

	Dependent variable: ROA				Dependent variable: NPL			
	Model (1)	Model (2)	Model (3)	Model (4)	Model (1)	Model (2)	Model (3)	Model (4)
$SIZE$	−0.1440	−0.1500	−0.1550	−0.0964	−0.0598	−0.0606	−0.0611	−0.1680
	(−1.14)	(−1.18)	(−1.21)	(−0.96)	(−0.36)	(−0.36)	(−0.36)	(−1.05)
CAR	−0.0338	−0.0350	−0.0359	−0.0234	−0.0226	−0.0227	−0.0226	−0.0019
	(−1.28)	(−1.32)	(−1.36)	(−1.04)	(−0.65)	(−0.65)	(−0.64)	(−0.05)
LDR	−0.0167***	−0.0167***	−0.0166***	−0.0173***	0.0132***	0.0132***	0.0132***	0.0100**
	(−4.58)	(−4.57)	(−4,57)	(−5.47)	(2.74)	(2.74)	(2.74)	(2.00)
ER	0.1120***	0.1120***	0.1120***	0.1450***	−0.0578	−0.0578	−0.0579	−0.0278
	(2.76)	(2.78)	(2,79)	(4.01)	(−1.09)	(−1.09)	(−1.09)	(−0.48)
$gM2$	-0.0091**	−0.0093**	−00095**	−0.0037	−0.0052	−0.0053	−0.0053	−0.0089*
	(−2.24)	(−2.28)	(−2.32)	(−1.19)	(−0.97)	(−0.98)	(−0.98)	(−1.78)
$gGDP$	−0.0240	−0.0250	−0.0261	−0.0135	−0.1010**	−0.1020***	−0.1020***	−0.1100**
	(−0.83)	(−0.86)	(-0.90)	(−0.51)	(−2.65)	(−2.66)	(−2.66)	(−2.61)

Table 2.7: Effect of diversification on profitability (ROA) and risk (NPL), linear component, city commercial banks

This table reports the regression results corresponding to the linear part of Equation (2.11) in which the dependent variable is profitability (ROA). $SIZE$ is bank size (as natural logarithm of total assets in ten thousands CNY in real terms), LDR is loan-deposit ratio, CAR is capital adequacy ratio, ER is equity ratio, $gM2$ is $M2$ growth rate, and $gGDP$ is GDP growth rate. Models (1)–(4) indicate semiparametric models with diversification indicators NII, HHI_a, $Entropy$ and $NIBATA$, respectively. t-statistics in parentheses, and *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

	Dependent variable: ROA				Dependent variable: NPL			
	Model (1)	Model (2)	Model (3)	Model (4)	Model (1)	Model (2)	Model (3)	Model (4)
$SIZE$	−0.2260**	−0.2260**	−0.2260**	−0.2420**	−0.5250***	−0.5250***	−0.5240***	−0.5250***
	(−2.33)	(−2.33)	(−2.33)	(−2.54)	(−3.09)	(−3.09)	(−3.08)	(−3.13)
CAR	−0.0046	−0.0046	−0.0046	0.0002	−0.0185	−0.0187	−0.0186	−0.0146
	(−0.34)	(−0.34)	(−0.33)	(0.02)	(−0.78)	(−0.78)	(−0.78)	(−0.63)
LDR	−0.0086*	−0.0086*	−0.0086*	−0.0088*	0.0045	0.0045	0.0045	0.0040
	(−1.89)	(−1.88)	(−1.88)	(−1.96)	(0.56)	(0.56)	(0.56)	(0.50)
ER	0.0571*	0.0570*	0.0570*	0.0594**	0.0055	0.0055	0.0059	0.0054
	(1.97)	(1.97)	(1.97)	(2.00)	(0.11)	(0.11)	(0.12)	(0.10)
$gM2$	−0.0089**	−0.0089**	−0.0089**	−0.0089**	−0.0187**	−0.0186**	−0.0184**	−0.0178**
	(−2.17)	(−2.17)	(−2.14)	(−2.33)	(−2.59)	(−2.58)	(−2.54)	(−2.64)
$gGDP$	−0.0452	−0.0451	−0.0451	−0.0387	−0.0132**	−0.1320**	−0.1330**	−0.1420***
	(−1.58)	(−1.58)	(−1.58)	(−1.36)	(−2.64)	(−2.64)	(−2.65)	(−2.84)

The relationship between bank performance and diversification for state-owned banks, national shareholding commercial banks and city commercial banks is also illustrated in Figures 2.3, 2.4 and 2.5. In the case of state-owned banks (Figure 2.3), we find that the relationships between profitability and non-performing loans and the different income diversification indicators considered are similar to each other, granting some robustness to the results. There is an inverted U-shaped relationship between income diversification and bank profitability, implying that diversification raises bank profitability until the diversification level reaches the average, while excessive diversification level reduces bank profitability. The relationship between income diversification and risk is U-shaped, indicating that risk declines in the income diversification level to a certain point, and then changes inversely. Hence, it may suggest that a middle-level income diversification strategy benefits Chinese state-owned banks by increasing profitability and reducing risk. This partially aligns with what Li and Li (2014) report; these authors argue that income diversification of large banks in China could increase profitability and spread risk.

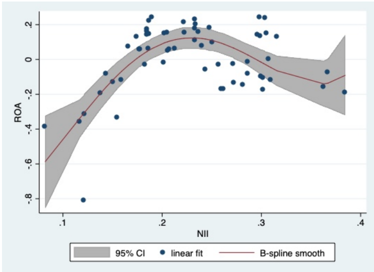
Figure 2.3 presents the relationship from an asset perspective. As shown in Figure 2.3.g, diversifying assets in the 0.45–0.55 range has no significant effect on profitability. However, when diversification is lower than 0.45, profitability increases, whereas for values higher than 0.55, it declines. Figure 2.3.h shows that risk declines for asset diversification levels under 0.55, and surges above this threshold, suggesting that less diversified asset portfolios might be beneficial for state-owned banks. Therefore, the comparison of results for the income and asset perspectives suggests that it is more beneficial for banks to engage in income rather than in asset diversification strategies—a finding in line with Moudud-Ul-Huq et al. (2018).

Figure 2.4 reports results for national shareholding commercial banks. For this group, the overall picture shows that income diversification strategies have no significant effect on bank profitability. Only for relatively low levels of diversification does profitability increase slightly. Figures 2.4.b, 2.4.d and 2.4.f show a U-shaped relationship between income diversification and risk, which is slightly flatter compared to state-owned banks. Risk declines with the degree of income diversification, but only to a certain extent. Thus, it can be concluded that a relatively low level of income diversification may slightly raise bank profitability and, simultaneously, reduce risk, while a high degree of income diversification may be linked to increasing risk for this group of financial institutions. These relationships, although intricate (and consequently difficult to fit for fully parametric specifications), are robust across income diversification measures.

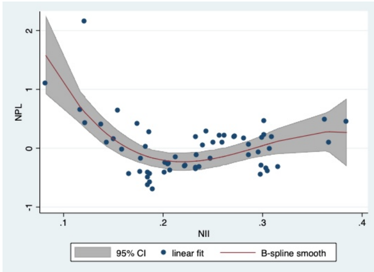
As for the asset diversification measures, reported in the lower panels of Figure 2.4, when a bank's diversification level is lower than 0.45, profitability rises slightly. However, above the 0.50 threshold of asset diversification, the relationship is negative.

Figure 2.3: Impact of income diversification on profitability (ROA) and risk (NPL), state-owned banks

NII

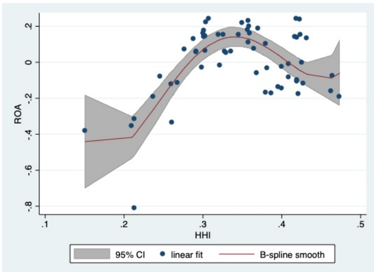


(a) ROA

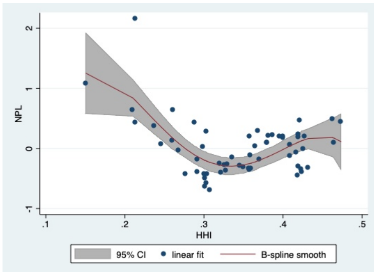


(b) NPL

HHI_a

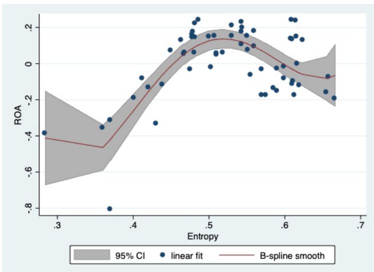


(c) ROA

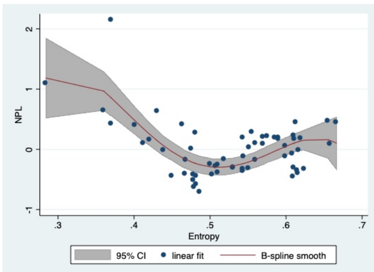


(d) NPL

Entropy

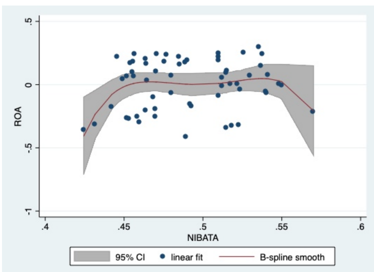


(e) ROA

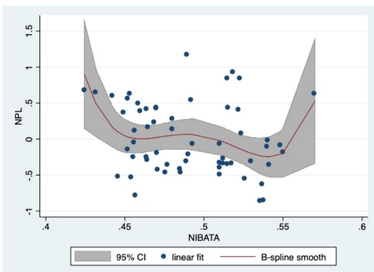


(f) NPL

$NIBATA$



(g) ROA

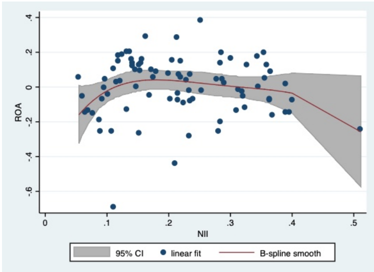


(h) NPL

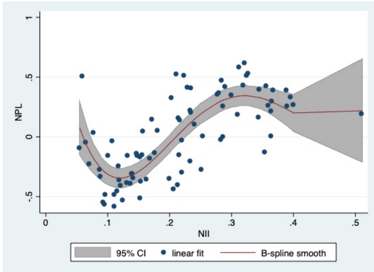
Note: ROA is return on assets ratio, NPL is non-performing loan ratio, NII is non-interest income ratio, HHI_a is the adjusted Hirschman-Herfindahl Index (HHI), and $NIBATA$ is the ratio of non-interest bearing assets to total assets.

Figure 2.4: Impact of income diversification on profitability (ROA) and risk (NPL), national shareholding commercial banks

NII

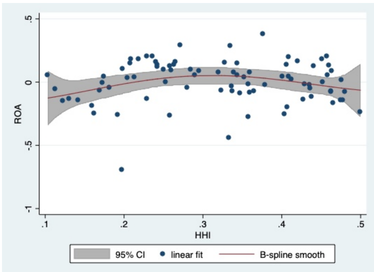


(a) ROA

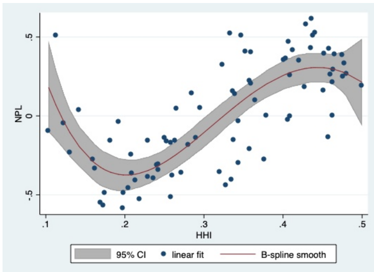


(b) NPL

HHI_a

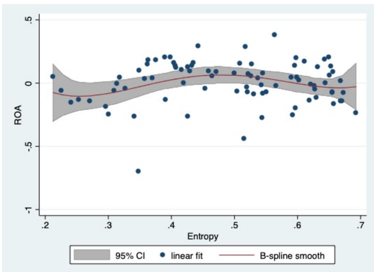


(c) ROA

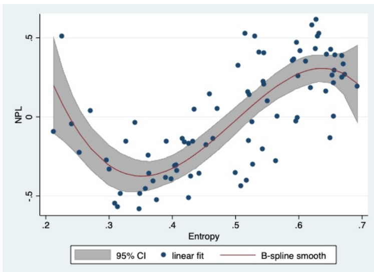


(d) NPL

Entropy

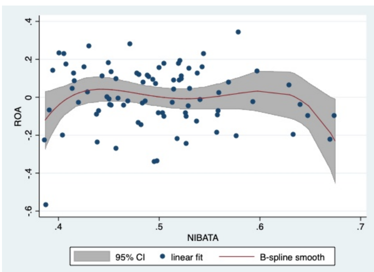


(e) ROA

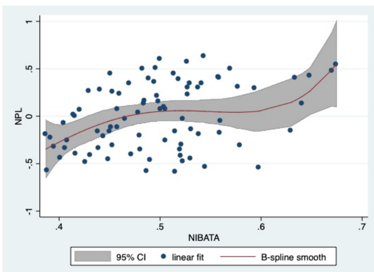


(f) NPL

$NIBATA$



(g) ROA

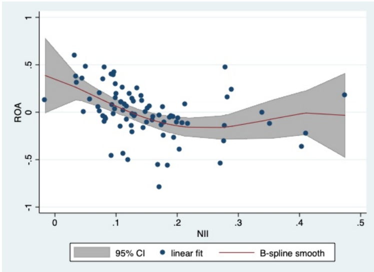


(h) NPL

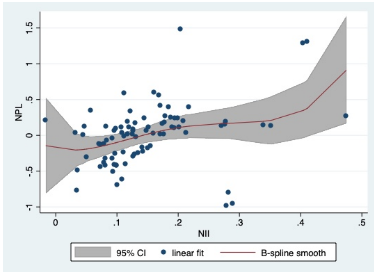
Note: ROA is return on assets ratio, NPL is non-performing loan ratio, NII is non-interest income ratio, HHI_a is the adjusted Hirschman-Herfindahl Index (HHI), and $NIBATA$ is the ratio of non-interest bearing assets to total assets.

Figure 2.5: Impact of income diversification on profitability (*ROA*) and risk (*NPL*), city commercial banks

NII

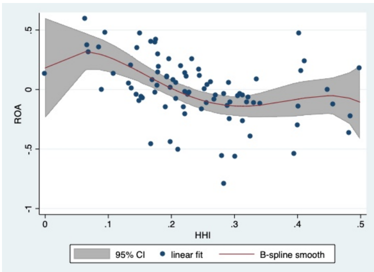


(a) *ROA*

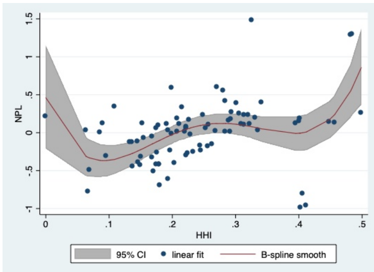


(b) *NPL*

HHI_a

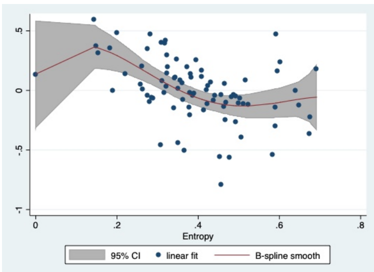


(c) *ROA*

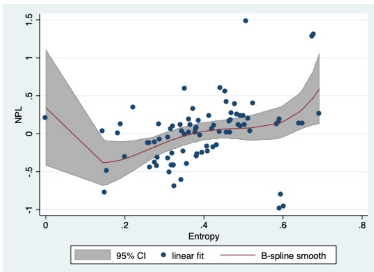


(d) *NPL*

Entropy

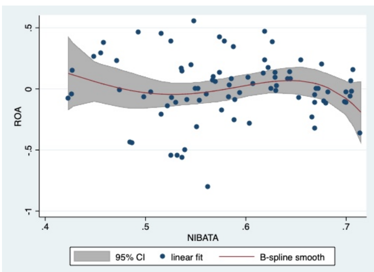


(e) *ROA*

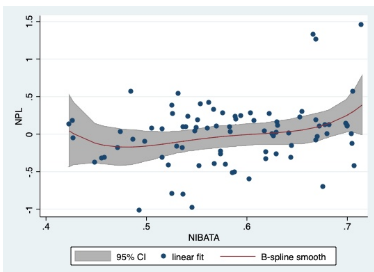


(f) *NPL*

NIBATA



(g) *ROA*



(h) *NPL*

Note: *ROA* is return on assets ratio, *NPL* is non-performing loan ratio, *NII* is non-interest income ratio, HHI_a is the adjusted Hirschman-Herfindahl Index (*HHI*), and *NIBATA* is the ratio of non-interest bearing assets to total assets.

In addition, asset diversification is only beneficial for reducing risk if a bank's asset diversification is lower than 0.45.

The relationships between diversification and bank performance for Chinese city commercial banks are shown in Figure 2.5. Income diversification has a positive effect of increasing bank profitability only when banks have a very low level income diversification strategy (i.e. < 0.05 for NII; < 0.10 for HHI_a; < 0.15 for Entropy). However, this result is entirely driven by an outlier. Once the effect of this outlier is isolated, the

impact of diversification on profitability is negative across the three income diversification measures considered (see Figures 2.5.a, 2.5.c and 2.5.e). In contrast, and as illustrated in Figures 2.5.b, 2.5.d and 2.5.f, the relationship between income diversification and risk has an almost entirely positive slope, with a negative impact existing only when risk is below a given degree of diversification (i.e. < 0.05 for NII; < 0.10 for HHI_a; < 0.15 for Entropy). Yet this effect is also due to the presence of an outlier. Therefore, for these banks, and once the effect of outliers is removed, low income diversification levels are beneficial in terms of both profitability and risk. This result is in line with Stiroh (2004b), whose findings indicate that higher income diversification levels are negatively related to the performance of small banks.

From the assets diversification perspective, we observe both in Figures 2.5.g and 2.5.h that diversification has a modest effect on profitability, with no clear sign (particularly in the case of profitability), but could contribute slightly to reducing risk when its level is lower than 0.45.

The results of the empirical analysis for sub-samples suggest two main points. First, income and asset diversification have proven to be beneficial in general, but vary across different tiers of Chinese banks. As the first tier banks, the Big Five have a much higher tolerance for diversification than the other commercial banks. This is because the Big Five enjoy significant advantages in terms of geographically diversified branches, client structure and supporting policies, which allow them to implement scale and scope economies more easily. In addition, bigger banks could discount fixed costs generated by introducing financial technologies during their diversification process. According to Berger et al. (2010), diversification discount by national shareholding commercial banks and city commercial banks might be due to inexperienced top management teams and an ineffective incentive mechanism to maximize shareholders' wealth. Thus, the Big Five state-owned banks benefit more than the other commercial banks. The second point is that there is a threshold for the positive effects of diversification on bank profitability and risk, although the threshold values vary among the three bank tiers. Benefits increase in the diversification level within the specific threshold area, but decline in the excessive diversification level.

2.6. Conclusions

Over the last few years, a significant stream of the banking literature has been evaluating the issue of whether banks should either diversify their portfolios (and/or territories where they operate) or, in contrast, specialize and focus on fewer business lines. This is the diversification-focus issue, on which no general consensus has yet been reached: while there is substantial evidence concluding that conglomerates underperform their specialized counterparts, the number of studies reaching opposite conclusions is not negligible. This evidence supporting either of the two conflicting views on the focus-diversification issue, however, has been mostly concerned with European and US markets. In contrast, the analyses evaluating other relevant contexts, particularly emerging economies, remains comparatively underexplored, at least in relatively recent years.

Our aim in this study was to bridge this gap in the literature. Specifically, we examined the impact of diversification on bank profitability/risk in the world's largest emerging economy, China, a context where banks did not have much choice in terms of product diversification until recently. We contribute to the literature by exploring the relationship between diversification and performance for Chinese listed banks over a critical and virtually unexamined period (2008–2019), considering semiparametric-partial linear methods, which have a higher degree of flexibility than more standard approaches. We also differentiated between income and asset diversification, considering a variety of diversification measures, namely non-interest income ratio, the revenue Herfindahl-Hirschman index, Entropy and non-interest bearing assets to total assets.

Interestingly, our study provides evidence that there is a non-linear relationship between diversification and bank profitability/risk from both income and asset aspects. Had we considered other less flexible approaches, this finding would remain largely concealed. Overall, the benefits for Chinese banks in terms of either income or asset diversification are modest, although results vary depending on the type of bank under analysis. State-owned banks have a higher tendency to income-diversify than their national shareholding commercial and city commercial counterparts. Nonetheless, the relationship is intricate, since only by employing semiparametric-partial methods do we learn that it is beneficial for state-owned banks to diversify up to a middle level, and up to a lower level for national shareholding commercial banks and city commercial banks. In addition, for equivalent income diversification levels, state-owned banks outperform (i.e. have higher profitability and lower risk) the other two types of banks, a result that is robust regardless of the perspective considered—either profitability or risk. This robustness is also found when evaluating the relationship between profitability/risk and diversification using different income diversification measures.

Results differ slightly from an asset diversification perspective. In this case, the effects are similar across types of bank, since it is beneficial to have asset portfolios with relatively low levels of diversification; again, this result was revealed because we used flexible techniques. Therefore, state-owned Chinese banks might enjoy some advantages when facing the new competitive environment. As for the other bank types, the results suggest they should take advantage of their expertise by focusing on one or a few business lines to cope with tighter competition in their markets.

Therefore, the diversification discount for Chinese banks found in previous relevant studies (notably Berger et al., 2010) is only partially confirmed in this research. Although the mechanisms are intricate, some explanations might be related to the ineffective incentive schemes for management teams to maximize shareholders' wealth, or the lack of managerial expertise. These factors are aggravated by the mechanisms for appointing top managers in China, which are highly dependent on managers' cooperation with local and central governments. However, according to Berger et al. (2010), this influence of different layers of government was expected to decline in the years following their study (1996–2006), which is precisely what we found when we analyzed the subsequent time period (2008–2019). We consider that our choice of a set of methodologies that more easily accommodates any possible nonlinearity present in the data also contributes to extend and refine the previous literature, since the premium or discount varies across the distribution of diversification.

Chapter 3

How does FinTech affect bank diversification versus specialization decisions?

3.1. Introduction

Digitalization is a broad phenomenon that has changed many industries in the past few years (Veit et al., 2014), including the financial industry. Since 2010, "FinTech", a *portmanteau* of 'financial' and 'technology', has become a highly discussed concept in both technological and financial areas, and typically covers topics such as cloud computing, blockchain, big data and complex AI/ML algorithms. On the one hand, with increasing customer demand for convenience and individuality, FinTech is playing a more important role in shaping the financial and banking landscape (Jagtiani and John, 2018). On the other hand, the development of FinTech services–such as blockchain services, crowdlending, peer-to-peer (P2P) lending and third party payment–raise customers' demands, and change the ways they think and act. Nowadays, FinTech is regarded as an era rather than simply an industry.

According to an Accenture report, the amount of investment in FinTech increased dramatically to U.S.$22.2 billion in 2015 (Skan et al., 2016), almost doubled the amount of U.S.$12.2 billion for 2014 and way higher than the U.S.$4.05 billion in 2013 (Skan et al., 2015). In the following years, global venture capital investment in FinTech continued to rise from U.S.$24.7 billion across 1,076 deals (2016) (KPMG, 2017b; Leong and Sung, 2018) to U.S.$111.8 billion (2018) (KPMG, 2018). In 2019, FinTech global investment remained high at over U.S.$135.7 billion (KPMG, 2020). The increasing and sizable investment in FinTech reflects the expectation for substantial change in the financial industry. Although the traditional financial sector does uese innovative technologies, financial technology startup companies (fintechs) are considered more agile and quicker in implementing new technology opportunities (Ansari and Krop, 2012; Christensen, 2013). The four tech giants (i.e. Apple, Google, Facebook and Amazon) together with mushrooming fintechs are changing the financial landscape (Hendrikse et al., 2018). They are expanding their business scope into advanced financial services that include online funds, lending services and Internet-based private banking services (Shim and Shin, 2016). Therefore, the traditional banking sector, as a financial sector deeply and widely affected by information networking, needs to be aware of the challenges it faces and transform in order to keep its place in the market.[1]

The newly emerging, and potentially disruptive, financial technologies, have been expanding rapidly in financial markets across the world, while their potential effects are still far from clear (Navaretti et al., 2017; Beck, 2020; Boot et al., 2021). Some previous literature generally claims FinTech has positive effect. For instance, Philippon (2016) point out that FinTech has helped to make services and products more available to users–and thus also represent a possible alternative to defy the menace of financial exclusion. It encourages traditional banks to innovate and to reconsider their business models to gain more market share (Frame et al., 2019). According to the Financial Stability Board (FSB, 2017), FinTech could expand banking business organisations' scale and scope, and promote intelligent banks to improve efficiency across the entire financial system. Jagtiani and John (2018) note a growing shift of market shares in banking activities from the regulated banking sector to the shadow banking sector. The potential risk increased by new diversified new activities can make banks less profitable and more fragile due to, for instance, high operational and regulation costs (Stulz, 2019). Large banks in particular would have more advantages from provide more diversified products and services due to their large customer bases. However, due to the heavy regulation, entrenched interests and massive bureaucracies they face, managing a large diversified bank effectively is complicated and difficult (Stulz, 2019), which makes them hesitant to become more diversified by developing FinTech. Although bankers, policy-makers, analysts and the academic community have concerns about whether banks should diversify more or not using FinTech development (DeYoung and Rice, 2004; Stiroh, 2004a), to date there is no empirical analysis of this issue due to data limitation. To brige this gap, our empirical study explores how does bank diversification strategies react to FinTech development over the period 2012–2018.

The Chinese banking industry is taken as an example in our study for a variety of reasons, among which we highlight two. First, China is emerging as a global FinTech leader in terms of market volume, growth rate, garnering increasing international following and innovation capabilities (Xiang et al., 2017). It is home toe some of the world's

[1]Several reviews have already been published on FinTech including, among others, the informative study by Liu et al. (2020).

major fintechs, such as Alibaba, which started as an e-commerce firm and is now one if the largest such business in the world (Kumar, 2014). According to KPMG (2021), FinTech investment in China reached US$ 1.3 billion in the first half of 2021. Second, China is known as a bank-based financing country. Traditional banks dominate the financial system and represent the main source for funding (Wang et al., 2020). With the rapid growth of FinTech in China, traditional banks are strengthening the links with it. Considering also the mega–industrial scale of the country, we can conclude that China is a relevant context in which to explore the effect of FinTech on bank diversification and specialization strategies.

From a methodological point of view, we use instrumental quantile regression (Harding and Lamarche, 2009; Lamarche, 2011), because, as indicated by Cade and Noon (2003), quantile regression provides relevant information as to the varying effects across different quantiles, which could offer a more complete picture of causal relationships missed by other regression models (e.g., OLS). Our results can be exploited in several dimensions, but they suggest FinTech has an overall positive effect on income diversification, whereas the impact on asset diversification–for the sample period and context analyzed–is not significant. After comparing and analysing different Chinese bank types, we also find that national shareholding commercial banks are more sensitive to FinTech, and more diversified than their state-owned and city commercial counterparts.

Thus, our study provides some contributions to the field. First, on the basis of our literature review, we empirically evaluate the relationship between FinTech and bank diversification and specialization strategies, as well as how this relationship is conditioned by the type of bank under analysis. To do this, diversification is measured from both income and asset perspectives, for different diversification indicators. In addition, our application is relatively innovative from a methodological point of view, as it uses the robust version of quantile regression (QR) which, up to now, has only been considered in the study by Demir et al. (2022), but not to explore the varying effects of FinTech across different quantiles on bank diversification.

The rest of this article is organised as follows. Section 3.2 presents the model, data and variables considered in the study. The results are presented and discussed in Section 2.5 and Section 3.5 concludes.

3.2. Empirical methodology: regression quantiles

The quantile regression model (QR) was introduced by Koenker and Bassett (1978). It was initially used in biology and ecology, and has been applied in relatively recent times to the economic area. It models the quantiles of the dependent variable conditioned to a linear function of independent variables. Consider a cross-section model $y_i = \mathbf{x}_i'\boldsymbol{\beta} + u_i$, where y_i is the dependent variable, $\mathbf{x}_i$ is the vector of independent variables and $\boldsymbol{\beta}$ is the vector of parameters. Then, given a quantile τ, the parameter estimates of the QR model are obtained by solving the following minimization problem,

$$\min_{\boldsymbol{\beta}} \sum_{i=1}^{N} \rho_\tau(y_i - \mathbf{x}_i'\boldsymbol{\beta}) \tag{3.1}$$

where $\rho_\tau(u_i) = u_i(\tau - \mathbb{I}_{u_i \leq 0})$ is the quantile-regression loss function, $\mathbb{I}$ is an indicator function, and the vector of parameters $\boldsymbol{\beta}$ depends on τ.

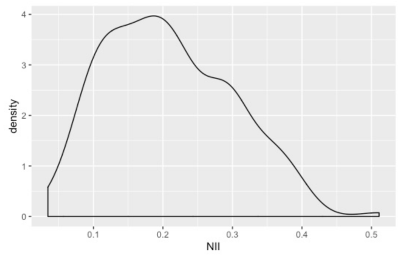
In the particular context of this paper, although OLS estimates are a useful starting point, QR is preferable to OLS for the following reasons. First, regarding the error terms, quantile estimators are more robust than OLS with non-normal or heteroscedastic data (Coad and Rao, 2008; Cameron et al., 2009; Alamá and Tortosa-Ausina, 2012). Figure 3.1 shows that the distribution of the dependent variables (i.e. diversification indicators from income and assets aspects) used in this study exhibits departures from normality, which would constitute evidence for using QR rather than OLS in these specific circumstances. Second, QR relaxes the restrictive assumption for OLS that error terms are distributed identically at all conditional distribution points, and provides a broader view through taking into account the entire distribution of the response variable. It is worth investigating banks with high or low diversification degrees rather than to dismiss them as outliers. Third, Cade and Noon (2003) claim that QR is specially useful when more than one factor is considered affecting the response variable, when factors have heterogeneous effects, and when not all factors are measured. In our context, QR could provide insights to explain whether the link between different bank diversification levels and FinTech's effects on diversification is remarkable or not.

However, QR has some disadvantages that it is fair to say also affect more well-known econometric methods. Specifically, endogeneity is a common issue in both cross-section and panel data regressions, making model estimates inconsistent due to their correlation with unobserved factors affecting the dependent variable. QR is not immune to this problem, but papers by Chernozhukov and Hansen (2005 and 2008) develop a model with instrumental variables in the presence of endogeneity along with a robust inference approach to partial or weak identification. The instrumental QR estimates are obtained in two steps and their covariance matrix has a standard sandwich formula representation (see Chernozhukov and Hansen (2008) for further details). In addition, the extension of the QR model for panel data with the introduction of fixed effects is straightforward (see Koenker (2004)). It is expressed as follows:

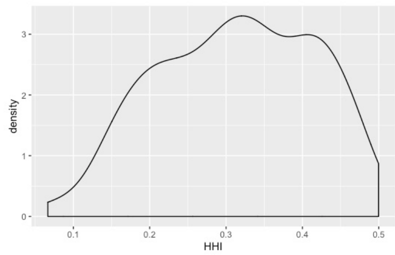
$$y_{it} = \mathbf{x}_{it}'\boldsymbol{\beta} + \mathbf{z}_{it}\boldsymbol{\alpha} + u_{it}, \quad i = 1, \ldots, N, \quad t = 1, \ldots, T \tag{3.2}$$

where y_{it} is the dependent variable for bank i and year t, $\mathbf{x}_{it}$ is the vector of independent variables of bank i and year t, $\mathbf{z}_{it}$ is the vector of bank and year effects and $\boldsymbol{\alpha}$ is the fixed effects' vector of parameters.

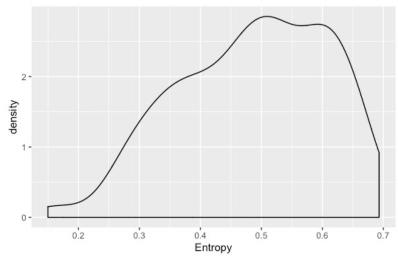
Figure 3.1: Distribution of diversification indicators



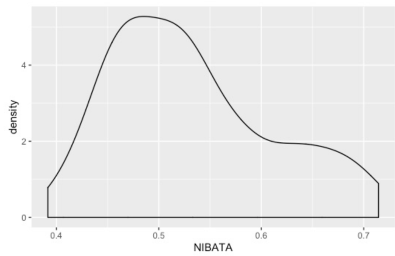
(a) NII



(b) HHI_a



(c) $Entropy$



(d) $NIBATA$

Notes: Figures show kernel density estimations of different diversification indicators.

Harding and Lamarche (2009) merge the above extensions of the QR model (from exogeneity to endogeneity and from cross-section data to panel data) to estimate covariate effects in a model with fixed effects and instrumental variables. To this end, they start from the instrumental QR approach by Chernozhukov and Hansen (2008) which is extended by allowing fixed effects as introduced by Koenker (2004), although in Harding and Lamarche (2009) approach the fixed effects estimators are also quantile-dependent.[2]

The model is written below:

$$y_{it} = \mathbf{d}'_{it}\delta + \mathbf{x}'_{it}\boldsymbol{\beta} + \mathbf{z}_{it}\boldsymbol{\alpha} + u_{it} \tag{3.3}$$

where $\mathbf{d}$ is a vector of endogenous variables, which is related to a vector of instrumental variables $\mathbf{w}$; $\mathbf{x}$ is a vector of exogenous variables; $\mathbf{z}$ is the the vector of province and year fixed effects; and u is the error term.

For a given quantile τ, the objective function for the relationship of conditional instrumental quantile would be:

[2]Koenker (2004) noted that the introduction of a large number of fixed effects can increase the variability of the estimations of the covariates. The solution he proposes consists of allowing the impact of the covariates to be quantile-dependent, whereas the fixed effects are not.

$$R(\tau,\delta,\boldsymbol{\beta},\gamma,\boldsymbol{\alpha}) = \sum_{i=1}^{N}\sum_{t=1}^{T}\rho_\tau(y_{it} - \mathbf{d}'_{it}\delta - \mathbf{x}'_{it}\boldsymbol{\beta} - \mathbf{z}_{it}\boldsymbol{\alpha} - \hat{\mathbf{d}}_{it}\gamma) \tag{3.4}$$

where $\hat{\mathbf{d}}$ is the ordinary least square projection of the endogenous variables $\mathbf{d}$ on the instrument variables $\mathbf{w}$ and the exogenous variables $\mathbf{x}$.

The estimation procedure will then be processed in two step: First, the estimation of $\boldsymbol{\beta}$, γ and $\boldsymbol{\alpha}$ are obtained as a functions of τ and δ, i.e.,

$$\Big(\hat{\boldsymbol{\beta}}(\tau,\delta), \hat{\gamma}(\tau,\delta), \hat{\boldsymbol{\alpha}}(\tau,\delta)\Big) \in \arg\min_{\boldsymbol{\beta},\gamma,\boldsymbol{\alpha}} R(\tau,\delta,\boldsymbol{\beta},\gamma,\boldsymbol{\alpha}) \tag{3.5}$$

The second step allows us to find an estimation of δ as a function of τ by looking for the value of δ that makes the instrumental variables coefficients as close to zero as possible, i.e.,

$$\hat{\delta}(\tau) \in \arg\min_{\delta} \hat{\gamma}(\tau,\delta)'\mathbf{A}\hat{\gamma}(\tau,\delta) \tag{3.6}$$

where $\mathbf{A}$ is a positive-definite matrix.

Thus, the parameter estimates are $(\hat{\delta}(\tau), \hat{\boldsymbol{\beta}}(\tau,\hat{\delta}(\tau)), \hat{\gamma}(\tau,\hat{\delta}(\tau)), \hat{\boldsymbol{\alpha}}(\tau,\hat{\delta}(\tau)))$, whose covariate matrix has a standard sandwich formula representation (see Harding and Lamarche (2009) for further details).

3.3. Variables and data

3.3.1. Measuring FinTech

We use the Peking University Digital Financial Inclusion Index of China (PKU-DFIIC), which has been introduced in Chapter 1 (see Section 1.2.1), in this study to indicate FinTech development. In addition to the aggregate index, PKU-DFIIC reports disaggregated indexes of three main dimensions, including coverage breadth, usage depth and digitization level. Considering the potential endogeneity issue mentioned in Section 3.2, we use the provincial-level coverage breadth dimension of digital finance index and take its average to measure FinTech in this study. The coverage breadth index consists of three indicators that are number of Alipay accounts owned per 10,000 people, proportion of Alipay users who have bank cards bound to their Alipay accounts, and average number of bank cards bound to each Alipay account. Meanwhile, the lagged values (one year) of the possible endogenous *FinTech* variables will be used as instruments. It is a common approach suggested by Temple (1999) to obtain instrumental variables in economics (see, for instance, Kellogg, 2014).

3.3.2. Measuring bank diversification

In this Chapter, we examine the effects of FinTech on bank diversification from *both* income and asset perspectives, which has been introduced in Chapter 2 (see Section 2.3).

3.3.3. Control variables

Based on previous studies (Qiu et al., 2018; Deng et al., 2021), we consider a set of control variables at both bank-specific and macroeconomic levels in our model (Table 2.2). $SIZE$ represents bank size and controls for the impact of size on bank diversification strategy; CAR is the capital adequacy ratio and controls for the influence of bank capital structure on diversification decisions; LDR is the loan-deposit ratio and controls for the influence of asset structure on diversification strategy; ROA is the return on assets ratio and controls for the impact of profitability on diversification; and NPL is the non-performing loans ratio and controls for the impact of credit risk on the decision to diversify. The ownership dummy variables of three different bank tiers—namely, state-owned banks ($Statebank$), national shareholding commercial banks ($Sharebank$) and city commercial banks ($Citybank$)–are included to control for the effect of different bank ownership on diversification; $gM2$ is the macroeconomic factor, representing the broad money growth rate. It controls for the effect of monetary policy on the whole banking sector. The definition of each variable is explained in Table 3.1.

3.3.4. Model specification

The benchmark model of this study is expressed as follows:

$$DIV_{it} = \alpha_i + \delta FinTech_{it} + \beta Control_{it} + \mu_{it} \tag{3.7}$$

where i indicates the cross-section dimension (i.e., bank), t denotes the time dimension. α_i denotes the fixed effect. $FinTech$ reflects the Financial innovation level in China, compiled by the Digital Finance Center of Peking University. Control variables contain bank size ($SIZE$), capital adequacy ratio (CAR), loan-deposit ratio (LDR), return on assets ratio (ROA), non-performing loans ratio (NPL), M2 growth rate ($gM2$) and ownership dummy varaibles (OWN) to capture the potential different effects of FinTech on bank diversification among three Chinese bank tiers. μ_{it} refers to the error term.

3.3.5. Data and descriptive statistics

After dropping banks' missing observations for any variable in the model, the data of 19 listed Chinese banks during the period 2012–2018 is finally used in this study. The

Table 3.1: Summary of variables

Category	**Factors**	**Variable**	**Definition**
Dependent	Diversification	Diversification indicators	Income-based and asset-based diversification
Independent	FinTech Index	China Digital Finance Index	Ln(the coverage breadth of city-level digital finance index)
Controls	Bank-level	Bank size (*SIZE*)	Ln(total assets in real terms (CNY))
		Capital adequacy ratio (*CAR*)	Capital/Risk-weighted assets
		Loan-deposit ratio (*LDR*)	Total loans/Total deposits
		Return on assets (*ROA*)	Income before tax/Total assets
		Non-performing loans (*NPL*)	Non-performing loans/Total loans
	Macroeconomic	*M2* growth rates (*gM2*)	Annual growth rates of *M2* (%)

banks are divided into three tiers: five state-owned banks (Bank of China, Industrial and Commercial Bank of China, Agricultural Bank of China, China Construction Bank, and Bank of Communications), seven national shareholding commercial banks (China CITIC Bank, China Merchants Bank, China Minsheng Bank, Hua Xia Bank, Industrial Bank, Ping An Bank and Shanghai Pudong Development Bank), and seven city commercial banks (Bank of Beijing, Bank of Changsha, Bank of Jiangsu, Bank of Nanjing, Bank of Ningbo, Bank of Zhengzhou and Jiangsu Zhangjiagang Rural Commercial Bank). Most bank-level data are drawn from Wind database, and some missing and/or questionable bank data are collected and checked from banks' official annual reports. As mentioned above, the FinTech index is obtained from the digital financial inclusion index compiled by the Digital Finance Center of Peking University. The macroeconomic factor data, $M2$ growth rates, are from Worldbank. We considered panel data to be an appropriate approach to explore the link between FinTech and bank diversification strategy. Table 3.2 presents correlation among variables. It can be seen that most variables are significantly related to bank diversification level.

Descriptive statistics of the variables are summarised in Table 3.3. There is a large gap between the maximum and minimum value of FinTech index prior to applying the log transformation (245.7926 and 34.2781, respectively). This reflects the rapid development of FinTech in China during the period 2012–2018. However, after applying a natural logarithm the FinTech value has a smoother change (the maximum and minimum are 5.5045 and 3.5345, respectively) and a small standard deviation (0.6416), which is reported in Table 3.3. Therefore, it is reasonable to take the value of logarithm into account. In addition, summarizing the three income-based diversification indicators reveals remarkable differences in the range for the entire sample, suggesting heterogeneous diversification strategies across banks.

3.4. Results

3.4.1. FinTech results

As discussed in Section 3.2, although OLS estimates provide useful insights, they only explain average effects on the response variable rather than the effects varying across different quantiles. Figures 3.2.a, 3.2.b, 3.2.c and 3.2.d show the results for OLS regression, the median regression and different percentiles (0.10, 0.25, 0.75, 0.90) with the non-interest income ratio (NII), the Herfindahl-Hirschman index (HHI_a), $entropy$, and non-interest bearing assets to total assets ($NIBATA$), respectively (more details can be found in the figure note). The plots illustrate how different percentiles have different slopes for FinTech indicator. This is in line with Koenker (2004)'s observation that quantile regression provides a natural complement to OLS and a more complete picture of

Table 3.2: Correlation matrix

This table shows correlation among variables over the period 2012–2018. *FinTech* is the provincial-level China Digital Finance Index compiled by Peking University Digital Finance Research Center. *NNI* is non-interest income ratio, HHI_a is adjusted *HHI*, *NIBATA* is the ratio of non-interest bearing assets to total assets, *SIZE* is bank size (as a natural logarithm of total assets in ten thousands), *CAR* is capital adequacy ratio, *LDR* is loan-deposit ratio, *ROA* is return on assets ratio, *NPL* is non-performing loan ratio and $gM2$ is $M2$ growth rate. All data are deflated by *GDP* deflator.

	NNI	HHI_a	*Entropy*	*NIBATA*	*FinTech*	*SIZE*	*CAR*(%)	*LDR*(%)	*ROA*(%)	*NPL*(%)	$gM2$(%)
FinTech	0.4791	0.4704	0.4634	-0.0118	1						
SIZE	0.6118	0.6782	0.6877	-0.5698	0.1660	1					
CAR(%)	0.0863	0.0958	0.0907	-0.2916	0.1267	0.1770	1				
LDR(%)	0.6248	0.5930	0.5780	-0.6322	0.2686	0.3800	-0.0062	1			
ROA(%)	-0.2358	-0.2148	-0.2184	-0.1736	-0.6003	0.1605	0.1190	-0.2395	1		
NPL(%)	0.5089	0.4971	0.4935	-0.2988	0.6784	0.2856	0.1611	0.4188	-0.4895	1	
$gM2$(%)	-0.4659	-0.4258	-0.4120	0.1071	-0.7232	-0.1469	-0.2886	-0.3582	0.5979	-0.5129	1

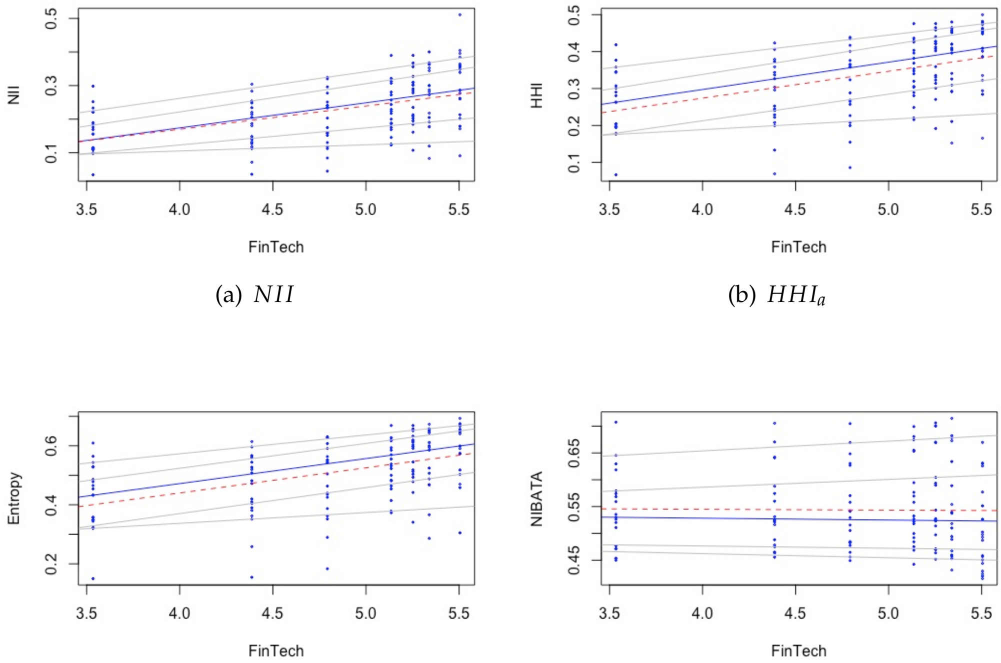
Table 3.3: Descriptive statistics

This table shows summary descriptive statistics for all variables on average over the period 2012–2018. *NNI* is non-interest income ratio, HHI_a is adjusted *HHI*, *NIBATA* is the ratio of non-interest bearing assets to total assets, *FinTech* is the city-level China Digital Finance Index compiled by Peking University Digital Finance Research Center, *SIZE* is bank size (as a natural logarithm of total assets in ten thousands), *CAR* is capital adequacy ratio, *LDR* is loan-deposit ratio, *ROA* is return on assets ratio, *NPL* is non-performing loan ratio and $gM2$ is $M2$ growth rate. All data are deflated by *GDP* deflator. Further details are provided in Table 2.2.

	NNI	HHI_a	*Entropy*	*NIBATA*	*FinTech*	*SIZE*	*CAR*(%)	*LDR*(%)	*ROA*(%)	*NPL*(%)	$gM2$(%)
# obs.	133	133	133	133	133	133	133	133	133	133	133
Mean	0.2287	0.3358	0.5126	0.5437	4.8495	19.3518	12.7947	71.0383	1.2646	1.2756	11.8000
S.D.	0.0927	0.0993	0.1182	0.0809	0.6416	1.5650	1.4405	12.5337	0.2696	0.4122	2.2738
Min.	0.0345	0.0665	0.1499	0.4157	3.5345	15.7600	9.8800	43.2000	0.7248	0.4300	8.0000
1st Qu.	0.1599	0.2687	0.4395	0.4753	4.3873	18.4500	11.7500	65.3900	1.0504	0.9200	9.1000
Median	0.2205	0.3437	0.5275	0.5260	5.1352	19.5800	12.4100	71.3700	1.2645	1.2800	12.3000
3rd Qu.	0.2981	0.4185	0.6092	0.5946	5.3397	20.2900	13.7100	76.7802	1.4487	1.5500	13.9000
Maximum	0.5109	0.4998	0.6929	0.7144	5.5045	21.7100	17.1900	109.9800	1.8536	2.4700	14.2000

covariate effects by estimating a family of conditional quantile functions.

Figure 3.2: Quantile slopes for *FinTech*



(a) NII (b) HHI_a

(c) $Entropy$ (d) $NIBATA$

Notes: The plots present differnts fits for models with different income and assets diversification indicators (i.e. NII, HHI_a, $Entropy$ and $NIBATA$), where FinTech indicator $FinTech$ is considered as explanatory variable together with an intercept. Some percentiles (0.10, 0.25, 0.75, 0.90) are gray solid lines; the median (quantile: 0.50) is in blue (solid); the OLS is in red (dashed).

Tables 3.4 and 3.5 report results for the instrumental quantile regression with different diversification indicators, namely, the non-interest income ratio (NII), the revenue Herfindahl-Hirschman index (HHI_a), the entropy index ($Entropy$) and non-interest bearing assets to total assets ($NIBATA$). The estimates are graphically displayed in Figure 3.3.

Results are robust to the diversification indicators considered. Note that the confidence intervals for the OLS estimation do not contain the zero in the models of income diversification (i.e. NII, HHI_a and $Entropy$), but they overlap the zero line in Figure 3.3.d with the assets diversification indicator $NIBATA$. This would imply that, on average, FinTech has significant effects on income diversification of Chinese banks for the 2012–2018 period, but not on the diversification of their assets. The confidence intervals represented by the shaded areas in Figures 3.3 are for the quantile estimation. They are computed by implementing the rank method suggested by Koenker (1994) for a small sample size. We can see that FinTech development is significant and positive for bank in-

Table 3.4: Determinants of bank diversification (NII and HHI_a), instrumental quantile regression

This table shows the results for the main percentiles over the period 2012–2018. Confidence indicators (shown in parentheses) are computed using the rank method, which is appropriate for small samples with fewer than 1000 observations (Koenker, 1994). The estimated coefficients in bold indicate the significance of the quantiles.

	Dependent variable: NII				
	Quantile (τ)				
Variables	τ = 0.10	τ = 0.25	τ = 0.50	τ = 0.75	τ = 0.90
(Intercept)	**-0.7780**	**-0.7594**	**-0.4910**	-0.3552	-0.5402
	(-1.3304,-0.6473)	**(-1.1302,-0.3589)**	**(-0.8580,-0.2365)**	(-0.6382,0.0116)	(-1.0594,0.6325)
FinTech	**0.0351**	**0.0288**	**0.0381**	**0.0394**	0.0121
	(0.0010,0.0867)	**(0.0052,0.0935)**	**(0.0214,0.0608)**	**(0.0076,0.0466)**	(-0.0334,0.0498)
SIZE	**0.0270**	**0.0273**	**0.0163**	0.0138	0.0493
	(0.0108,0.0440)	**(0.0066,0.0409)**	**(0.0085,0.0317)**	(-0.0002,0.0303)	(-0.0333,0.0787)
CAR(%)	0.0058	0.0092	**0.0048**	0.0124	-0.0088
	(-0.0014,0.0145)	(-0.0028,0.0214)	**(0.0003,0.0133)**	(-0.0035,0.0213)	(-0.0295,0.0362)
LDR(%)	**0.0025**	**0.0021**	**0.0020**	**0.0013**	0.0022
	(0.0005,0.0036)	**(0.0009,0.0033)**	**(0.0006,0.0026)**	**(0.0002,0.0022)**	(-0.0031,0.0046)
ROA	0.0040	-0.0381	-0.0028	-0.0077	-0.0216
	(-0.1135,0.1066)	(-0.0846,0.0867)	(-0.0561,0.0282)	(-0.0635,0.0200)	(-0.1384,0.0593)
NPL	0.0032	0.0080	0.0018	-0.0235	0.0201
	(-0.0520,0.0668)	(-0.0661,0.0910)	(-0.0324,0.0333)	(-0.0521,0.0341)	(-0.1058,0.0777)
gM2(%)	-0.0014	0.0036	-0.0018	**-0.0090**	-0.0131
	(-0.0110,0.0096)	(-0.0070,0.0096)	(-0.0076,0.0032)	**(-0.0148,-0.0032)**	(-0.0255,0.0034)
Statebank	-0.0185	-0.0026	0.0286	0.0488	-0.1224
	(-0.1466,0.0912)	(-0.1095,0.0574)	(-0.0027,0.0587)	(-0.0681,0.1095)	(-0.2359,0.1725)
Sharebank	0.0313	**0.0338**	**0.0699**	0.1016	-0.0606
	(-0.0064,0.0692)	**(0.0020,0.0705)**	**(0.0194,0.0922)**	(-0.0365,0.1504)	(-0.2221,0.2021)

	Dependent Variable: HHI_a				
	Quantile (τ)				
Variables	τ = 0.10	τ = 0.25	τ = 0.50	τ = 0.75	τ = 0.90
(Intercept)	**-1.2781**	**-0.8032**	**-0.4477**	**-0.3470**	-0.3893
	(-1.5750,-0.7507)	**(-1.2653,-0.4519)**	**(-0.9495,-0.2909)**	**(-0.5477,-0.0705)**	(-1.0527,0.3462)
FinTech	**0.0542**	**0.0427**	**0.0443**	**0.0474**	0.0406
	(0.0148,0.1117)	**(0.0158,0.1138)**	**(0.0327,0.0723)**	**(0.0140,0.0590)**	(-0.0052,0.0574)
SIZE	**0.0492**	**0.0299**	**0.0240**	**0.0165**	**0.0386**
	(0.0173,0.0752)	**(0.0140,0.0618)**	**(0.0094,0.0358)**	**(0.0112,0.0349)**	**(0.0051,0.0644)**
CAR(%)	**0.0100**	0.0091	0.0027	0.0114	0.0001
	(0.0074,0.0139)	(-0.0042,0.0211)	(-0.0052,0.0188)	(-0.0034,0.0237)	(-0.0129,0.0252)
LDR(%)	**0.0025**	**0.0022**	**0.0015**	0.0008	-0.0001
	(0.0009,0.0051)	**(0.0009,0.0037)**	**(0.0004,0.0027)**	(-0.0003,0.0022)	(-0.0033,0.0029)
ROA	-0.0270	-0.0342	-0.0296	-0.0140	-0.0594
	(-0.1734,0.0679)	(-0.1368,0.0439)	(-0.1047,0.0281)	(-0.0986,0.0224)	(-0.1144,0.0855)
NPL	-0.0157	0.0050	-0.0111	-0.0152	-0.0298
	(-0.0701,0.0598)	(-0.0772,0.0529)	(-0.0687,0.0231)	(-0.0576,0.0502)	(-0.0670,0.0741)
gM2(%)	0.0061	0.0058	-0.0020	-0.0045	-0.0028
	(-0.0058,0.0100)	(-0.0091,0.0118)	(-0.0069,0.0086)	(-0.0109,0.0016)	(-0.0214,0.0041)
Statebank	-0.0340	0.0123	**0.0429**	0.0622	-0.0280
	(-0.1673,0.1132)	(-0.0933,0.0822)	**(0.0061,0.0909)**	(-0.0231,0.0871)	(-0.1939,0.1147)
Sharebank	**0.0405**	**0.0471**	**0.0748**	**0.1050**	0.0282
	(0.0007,0.0621)	**(0.0062,0.0822)**	**(0.0436,0.1029)**	**(0.0030,0.1333)**	(-0.2152,0.1755)

Table 3.5: Determinants of bank diversification (*Entropy* and *NIBATA*), instrumental quantile regression

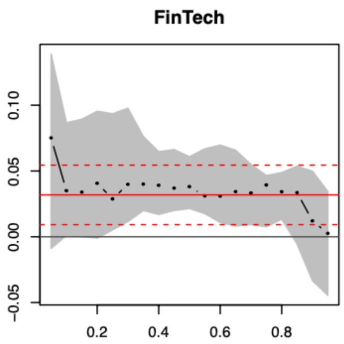
This table shows the results for the main percentiles over the period 2012–2018. Confidence indicators (shown in parentheses) are computed using the rank method, which is appropriate for small samples with fewer than 1000 observations (Koenker, 1994). The estimated coefficients in bold indicate the significance of the quantiles.

	Dependent variable: Entropy				
	Quantile (τ)				
Variables	τ = 0.10	τ = 0.25	τ = 0.50	τ = 0.75	τ = 0.90
(Intercept)	**-1.4537**	**-0.8466**	**-0.4108**	-0.3003	-0.2340
	(-1.9077,-0.8645)	**(-1.3442,-0.5598)**	**(-0.9601,-0.2228)**	(-0.5624,0.0511)	(-1.0471,0.5387)
FinTech	**0.0710**	**0.0475**	**0.0529**	**0.0548**	0.0396
	(0.0190,0.1346)	**(0.0197,0.1321)**	**(0.0375,0.0905)**	**(0.0141,0.0731)**	(-0.0096,0.0734)
SIZE	**0.0602**	**0.0360**	**0.0299**	**0.0215**	**0.0429**
	(0.0195,0.1102)	**(0.0177,0.0847)**	**(0.0085,0.0416)**	**(0.0141,0.0459)**	**(0.0094,0.0752)**
CAR(%)	**0.0114**	0.0071	0.0118	0.0120	0.0023
	(0.0059,0.0165)	(-0.0042,0.0213)	(-0.0085,0.0214)	(-0.0048,0.0249)	(-0.0145,0.0290)
LDR(%)	**0.0029**	**(0.0031)**	**0.0018**	0.0008	-0.0005
	(0.0010,0.0054)	**(0.0012,0.0046)**	**(0.0005,0.0030)**	(-0.0002,0.0023)	(-0.0040,0.0031)
ROA	-0.0598	-0.0282	-0.0386	-0.0154	-0.0762
	(-0.2100,0.0499)	(-0.1594,0.0525)	(-0.1194,0.0233)	(-0.1173,0.0245)	(-0.1238,0.0937)
NPL	-0.0267	0.0180	-0.0234	-0.0208	-0.0342
	(-0.0734,0.0936)	(-0.0861,0.0512)	(-0.0755,0.0218)	(-0.0653,0.0431)	(-0.0741,0.0826)
gM2(%)	-0.0098	0.0067	-0.0020	-0.0046	-0.0047
	(-0.0040,0.0165)	(-0.0066,0.0132)	(-0.0071,0.0086)	(-0.0113,0.0033)	(-0.0233,0.0050)
Statebank	-0.0282	0.0119	**0.0495**	0.0631	-0.0281
	(-0.2297,0.0934)	(-0.0993,0.0860)	**(0.0152,0.0965)**	(-0.0355,0.0940)	(-0.2135,0.1202)
Sharebank	0.0519	**0.0408**	**0.0809**	0.1132	0.0420
	(-0.0095,0.0743)	**(0.0144,0.0970)**	**(0.0557,0.1206)**	(-0.0106,0.1481)	(-0.2355,0.1884)

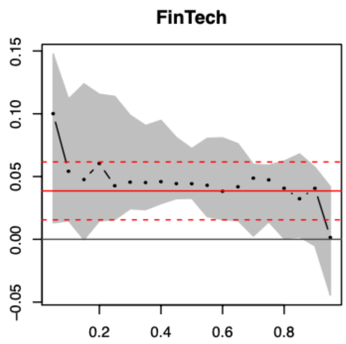
	Dependent variable: NIBATA				
	Quantile (τ)				
Variables	τ = 0.10	τ = 0.25	τ = 0.50	τ = 0.75	τ = 0.90
(Intercept)	0.5331	**0.5185**	**0.5633**	**0.8608**	**0.9949**
	(-0.0385,0.8104)	**(0.2520,0.8832)**	**(0.4038,0.7582)**	**(0.6395,1.0514)**	**(0.7255,1.2546)**
FinTech	**0.0442**	0.0321	-0.0019	-0.0078	0.0088
	(0.0177,0.0986)	(-0.0173,0.0759)	(-0.0141,0.0248)	(-0.0142,0.0069)	(-0.0150,0.0139)
SIZE	0.0101	**0.0153**	**0.0223**	0.0079	-0.0029
	(-0.0037,0.0259)	**(0.0035,0.0271)**	**(0.0055,0.0284)**	(-0.0094,0.0267)	(-0.0194,0.0122)
CAR(%)	-0.0064	-0.0073	-0.0026	-0.0001	0.0035
	(-0.0187,0.0023)	(-0.0168,0.0037)	(-0.0093,0.0009)	(-0.0051,0.0044)	(-0.0089,0.0117)
LDR(%)	**-0.0033**	**-0.0036**	**-0.0045**	**-0.0045**	**-0.0044**
	(-0.0050,-0.0024)	**(-0.0049,-0.0030)**	**(-0.0050,-0.0039)**	**(-0.0052,-0.0033)**	**(-0.0057,-0.0035)**
ROA	-0.0651	-0.0271	**-0.0366**	**-0.0495**	**-0.0678**
	(-0.1643,0.0483)	(-0.1108,0.0301)	**(-0.0623,-0.0006)**	**(-0.1149,-0.0268)**	**(-0.1226,-0.0511)**
NPL	**-0.0563**	-0.0367	-0.0027	0.0209	-0.0020
	(-0.1257,-0.0079)	(-0.0917,0.0310)	(-0.0422,0.0162)	(-0.0047,0.0371)	(-0.0112,0.0617)
gM2(%)	0.0057	0.0035	0.0026	-0.0002	-0.0013
	(-0.0021,0.0106)	(-0.0038,0.0083)	(-0.0021,0.0055)	(-0.0037,0.0048)	(-0.0080,0.0054)
Statebank	**-0.0917**	**-0.1398**	**-0.1726**	**-0.1420**	**-0.0928**
	(-0.1961,-0.0508)	**(-0.2069,-0.0715)**	**(-0.2023,-0.1201)**	**(-0.1956,-0.0832)**	**(-0.1263,-0.0613)**
Sharebank	**-0.0512**	**-0.0763**	**-0.0804**	-0.0209	0.0276
	(-0.0807,-0.0315)	**(-0.1001,-0.0367)**	**(-0.0999,-0.0450)**	(-0.1637,0.0149)	(-0.0359,0.0537)

come diversification in the quantile range approximately from τ=0.20 to τ=0.80 (slightly differ across indicators). This suggests a significant relationship between FinTech and Chinese banks with various income diversification levels. Meanwhile, the coefficient of $FinTech$ increases slightly with the the quantile from τ=0.25 to τ=0.75 in all income-based models. However, it is different from Wang et al. (2020)'s findings that banks with diversified income sources are not affected by the growth of FinTech. In the assets diversification model, there is no significant relationship between FinTech development and non-interest bearing assets to total assets ($NIBATA$).

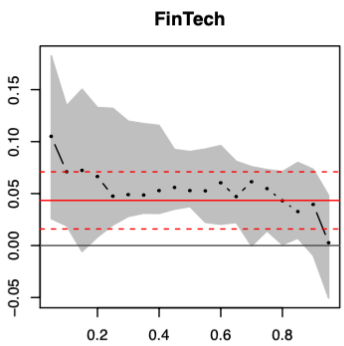
Figure 3.3: Regression quantiles for $FinTech$



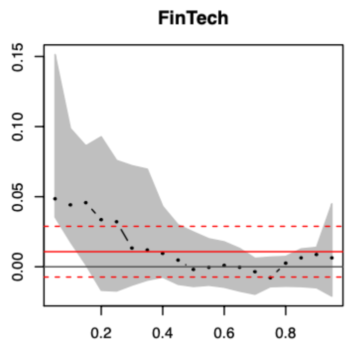
(a) NII



(b) HHI_a



(c) $Entropy$



(d) $NIBATA$

Notes: The x-axis represents the different quantiles, and the y-axis represents the estimated coefficient for each quantile. The red solid line is the $FinTech$ coefficient of OLS. The red dashed lines are the confidence intervals for OLS. The shaded areas are the quantile estimations. When the zero is contained in the confidence bands, the coefficient is not significant.

3.4.2. Results for different bank tiers

Tables 3.4 and 3.5 confirm that the effect varies across bank types. More specifically, Tables 3.4 and 3.5 show that, *Sharebank* is significant at the 0.25 and 0.50 quantiles with income diversification indicators, while *Statebank* is not significant. This indicates a significant gap between national shareholding commercial banks and city commercial banks, and the similar effect of state-owned banks and city commercial banks. The positive coefficients of *Sharebank* imply that national shareholding commercial banks, especially those with low-to-medium income diversification levels, are more sensitive to FinTech development than state-owned banks and city commercial banks. This result is partially consistent with Wang et al. (2020), whose findings suggest that large banks are more hesitant to engage with the FinTech wave, considering their complex organisational structures, high investment costs and large-scale business processes. Meanwhile, Tables 3.4 and 3.5 show that the coefficients of *Sharebank* increase slightly from the 0.25 quantile to the 0.50 quantile (from 0.0338 to 0.0699 in the NII model; from 0.0471 to 0.0748 in the HHI model; from 0.0408 to 0.0809 in the $Entropy$ model). This means the difference of effects between national shareholding commercial banks and the other two bank tiers increases with a higher diversification level of the national shareholding commercial banks.

3.4.3. Results for control variables

Tables 3.4 and 3.5 also present results for the control variables. As for models with income diversification indicators, bank size ($SIZE$) and loan-deposit ratio (LDR) are more significant in explaining bank income diversification strategy than other factors. Both bank size and loan-deposit ratio affect income diversification positively, indicating a greater degree of income diversification for larger banks compared to small banks. This is in line with the positive relationship between bank size and diversification found by Demsetz and Strahan (1997). From the assets diversification perspective, most control variables are significantly related to the independent variable non-interest bearing assets to total assets ($NIBATA$)—with the exception of capital adequacy ratio (CAR), non-performing loans (NPL) and annual growth rates of M2 ($gM2$).

Therefore, results can be summarized into two points. First of all, FinTech has significant and positive effects on income diversification in general. The significant relationship between FinTech and income diversification varies across different bank tiers: compared to state-owned banks and city commercial banks, national shareholding commercial banks are more sensitive to FinTech development in making income diversification decisions. Second, FinTech has non-significant effects on assets diversification for banks at any tier or assets diversification level.

3.5. Conclusion

In recent years, FinTech development has had a considerable impact on the global financial markets. China, as an emerging economy, is witnessing the rapid development of FinTech, which has played an important role in its banking sector. This phenomenon can encourage banks to expand their products and services to better compete with FinTech firms and win a bigger market share, despite some concern about the potential risks raised by diversified new activities, for instance of intensified agency problems and high regulatory costs (Stulz, 2019; Carlini et al., 2021). To the best of our knowledge, the effect of FinTech on banks' diversification strategies has barely been covered in the existing literature, which led us to examine this issue empirically in this study.

We use the digital financial index compiled by the Digital Finance Research Center of Peking University over the period 2012–2018 to explore the relationship between FinTech development and diversification of three different Chinese bank tiers. An instrumental quantile regression model is used for the first time to explore this issue, as it could more comprehensively explain banks reactions to FinTech in terms of diversification strategy at different quantiles. In addition, we differentiated between income and asset diversification, considering a variety of diversification measures, namely the non-interest income ratio, the revenue Herfindahl-Hirschman index, entropy and non-interest bearing assets to total assets.

Our study contributes three main findings. First, overall, there is a significant and positive relationship between FinTech development and income diversification of Chinese banks over the sample period. Second,the effect of FinTech on income diversification varies across types of banks. Compared to state-owned banks and city commercial banks, national shareholding commercial banks with low-to-medium income diversification levels are more sensitive to FinTech. Third, banks' assets diversification strategies are not affected by FinTech.

Our findings contribute to limited existing empirical literature on FinTech and its effects on bank diversification strategy. In general, FinTech development encourages Chinese banks, especially national shareholding commercial banks, to diversify. The relative low sensitivity to FinTech among state-owned banks might be due to their complex organisational structure, high investment costs and large-scale business processes. Partially in line with Berger et al. (2010), diversification discount caused by inexperienced top management teams and an ineffective incentive mechanism to maximize shareholders' wealth could be the reasons to explain why city commercial banks hesitate to engage with the FinTech wave.

Chapter 4

FinTech and regional economic performance in China, 2012-2019

4.1. Introduction

The link between financial development and economic growth has been discussed extensively in previous literature, from early studies by Schumpeter (1911), Robinson (1952) and Solow (1956), to more relatively recent approaches (e.g., King and Levine, 1993b; Levine, 2005). The connection has also been studied for different proxies for financial development (including indicators of banking development such as branches; see Jayaratne and Strahan, 1996), developed and developing countries (Arribas et al., 2020), as well as comparisons both among and within countries (Pastor et al., 2017).

The recent wave of innovations in financial technology, FinTech, represents a new form of financial development. It has emerged across the world, thriving particularly well in China, and provides unprecedented opportunities and challenges to the traditional financial sector. As indicated in the "FinTech Development Plan (2022-2025)" released by the People's Bank of China (PBOC), FinTech is an important engine for deepening structural reform of finance from the supply side and enhancing the ability of finance to serve the real economy. In contrast to other markets, FinTech in China targets the "small and micro level", and focuses on developing mobile payment and online lending/investment rather than on cryptocurrency, cross-border payment and data protection, and cybersecurity as in the European market. Individuals and small-to-medium-sized enterprises (SMEs) benefit the most from the rapid development of FinTech in China (DBS and EY, 2017). Specifically, from the consumers' perspective, convenient online shopping and online payment drive their consumption behavior. In addition, consumer loan products, such as the Ant Group's Huabei, make it possible and easier for consumers to bring forward their consumption. For SMEs, China constantly innovates credits through big data mining to greatly reduce the information asymmetry, credit, and financing costs of small and micro firms (Yun and Ruibo, 2014). It contributes to the dramatic transformation in affordability and accessibility of financial services in China, particularly for groups that previously lagged financially, by promoting the development of SME financing and encouraging their sustainable growth.

Although FinTech has been discussed extensively since 2010, very few studies have examined the direct effect of FinTech on economic development, mainly because of data limitations. The few exceptions include Demir et al. (2022), who evaluate the interrelationship between FinTech, financial inclusion and income inequality for a panel of 140 countries. They provide new evidence that FinTech reduces income inequality indirectly through financial inclusion. Considering the Chinese case, Zhang et al. (2018) investigate the implications of FinTech for inclusive finance and inclusive growth and find that FinTech narrows the gap between urban and rural areas in China by promoting entrepreneurial activity among rural residents. Muganyi et al. (2022) analyze the impact of FinTech on financial development in China. Their results show a positive causal relationship between FinTech and different aspects of financial development. However, evidence regarding the direct impact of FinTech on economic development is still scarce.

From a methodological point of view, we employ quantile regression, which is first introduced by Koenker and Bassett (1978). Cade and Noon (2003) point out that, quantile regression provides a more complete picture of missed causal relationships by other regression models (e.g., OLS). It has become increasingly popular in the area of growth (see, for instance, Crespo-Cuaresma et al., 2011; Pastor et al., 2017; Demir et al., 2022, among others). Henderson et al. (2013) indicate that, while on average the impact of financial development on growth has increased over time, it varies across countries at different growth levels. Quantile regression takes into account the stage of economic development of the provinces, which has been demonstrated to be particularly important when examining the relationship between finance and growth at the country level (Rioja and Valev, 2004a,b), but to date, there is no evidence when evaluating the specific case of FinTech for China.

This study's exploration of the relationship between FinTech and economic development in China makes two main contributions to the literature. First, it sheds light on the effect of FinTech on economic development in China, also providing results for different economic areas of the country. China was initially classified into the Eastern, Central and Western regions based on geographic locations and economic conditions and levels during the 7$^{\text{th}}$ and the 8$^{\text{th}}$ Five-Year Plans for Economic and Social Development. It is interesting and significant to explore regional differences and propose regional policies, with the aim of encouraging connections between provinces to increase efficiency. Second, quantile regression is used in this study. Although FinTech is an aspect of financial development, as indicated by Philippon (2016), it has some specificities that should be considered. The issue of endogeneity is particularly important when evaluating the finance-growth nexus and, in the context of quantile regression, we address it in all the models using state-of-the-art instrumental variable approaches, following proposals by Chernozhukov and Hansen (2005, 2008) and Lamarche (2011).

Our results show that FinTech has a positive and significant impact on economic development in China in general, although the effects are uneven across regions and dimensions of FinTech. With respect to different regions, the impact of FinTech is more significant in the relatively underdeveloped western region than in the Eastern and the Central. Coverage breadth and digitization level are the two FinTech dimensions that are relevant for increasing GDP per capita and labor productivity, especially in those provinces at medium-to-high economic development levels. These results are robust after controlling for potential endogeneity issues.

The rest of this paper is organized as follows. Section 4.2 presents the models to be estimated, as well as data and variables. The empirical results are discussed in Section 4.3. Section 4.4 concludes.

4.2. Model specification and data description

4.2.1. Model

To examine the impact of FinTech on economic development, the following benchmark model is used in this study:

$$ED_{it} = \alpha + \beta_i + \gamma_t + \delta FINTECH_{it} + \zeta Control_{it} + \mu_{it} \tag{4.1}$$

where i and t denote the province and time, respectively. β_i and γ_t represent individual and time dummies, respectively. We use real GDP per capita $GDPPC$ and real GDP per worker $LABORP$ to measure economic development ED_{it}. $FINTECH$ is the variable of interest, compiled by the Digital Finance Center of Peking University (see Section 1.2.1) . A set of control variables commonly used in the previous financial development and growth literature is included sequentially to control for the impact of other important growth determinants. Specifically, Model 1 only includes $FINTECH$. $HCAP$, which is the average years of schooling for people aged six and above; $PGROWTH$, corresponding to the population growth [1]; and $INVESTMENT$, measuring the rate of gross fixed capital formation as a percentage of GDP are added to Model 2. Model 3 incorporates additional control variables, including GOV, which is the ratio of the local

[1]Following Mankiw et al. (1992), a fixed coefficient of 0.05 to capture depreciation and technical change is added.

government's general budgetary expenditure to GDP; $OPENNESS$, capturing the degree of trade openness; IND, which is the ratio of value-added of the secondary and tertiary industries to GDP; and URB, which takes the proportion of the urban population of the resident population to measure the degree of urbanization. The individual effects variable β_i is added to Model 4. Model 5 is the final model, incorporating the time effects variable γ_t.

To deal with the endogeneity of financial development, we use an instrumental regression approach. It is complicated of choosing valid instruments in the present context and we've tried several possible instruments, such as the number of mobile users, the number of internet sites and the popularization rate of the internet, which are considered the IV for FinTech in the limited previous studies (Muganyi et al., 2022; Yang et al., 2020). Those variables are all more correlated with GDP per capita and labor productivity rather than the FinTech index, and, thus, are not appropriate in our context. Consequently, this study uses one year lagged value of FinTech as an instrument suggested by Temple (1999). In addition, considering the great disparities in GDP per capita across Chinese provinces, we estimate quantile regression models, which have been introduced in Chapter 3 (see Section 3.2). These are preferable to other regression models such as ordinary least squares (OLS) because they relax the restrictive assumption that error terms are distributed identically at all conditional distribution points. Additionally, they provide a broader view by taking into account the level of economic development in each province. The endogeneity issues in the quantile regression framework are tackled following Harding and Lamarche (2009), allowing for fixed effects as introduced in Koenker (2004) and instrumental variables in the presence of endogeneity as developed in Chernozhukov and Hansen (2008).

4.2.2. Data and descriptive statistics

The data is available for 31 provincial administrative regions in China, including 22 provinces (excluding Taiwan due to a lack of data), five autonomous regions and four municipalities directly under the central government, between 2012 and 2019, having a balanced panel. The economic development data at provincial level and the rest of the control variables come mainly from three sources: the database of the National Bureau of Statistics of China, the China Statistical Yearbook and the statistical yearbook of each province. The definition of all variables are presented in Table 4.1.

Descriptive statistics of variables are summarized in Table 4.2. There exist notable disparities between the maximum and minimum values of FinTech index and its three sub-indexes. It implies a rapid FinTech development in China during the period of 2012-2019. In addition, Table 4.2 shows that the other variables present remarkable differences in the range for the entire sample. Table 4.3 reports the development of FinTech in China

Table 4.1: Summary of variables

Variable	Definition
GDP per capita (log) (*GDPPC*)	Real per capita gross domestic product
Labor productivity (log) (*LABORP*)	Real GDP per worker
FinTech index (*FINTECH*)	The Peking University Digital Financial Inclusion Index
Human capital (*HCAP*)	Average years of schooling (ages 6 and above)
Population growth (*PGROWTH*)	Growth of population
Investment (*INVESTMENT*)	Gross fixed capital formation / GDP
Government expenditure (*GOV*)	Local government general budgetary expenditure/ GDP
Trade openness (*OPENNESS*)	Total value of imports and exports of operating units / GDP
Industrial structure (*IND*)	Value-added of the secondary and tertiary industries / GDP
Urbanization (*URB*)	Urban population/Resident population

Notes: *FINTECH* index is collected from Institute of Digital Finance, Peking University. The data of dependent variables *GDPPC* and *LABORP*, as well as all control variables, are collected from the database of National Bureau of statistics of China and the statistical yearbook at national and provincial levels.

during the sample period by showing the mean value of key variables in China as a whole and in the three regions in the initial year (2012) and the last year (2019) of our sample. It can be seen that China experienced rapid growth of FinTech in general, as well as GDP per capita and labor productivity, during the 2012-2019 period. While there are also remarkable differences by geographical area. Specifically, FinTech development in the Eastern region is well above the average level for the whole of China, and is more advanced than the Central and the Western. Figure 4.1 displays scatterplots showing FinTech and economic development (from *GDPPC* and *LABORP* aspects, respectively). It presents a generally tight positive correlation between FinTech and GDP per capita and labor productivity in China.

4.3. Empirical results

4.3.1. Ordinary least squares (OLS) regression

We start by using ordinary least squares to estimate the average effect of FinTech on economic development. Tables 4.4 and 4.5 report the baseline results for all five models. It can be seen that, in general, FinTech has positive effects on economic development. Although the magnitude of FinTech's effect declines slightly as expected with adding other variables to the more comprehensive models 2,3,4, and 5, the coefficient of FinTech is still significant after controlling for other variables and province and time effects. While FinTech in model 5 of labor productivity loses significance by adding time-fixed

Table 4.2: Descriptive statistics

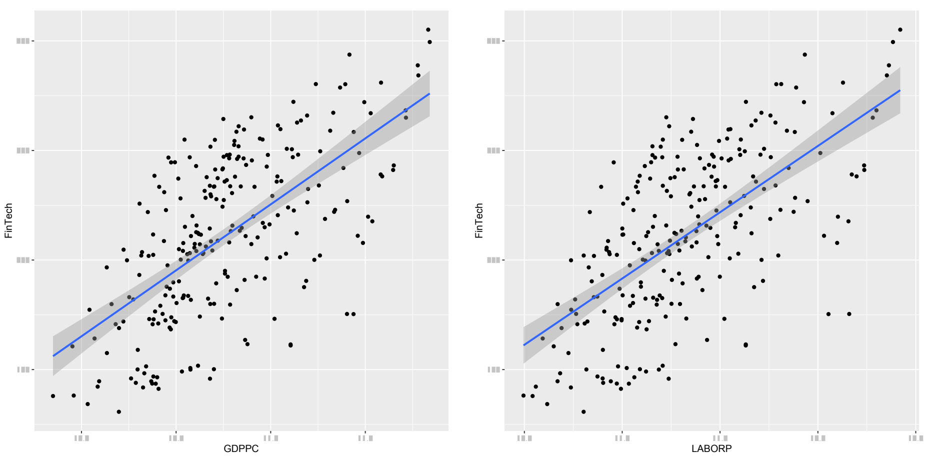
Varaible	*Obs.*	*Mean*	*S.D.*	*Min.*	*1stQu.*	*Median*	*3rdQu.*	*Max.*
GDPPC	248	10.7660	0.4012	9.8494	10.4824	10.7058	11.0116	11.8406
LABORP	248	11.3265	0.4007	10.4956	11.0508	11.2701	11.5605	12.4207
FINTECH	248	222.6189	75.4165	61.4700	165.1350	223.5400	282.3275	410.2800
BREADTH	248	200.7477	77.6608	32.8600	149.1950	197.2300	266.2275	384.6600
DEPTH	248	215.7900	78.5856	51.8500	153.2400	203.0200	276.2875	439.9100
DIGITIZATION	248	307.4103	89.0740	107.0700	248.5600	323.2500	382.2450	462.2300
HCAP	248	9.1042	1.1400	4.2219	8.7092	9.1296	9.4852	12.6811
PGROWTH	248	0.0554	0.0096	0.0271	0.0508	0.0545	0.0609	0.0803
INVESTMENT	248	0.6626	0.2668	0.2700	0.4722	0.6140	0.7707	1.6428
GOV	248	0.2989	0.2123	0.1200	0.1947	0.2377	0.3273	1.3538
OPENNESS	248	0.2661	0.2799	0.0128	0.0883	0.1385	0.3247	1.3541
IND	248	0.9024	0.0522	0.7548	0.8784	0.9035	0.9336	0.9972
URB	248	0.5726	0.1312	0.2222	0.4952	0.5625	0.6277	0.9415

Table 4.3: Regional FinTech development

	Fullsample		*Eastern*		*Central*		*Western*	
	2012	2019	2012	2019	2012	2019	2012	2019
GDPPC	10.51	10.99	10.89	11.32	10.37	10.89	10.26	10.77
LABORP	11.07	11.57	11.45	11.86	10.89	11.45	10.84	11.38
FINTECH	99.69	323.70	121.74	354.10	91.93	315.14	84.63	301.54
BREADTH	80.43	307.76	108.09	334.32	68.05	295.63	63.32	295.51
DEPTH	116.50	312.83	114.84	356.57	113.48	306.42	92.54	277.01
DIGITIZATION	132.72	396.30	124.86	415.52	131.69	395.46	140.61	379.24

Notes: The Eastern region includes the 11 coastal provinces of Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong and Hainan, The Central region includes the eight provinces of Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei and Hunan. The 12 provinces making up the Western region are Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Xizang, Shaanxi, Gansu, Gansu, Qinghai, Ningxia and Xinjiang.
GDPPC takes the logarithm of GDP per capita; *LABORP* takes the logarithm of GDP per worker; *FINTECH* is an index series with points as its measurement unit; *BREADTH*, *DEPTH* and *DIGITIZATION* are the three main dimensions of *FINTECH*.

Figure 4.1: The link between FinTech and economic development



(a) *GDPPC* (b) *LABORP*

effects. In particular, Model 5 of GDP per capita shows that an increase of 10 points in the FinTech index enhances GDP per capita by 0.9%.

Tables 4.4 and 4.5 also present the results for the control variables. In Table 4.4, the variables population growth ($PGROWTH$) and urbanization (URB) are positive and significant for all models where it is included, and the effect of government expenditure (GOV) is also significant while negative for all models. The human capital variable ($HCAP$) is only significant in Model 2. The investment ($INVESTMENT$) is significant in the more comprehensive models (Models 4 and 5). The trade openness ($OPENNESS$) loses significance by adding time-fixed effects to the model. The industry structure (IND) is only relevant for GDP per capita in Model 3. Table 4.5 shows the results for control variables in the labor productivity model. Different from those obtained from $GDPPC$, Investment ($INVESTMENT$) and trade openness ($OPENNESS$) is non-significant for all models where they are included. The variable of government expenditure (GOV) is only significant in Model 3.

Although the issue of missing variables can be solved by the fixed effects models to a certain extent, endogeneity is still possible between FinTech and economic development that biases our results. To this end, we also use IV estimations to check the robustness of the preliminary OLS results. Estimation results report that FinTech has significant effects on GDP per capita and labor productivity at 1% and 10% significance levels, respectively. An increase of 10 points in the FinTech index enhances GDP per capita by 2.1%; a 10 points increase in FinTech enhances GDP per worker by 2.5%. The connection between FinTech and economic development continues to hold after correcting for the possible endogeneity issue, indicating the robustness of our results.

Beyond the generally positive result, the impact is different for the three individual dimensions of FinTech introduced in Section 4.2.1, namely coverage breadth ($BREADTH$), usage depth ($DEPTH$) and digitization ($DIGITIZATION$). Table 4.6 presents the results. $BREADTH$ has a positive effect on GDP per capita. It can be argued that the increasing $BREADTH$ of FinTech services, for instance, third-party payment, might stimulate consumption and promote entrepreneurship in financially excluded regions, which in the end drives income per capita. $DEPTH$ exhibits significant effects on GDP per capita in Chinese provinces at 1% significance level. A potential explanation may be the excess of FinTech in China during the sample period. Limited regulatory capability and intense competition in the FinTech industry may have resulted in the oversupply of diversified FinTech products and services. This increases economic volatility and financial risks, which in turn could limit or cancel out the positive effects of financial depth on economic development, in line with Arcand et al. (2015)'s finding suggesting the *vanishing effects* of financial depth on economic growth associated with *too much* finance. $DIGITIZATION$ is significantly and positively linked to GDP per capita. In the lower $LABORP$ panel, it can be seen that, after correcting for the endogeneity is-

Table 4.4: Determinants of GDP per capita (*GDPPC*) at provincial level

	Without IV					With IV				
	*Model*1	*Model*2	*Model*3	*Model*4	*Model*5	*Model*1	*Model*2	*Model*3	*Model*4	*Model*5
(*Intercept*)	10.0074***	7.7761***	7.9560***	9.8006***	10.2265***	10.0466***	7.7848***	7.9536***	10.1973***	10.0704***
	(0.0612)	(0.1790)	(0.2360)	(0.2565)	(0.2417)	(0.0621)	(0.1791)	(0.2361)	(0.2724)	(0.2605)
FINTECH	0.0034***	0.0024***	0.0018***	0.0016***	0.0009***	0.0032***	0.0023***	0.0018***	0.0018***	0.0021***
	(0.0003)	(0.0002)	(0.0001)	(0.0001)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0001)	(0.0005)
HCAP		0.2093***	−0.0211	0.0007	0.0062		0.2101***	−0.0213	−0.0032	0.0039
		(0.0134)	(0.0190)	(0.0094)	(0.0084)		(0.0134)	(0.0190)	(0.0096)	(0.0088)
PGROWTH		10.2829***	4.8043***	1.0549***	0.6107*		10.4069***	4.8363***	1.2105***	0.5321
		(1.4271)	(1.2013)	(0.3862)	(0.3481)		(1.4049)	(1.2029)	(0.3941)	(0.3667)
INVESTMENT		−0.0303	−0.0190	0.0614***	0.0966***		−0.0343	−0.0217	0.0583***	0.0599***
		(0.0562)	(0.0478)	(0.0165)	(0.0169)		(0.0563)	(0.0481)	(0.0168)	(0.0226)
GOV			−0.1500**	−0.2133***	−0.2278***			−0.1479**	−0.2036***	−0.2187***
			(0.0638)	(0.0731)	(0.0667)			(0.0640)	(0.0744)	(0.0701)
OPENNESS			0.1640**	−0.0966***	0.0000			0.1601**	−0.0494	0.0046
			(0.0687)	(0.0333)	(0.0316)			(0.0691)	(0.0351)	(0.0332)
IND			1.5674***	0.1476	0.0903			1.5695***	−0.0715	−0.0352
			(0.2192)	(0.2334)	(0.2082)			(0.2192)	(0.2413)	(0.2237)
URB			1.6296***	1.4799***	1.0032***			1.6416***	1.2049***	1.1517***
			(0.2148)	(0.1240)	(0.1276)			(0.2160)	(0.1373)	(0.1453)
YearFE	*No*	*No*	*No*	*No*	*Yes*	*No*	*No*	*No*	*No*	*Yes*
ProvinceFE	*No*	*No*	*No*	*Yes*	*Yes*	*No*	*No*	*No*	*Yes*	*Yes*
$R-sq$	0.4103	0.7380	0.9008	0.9972	0.9980	0.4092	0.7376	0.9008	0.9971	0.9978
$adj.R-sq$	0.4079	0.7337	0.8975	0.9967	0.9975	0.4068	0.7344	0.8975	0.9966	0.9973
Observations	248	248	248	248	248	248	248	248	248	248

Notes: We assume endogeneity in financial innovation level and use the first lag of the variable as the instrument in IV regresion.
Standard errors are shown in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 4.5: Determinants of labor productivity (*LABORP*) at provincial level

	Without IV					With IV				
	Model1	*Model2*	*Model3*	*Model4*	*Model5*	*Model1*	*Model2*	*Model3*	*Model4*	*Model5*
(*Intercept*)	10.5661***	8.1754***	8.4209***	10.6857***	11.6419***	10.6016***	8.1821***	8.4198***	10.9070***	11.3583***
	(0.0610)	(0.1758)	(0.2559)	(0.5983)	(0.6256)	(0.0618)	(0.1759)	(0.2559)	(0.6252)	(0.6583)
FINTECH	0.0034***	0.0025***	0.0018***	0.0018***	0.0002	0.0033***	0.0024***	0.0018***	0.0019***	0.0025*
	(0.0003)	(0.0002)	(0.0002)	(0.0001)	(0.0007)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0014)
HCAP		0.2182***	0.0302	−0.0088	−0.0127		0.2189***	0.0301	−0.0110	−0.0169
		(0.0131)	(0.0206)	(0.0220)	(0.0216)		(0.0131)	(0.0206)	(0.0221)	(0.0223)
PGROWTH		10.4627***	5.9529***	2.2256**	1.7817**		10.4451***	5.9679***	2.3124**	1.6388*
		(1.4016)	(1.3024)	(0.9008)	(0.9010)		(1.4018)	(1.3041)	(0.9044)	(0.9265)
INVESTMENT		0.0539	−0.0465	−0.0069	0.0666		0.0508	−0.0477	−0.0086	−0.0000
		(0.0552)	(0.0519)	(0.0386)	(0.0438)		(0.0553)	(0.0522)	(0.0386)	(0.0570)
GOV			0.1370**	−0.0160	0.0192			0.1380**	−0.0105	0.0359
			(0.0692)	(0.1704)	(0.1726)			(0.0693)	(0.1707)	(0.1772)
OPENNESS			0.1220	0.0100	0.1303			0.1202	0.0363	0.1386
			(0.0745)	(0.0776)	(0.0819)			(0.0749)	(0.0806)	(0.0840)
IND			1.0108***	−0.3666	−0.5280			1.0118***	−0.4888	−0.7560
			(0.2376)	(0.5444)	(0.5390)			(0.2377)	(0.5539)	(0.5653)
URB			1.6568***	1.5899***	0.8471**			1.6624***	1.4366***	1.1169***
			(0.2329)	(0.2892)	(0.3303)			(0.2342)	(0.3151)	(0.3671)
YearFE	*No*	*No*	*No*	*No*	*Yes*	*No*	*No*	*No*	*No*	*Yes*
ProvinceFE	*No*	*No*	*No*	*Yes*	*Yes*	*No*	*No*	*No*	*Yes*	*Yes*
$R-sq$	0.4133	0.7467	0.8831	0.9849	0.9864	0.4124	0.7466	0.8831	0.9848	0.9857
$adj.R-sq$	0.4109	0.7425	0.8792	0.9821	0.9834	0.4100	0.7424	0.8792	0.9821	0.9826
Observations	248	248	248	248	248	248	248	248	248	248

Notes: We assume endogeneity in financial innovation level and use the first lag of the variable as the instrument in IV regresion.
Standard errors are shown in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

sue, *DIGITIZATION* has positive effects on labor productivity, which is significant at 5%. A higher digitization level, which reflects convenience and low costs, positively affects economic development through increased affordability and accessibility of FinTech services and optimized resource allocation.

Considering the economic disparities between the three regions in China, we estimate the effect of FinTech on economic performance for the three economic areas introduced in Section 4.1. Table 4.7 reports the results. In the Western region, FinTech has positive effects on GDP per capita and labor productivity. It benefits the most from FinTech development, owing to easier and faster penetration of FinTech into a less developed region. A 10-point increase in FinTech development would increase GDP per capita and GDP per worker by 5.0% and 4.9% (Table 4.7, with IV), respectively, in the Western region, which outweighs the average (2.1% and 2.5%, respectively) obtained for the whole sample (Table 4.4 and 4.5 with IV model5). SMEs in the remote Western region, which were facing great financing challenges, develop rapidly with FinTech support and make a remarkable contribution to economic development as a result. In the Eastern region, FinTech only contributes to GDP per capita. As the most developed region, the less significant impact of FinTech in the Eastern region is consistent with the 13^{th} and 14^{th} Five-Year Plans for Economic and Social Development between 2012 and 2019. The plans of most provinces in the Eastern region highlight their focus on FinTech regulation and supervision for sustainable development during our sample period. Economic development in the Central region is not sensitive to FinTech development. This region, mainly based on the traditional manufacturing industry, has a deeply entrenched traditional culture, which results in a relatively "conservative" attitude towards emerging digital innovations and insufficient integration between FinTech and local traditional industries.

4.3.2. Instrumental quantile regression

Although ordinary least squares (OLS) provides a picture of FinTech's effects in the different regions, it is based on average effects. FinTech's effects may vary across provinces at different economic levels. Therefore, we take each province's level of economic development into account by using instrumental quantile regression with fixed effects in this section, to explore different effects of FinTech in poor and rich provinces under various dimensions. Table 4.8 shows the results of key variables.

In the upper *GDPPC* panel, overall, FinTech development is significant for those provinces at medium-to-high GDP per capita levels (from τ=0.50 to τ=0.90). The better business environment, policy system and innovation capacity in those provinces facilitate FinTech development which consequently promotes local economic development. While the impact declines when a province reaches a very high development

Table 4.6: The effects of three FinTech dimensions

	WithoutIV (i)	(ii)	(iii)	*WithIV* (i)	(ii)	(iii)
Dependent variable: GDPPC (in logs)						
(Intercept)	10.3495***	10.3146***	10.2308***	10.3535***	10.2972***	9.8361***
	(0.2406)	(0.2440)	(0.2491)	(0.2413)	(0.2466)	(0.3160)
BREADTH	0.0011***			0.0015***		
	(0.0004)			(0.0005)		
DEPTH		0.0003*			0.0005	
		(0.0002)			(0.0004)	
DIGITIZATION			0.0002**			0.0008***
			(0.0001)			(0.0002)
HCAP	0.0067	0.0050	0.0097	0.0063	0.0030	0.0163
	(0.0084)	(0.0086)	(0.0085)	(0.0084)	(0.0093)	(0.0099)
PGROWTH	0.4699	0.5962*	0.7820**	0.3935	0.5458	1.1991***
	(0.3561)	(0.3562)	(0.3580)	(0.3638)	(0.3672)	(0.4309)
INVESTMENT	0.1070***	0.1135***	0.1117***	0.1008***	0.1068***	0.0703***
	(0.0160)	(0.0161)	(0.0162)	(0.0170)	(0.0196)	(0.0238)
GOV	−0.2168***	−0.2373***	−0.2332***	−0.2099***	−0.2394***	−0.2284***
	(0.0673)	(0.0679)	(0.0678)	(0.0678)	(0.0683)	(0.0761)
OPENNESS	0.0099	0.0033	−0.0135	0.0150	0.0079	−0.0506
	(0.0321)	(0.0324)	(0.0325)	(0.0325)	(0.0334)	(0.0391)
IND	0.0429	0.1557	0.1750	−0.0104	0.1378	0.1534
	(0.2129)	(0.2106)	(0.2098)	(0.2189)	(0.2135)	(0.2357)
URB	0.8667***	0.9387***	0.9895***	0.8553***	0.9689***	1.3300***
	(0.1245)	(0.1279)	(0.1339)	(0.1253)	(0.1377)	(0.1966)
$R-sq$	0.9980	0.9979	0.9979	0.9979	0.9979	0.9974
$\bar{R}^2$	0.9975	0.9974	0.9974	0.9975	0.9974	0.9968
Dependent variable: LABORP (in logs)						
(Intercept)	11.6770***	11.6972***	11.5847***	11.6791***	11.6616***	10.7872***
	(0.6177)	(0.6192)	(0.6341)	(0.6178)	(0.6250)	(0.7729)
BREADTH	0.0010			0.0012		
	(0.0009)			(0.0013)		
DEPTH		−0.0003			0.0001	
		(0.0004)			(0.0009)	
DIGITIZATION			0.0001			0.0014**
			(0.0002)			(0.0006)
HCAP	−0.0134	−0.0089	−0.0109	−0.0136	−0.0130	0.0025
	(0.0216)	(0.0219)	(0.0217)	(0.0216)	(0.0236)	(0.0242)
PGROWTH	1.6088*	1.8813**	1.8818**	1.5686*	1.7781*	2.7245**
	(0.9144)	(0.9040)	(0.9111)	(0.9312)	(0.9306)	(1.0540)
INVESTMENT	0.0575	0.0842**	0.0639	0.0542	0.0704	−0.0198
	(0.0410)	(0.0408)	(0.0412)	(0.0434)	(0.0496)	(0.0583)
GOV	0.0343	0.0212	0.0187	0.0379	0.0170	0.0283
	(0.1728)	(0.1723)	(0.1725)	(0.1736)	(0.1730)	(0.1862)
OPENNESS	0.1419*	0.1215	0.1217	0.1446*	0.1310	0.0467
	(0.0824)	(0.0822)	(0.0828)	(0.0833)	(0.0847)	(0.0955)
IND	−0.6373	−0.4769	−0.5121	−0.6653	−0.5134	−0.5557
	(0.5466)	(0.5346)	(0.5339)	(0.5603)	(0.5411)	(0.5765)
URB	0.7954**	0.7709**	0.8942***	0.7895**	0.8328**	1.5822***
	(0.3196)	(0.3245)	(0.3407)	(0.3207)	(0.3490)	(0.4809)
$R-sq$	0.9865	0.9865	0.9864	0.9865	0.9864	0.9842
$\bar{R}^2$	0.9835	0.9835	0.9834	0.9835	0.9834	0.9807
Year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Province FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
# observations	248	248	248	248	248	248

Notes: We assume endogeneity in financial innovation level and use the first lag of the variable as the instrument. Standard errors are shown in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 4.7: The effects of FinTech in different regions

	WithoutIV			*WithIV*		
	Eastern	*Central*	*Western*	*Eastern*	*Central*	*Western*
Dependent variable: GDPPC (in logs)						
(Intercept)	10.2083***	9.1220***	9.4105***	10.1579***	8.9901***	9.3299***
	(0.4425)	(0.4596)	(0.4303)	(0.4521)	(0.5389)	(0.5631)
FINTECH	0.0008**	−0.0015***	0.0019***	0.0013**	0.0006	0.0050***
	(0.0003)	(0.0005)	(0.0004)	(0.0005)	(0.0011)	(0.0016)
HCAP	0.0292**	−0.0369**	0.0055	0.0264*	−0.0466**	−0.0065
	(0.0136)	(0.0163)	(0.0092)	(0.0141)	(0.0195)	(0.0132)
PGROWTH	−0.1021	−1.3398	−0.7623	−0.1168	−1.5680	−1.0767
	(0.3558)	(1.5810)	(0.7029)	(0.3622)	(1.8447)	(0.9298)
INVESTMENT	0.2432***	0.2995***	0.0145	0.2205***	0.2018***	−0.0387
	(0.0330)	(0.0434)	(0.0170)	(0.0386)	(0.0679)	(0.0336)
GOV	−0.4357***	−0.6130**	−0.2402***	−0.3757**	−0.2989	−0.2046**
	(0.1380)	(0.2294)	(0.0725)	(0.1491)	(0.3044)	(0.0961)
OPENNESS	0.0783**	−0.3975**	−0.0981*	0.0824**	−0.2487	−0.1088
	(0.0315)	(0.1561)	(0.0507)	(0.0322)	(0.1945)	(0.0664)
IND	0.3526	1.4028***	−0.0520	0.3225	1.1228***	−0.0299
	(0.4710)	(0.3030)	(0.3191)	(0.4798)	(0.3761)	(0.4167)
URB	0.3594***	0.8414**	2.0019***	0.3925***	1.3819**	1.9218***
	(0.1209)	(0.3899)	(0.3753)	(0.1261)	(0.5188)	(0.4914)
$R-sq$	0.9991	0.9968	0.9978	0.9991	0.9956	0.9963
$\bar{R}^2$	0.9987	0.9951	0.9970	0.9987	0.9933	0.9949
Dependent variable: LABORP (in logs)						
(Intercept)	11.2762***	7.7528***	10.7034***	11.2200***	7.4054**	10.6288***
	(0.9490)	(2.8598)	(0.5425)	(0.9576)	(2.9690)	(0.6388)
FINTECH	−0.0009	−0.0005	0.0020***	−0.0004	0.0049	0.0049***
	(0.0007)	(0.0033)	(0.0006)	(0.0012)	(0.0063)	(0.0018)
HCAP	−0.0502*	0.0460	0.0134	−0.0533*	0.0204	0.0024
	(0.0293)	(0.1012)	(0.0115)	(0.0298)	(0.1073)	(0.0150)
PGROWTH	0.6514	16.5907*	−1.3554	0.6350	15.9894	−1.6465
	(0.7631)	(9.8370)	(0.8861)	(0.7671)	(10.1634)	(1.0547)
INVESTMENT	0.2037***	0.5344*	−0.0106	0.1785**	0.2773	−0.0598
	(0.0708)	(0.2701)	(0.0214)	(0.0818)	(0.3739)	(0.0382)
GOV	−0.4710	2.3071	−0.1651*	−0.4042	3.1346*	−0.1321
	(0.2959)	(1.4275)	(0.0913)	(0.3158)	(1.6770)	(0.1090)
OPENNESS	0.0931	−0.8913	−0.0863	0.0976	−0.4995	−0.0963
	(0.0675)	(0.9713)	(0.0639)	(0.0682)	(1.0715)	(0.0753)
IND	1.1925	1.7897	0.1312	1.1590	1.0521	0.1516
	(1.0101)	(1.8853)	(0.4023)	(1.0163)	(2.0720)	(0.4727)
URB	0.2293	−0.8737	0.4116	0.2662	0.5501	0.3375
	(0.2594)	(2.4260)	(0.4731)	(0.2672)	(2.8581)	(0.5574)
$R-sq$	0.9959	0.9190	0.9969	0.9959	0.9138	0.9958
$\bar{R}^2$	0.9943	0.8755	0.9958	0.9942	0.8675	0.9942
Year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Province FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
# observations	88	64	96	88	64	96

Notes: We assume endogeneity in financial innovation level and use the first lag of the variable as the instrument. Standard errors are shown in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 4.8: Determinants of economic development, instrumental quantile regression

	Quantile (τ)				
	$\tau = 0.10$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.90$
Dependent variable: GDPPC (in logs)					
FINTECH	0.0000	0.0019	0.0021***	0.0023***	0.0010***
	(30.1206)	(0.2120)	(0.0001)	(0.0000)	(0.0000)
BREADTH	0.0006***	0.0005	0.0006	0.0014***	0.0021***
	(0.0000)	(0.0004)	(0.0061)	(0.0000)	(0.0001)
DEPTH	0.0009***	−0.0003	0.0008***	0.0008***	0.0000
	(0.0003)	(0.0004)	(0.0001)	(0.0001)	(0.0000)
DIGITIZATION	0.0009*	0.0011	0.0011***	0.0005	0.0009***
	(0.0006)	(0.0027)	(0.0000)	(0.0128)	(0.0000)
Dependent variable: LABORP (in logs)					
FINTECH	0.0015	0.0007***	0.0011**	0.0017***	0.0016
	(0.0013)	(0.0001)	(0.0006)	(0.0001)	(0.0026)
BREADTH	−0.0011***	−0.0009***	0.0004***	0.0016***	0.0018***
	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
DEPTH	−0.0010	−0.0001	0.0001	−0.0002**	−0.0011***
	(0.0017)	(0.0001)	(0.0003)	(0.0001)	(0.0001)
DIGITIZATION	0.0000	0.0007	0.0008***	0.0023***	0.0049***
	(0.1544)	(0.0032)	(0.0003)	(0.0001)	(0.0001)
Control variables	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Province FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

Notes: The instrumental quantile regressions assume endogeneity in financial innovation level and use the first lag of the variable as the instrument. For each regression, the table only displays the results for the variable of interest, but control variables together with province and time fixed effects are also included.
Standard errors are shown in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

level ($\tau = 0.90$) due to the diminishing marginal effect. Specifically, the effect of $BREADTH$ is non-significant for provinces at the low-to-medium economic development level ($\tau = 0.25$, $\tau = 0.50$). The contribution is highest in the richest provinces. It can be explained that more people hold e-accounts in the rich provinces due to more advanced financial infrastructure and internet technologies than in other provinces, which might stimulate consumption and contribute to local economic development. However, $DEPTH$ can not explain economic development in the richest provinces. *Too much* finance mentioned above might be the reason. $DIGITIZATION$ is positively related to economic development in the extremely poor and rich provinces ($\tau = 0.10$, $\tau = 0.90$) at 10% and 1% significance levels, respectively. Its significance holds when a province has a medium level of development.

The results for the effect of FinTech on labor productivity are presented in the lower panel of Table 4.8. It can be seen that FinTech has positive and significant effects in those provinces at medium GDP per worker levels (from τ=0.25 to τ=0.75). The effect rises slightly with the quantiles. Provinces at various labor productivity levels benefit from different FinTech dimensions. In the low labor productivity provinces (τ=0.10, τ=0.25), $BREADTH$ has a negative effect while $DEPTH$ and $DIGITIZATION$ are non-significant. It is partially consistent with Lin et al. (2019), whose finding suggests that the heterogeneous effects of FinTech on different industries may be the potential explanation. The increasing coverage breadth of FinTech services may attract more workers to the tertiary industries and result in declining labor productivity in the primary and secondary industries which the underdeveloped provinces are mainly based on. $BREADTH$ and $DIGITIZATION$ contribute when a province has a medium-to-high level of labor productivity (from τ=0.50 to τ=0.90). The contribution increases progressively and reaches the peak at the highest quantile. It suggests the significance of increasing the coverage rate of e-account and higher mobility and lower expense of FinTech services in terms of promoting labor productivity in those provinces. $DEPTH$ is significantly but negatively linked to labor productivity after the 75 percentile. It is consistent with the view of some researchers (see, for instance Kneer, 2013; Philippon and Reshef, 2013; Arcand et al., 2015, among others) that in countries with large financial sectors, the marginal effects of finance depth are declining in the level of economic development and may turn negative through a brain drain from productive industries of the economy.

4.4. Conclusion

Our study examines the nexus between FinTech and economic development for a sample of 31 provinces in mainland China during the period from 2012 to 2019. The connection between financial development and economic growth has been well discussed in the literature. While the impact of FinTech, which represents a new form of financial development, on economic growth is still far from clear due to data limitations. This study tries to fill this gap.

The contribution has been made to the literature in two main dimensions. First, this study provides evidence for the impact of FinTech and its three dimensions at regional and provincial levels in China. Second, we employ ordinary least squares and IV regression as the first approach to estimate the average effect of FinTech, and use instrumental quantile regression with fixed effects in the second stage to examine the effect of FinTech in provinces at different economic development levels.

We find that the impact of FinTech on economic development is positive and significant overall. It is changing across different regions and FinTech dimensions. In particular, the estimations of quantile regression show that FinTech has more significant effects in those provinces at medium-to-high economic development levels when compared to others. After controlling for potential endogeneity issues, these results are robust to different models including additional control variables sequentially.

Our findings have some policy implications. First, the significant role of FinTech in promoting economic development in China suggests that comprehensive policies promoting FinTech growth should be welcomed and developed. For instance, as indicated in Chapter 3, traditional banks, especially the state-owned banks and city commercial banks, are not sensitive to FinTech development due to high investment costs, complex organizational structures and large-scale business processes. Considering the dominating role of traditional commercial banks in China's economic system, relevant policies should be developed to encourage banks to corporate with fintechs or establish their own FinTech subsidiaries. Second, with the rapid growth of FinTech in China, it is significant to formulate and implement a robust FinTech regulatory framework to preserve a stable financial environment, such as increasing the regulatory capacity through regtech and cooperation with FinTech regulators worldwide. Third, our quantile regression results suggest that, for the provinces with development levels between extremely low and medium, focusing on some other aspects such as accelerating urbanization and optimizing industrial structure, rather than encouraging FinTech development, might contribute more to economic development.

Chapter 5

Conclusions and future research

5.1. Summary of main findings

FinTech, as an umbrella for the newly emerging and disruptive technology-enabled innovations in the financial industry, has expanded rapidly. It represents a new form of financial development and provides unprecedented opportunities and challenges to the financial sector worldwide. The absence of a standard, unified, and comprehensive definition and index of FinTech is a big challenge for conducting an empirical study, which has resulted in limited previous evidence on this issue.

Chapter 1 has mainly discussed some relevant points, including the definitions of FinTech, FinTech indicators commonly used in Chinese Fintech-related studies, FinTech development in China, and the connection between FinTech and traditional banks and economic development from a historical perspective. Although FinTech has been discussed extensively, evidence on the direct implications of FinTech is still a gap due to data limitations. Most of the previous studies focus on theoretical arguments from different perspectives. This thesis has attempted to offer some additional evidence on the FinTech issue. To this end, each body chapter (Chapters 2–4) deals with a different problem, respectively, and has contributed to the academic FinTech research area with scant empirical evidence.

Chapter 2 investigated the impact of bank diversification on bank performance in China by using data on 19 listed commercial banks in disruptive times (2008–2019), a particularly turbulent period for macroeconomics (the 2007/08 financial crisis as well as innovation in the industry such as FinTech). To this end, measures of diversification from both the two main perspectives were taken into account, namely, income-based indicators and asset-based indicators. In the case of income-based indicators, we considered further categories—the non-interest income ratio, the Herfindahl-Hirschman index, and the entropy index. We evaluated the impact of the different indicators considered on measures of risk and profitability, and whether this impact varies depending on the type of bank—state-owned banks, national shareholding commercial banks, and city commercial banks. We argued that the links can be too intricate to be captured by linear models and, complementing the previous literature, evaluate them considering semiparametric specifications.

Our results show that the connection between diversification and bank profitability/risk is non-linear from both income and asset aspects. The benefits of diversification for Chinese banks are modest by either following income or asset diversification strategies overall, although they are changing across different bank tiers. In particular, state-owned banks have a higher tolerance for income diversification than national shareholding commercial banks and city commercial banks due to their significant advantages such as client structure and supporting policies. Thus, they benefit more from income diversification than others. However, the relationship is intricate since it is only beneficial for state-owned banks to diversify up to a middle level, and up to a lower level for national shareholding commercial banks and city commercial banks. With respect to asset diversification, the impact is similar across bank types. There is no significant relationship between asset diversification and profitability/risk in general, only when diversification is sufficiently low.

Chapter 3 examined how Fintech affect bank diversification and focus strategies on traditional Chinese banks between 2012–2018. This chapter also took into account income-based and asset-based indicators of diversification as in Chapter 2. The Digital Financial Inclusion Index compiled by Peking University was considered to measure FinTech development in China. Methodologically, we applied the instrumental quantile regression approach, which offers relevant information as to the varying impact across different bank diversification levels.

The results suggested a significant and positive relationship between FinTech and income diversification of Chinese banks overall during the sample period. In particular, there are remarkable differences in bank types. National shareholding commercial banks with low-to-medium diversification levels are more sensitive to Fintech than state-owned banks and city commercial banks. In addition, the difference in effects between national shareholding commercial banks and the other two bank types grows with increasing diversification levels of national shareholding commercial banks. However, FinTech has no significant impact on banks' asset diversification strategies.

Chapter 4 empirically discussed FinTech'e effects from a macro perspective. This Chapter explored the mechanisms linking FinTech, which represents a new form of financial development, and economic development in China as a whole and in three different economic regions (namely the Eastern, the Central, and the Western regions) during the period 2012–2019. We used the Peking University Digital Financial Inclusion Index and its three dimensions, including coverage breadth, usage depth, and digitization level, to reflect FinTech development in China. Two indicators measuring economic activities are real GDP per capita and real GDP per worker. To this end, we started by using OLS to obtain the average impact of Fintech on economic development and then employed instrumental quantile regression, which takes into account the stage of economic development of the provinces, as our second stage method.

The results are robust after controlling for endogeneity issues, space, and the different indicators of FinTech. The OLS results showed positive and significant effects on economic development. Beyond the general result, the effect is different for the three FinTech dimensions. Both coverage breadth and digitization promote GDP per capita, while only digitization has positive effects on increasing labor productivity in China. In addition, the effect is changing across different regions. GDP per capita in the Eastern and the Western regions benefits from FinTech development, while, in particular, the Western region benefits the most due to faster and easier penetration of FinTech into a less developed region. FinTech has no significant effect in the Central region. Labor productivity only benefits from FinTech in the Western region. With respect to the results of instrumental quantile regression, provinces at various economic development levels benefit from different FinTech dimensions, which offer interesting clues for the design of specific policies.

Therefore, the results of the thesis provide new evidence for the empirical FinTech area with limited previous studies. A summary of the main results obtained is the following: i) positive effects of FinTech on bank diversification strategies and economic development are robust after controlling for endogeneity and different measures; ii) the magnitude and significance of the effect vary across bank types, provinces, regions and dimensions of FinTech, pointing out the convenience of designing policies that take into account the disparities across banks, regions, and provinces.

5.2. Contributions to the literature

The emerging FinTech has been discussed extensively, which has attracted an increasing number of researchers to contribute to this area. This tendency shows a signal of scholars' increasing interest in a better understanding of the potentially significant and strong impact of FinTech and how FinTech affects the financial service sector and the economy. To this end, different chapters of this thesis have attempted to offer evidence on some relevant but unexamined issues regarding FinTech, traditional banking, and economic development.

First of all, in general, this thesis contributes to a limited but growing literature on FinTech development. Financial development has been a long-standing and well-discussed topic dating back to the early 20 century. There are numerous studies on financial development and its different proxies, such as bank branches. While with the emerging digital innovations, FinTech represents a new form of financial development and is considered a new proxy for it. The limited previous literature on the FinTech issue is mostly from a theoretical perspective rather than an empirical one due to data limitations.

This thesis also contributes to some particular aspects. Bank diversification in Chapter 2 and Chapter 3 is measured from both income and asset perspectives, for different diversification indicators. Based on a large number of previous bank diversification–related studies, Chapters 2 and Chapter 3 consider novel aspects, namely bank diversification in disruptive times and the impact of FinTech on bank diversification. Chapter 2 extends the analysis from Berger et al. (2010)' research. It focuses on the most recent period of 2008–2019, which is turbulent with financial risk and emerging digital innovations. In addition, most previous literature, to my knowledge, has addressed the specific issue of bank focus and diversification with the US and European financial institutions. Chapter 2 and Chapter 3 provide more evidence of the emerging and transition economy. China, as the largest emerging and transition economy, has been growing rapidly in FinTech and has a huge influence on the global economy. It is significant to examine the issue related to bank diversification and FinTech, as well as the potentially more marked impact of traditional banks, in the highly disruptive context in China.

Another contribution is the use of quantile regression to investigate the effect of FinTech in Chapter 3 and Chapter 4. Compared with other regression models such as OLS, quantile regression gives a more complete picture of a missed causal relationship. It also takes into account the level of bank diversification and provincial economic development, which is relatively innovative from a methodological standpoint and has been demonstrated to be important when examining finance and growth issues. This technique has only been used in the research by (Demir et al., 2022), not to examine the changing effects of FinTech across different bank diversification levels or economic development levels.

In addition, this thesis provides an in-depth exploration of the link between FinTech and economic development for different geographical levels and FinTech dimensions in Chapter 4. It sheds light on the impact of FinTech on economic development at provincial level in China, also providing results for three different economic areas of the country. Aiming at promoting connections between provinces to increase efficiency, it is significant and interesting to study regional differences and propose regional policies.

5.3. Policy implications

The findings of this thesis have some policy implications. First, considering the significant role of FinTech in the traditional banking sector, as well as in promoting economic growth, comprehensive policies driving FinTech growth should be developed. China has witnessed a rapid development of FinTech. The evidence found in Chapters 2 and 3 supports a positive and significant relationship between FinTech and traditional commercial banks in China in terms of diversification strategies, which contributes to increasing bank profitability and reducing risk. Therefore, traditional banks are suggested to increase investment in FinTech in terms of expanding money input, having an experienced management team, and establishing an effective incentive mechanism.

In addition, the cooperation between traditional commercial banks, which dominate the economic system in China, and fintechs should be politically encouraged and supported. As indicated in Chapter 3, the state-owned banks and city commercial banks are not sensitive to FinTech development due to high costs, complex organizational structures, and large-scale business processes. To this end, the cooperation between banks and fintechs might be essential for promoting banks to diversify by reducing operational costs, such as spending on staff and physical support for branches.

Another policy implication is addressed to the regulatory framework. Although the rapid FinTech development has brought new opportunities, limited regulatory capacity and intense competition in the FinTech industry in China have resulted in economic volatility and financial risks. Thus, formulating and implementing a robust regulatory framework is important to preserve a stable environment, such as having higher regulatory capacity by regtech and cooperating with FinTech regulators worldwide.

Finally, another policy implication is drawn from the study of the FinTech-growth nexus at regional level. Considering the economic disparities between different regions in China, which were classified based on geographic locations and economic conditions, this thesis has highlighted the significance of exploring regional differences and proposing regional policies, with the aim of encouraging connections between provinces to increase efficiency. For instance, the results found in Chapter 4 suggest that provinces with extremely low and medium economic development levels benefit from focusing on accelerating urbanization and optimizing industrial structure rather than promoting FinTech development.

5.4. Future lines of research

Although this thesis has provided new evidence and insights on the topic of FinTech, traditional banking, and economic development, more studies should be conducted on this and other relevant issues for further understanding. In particular, the greater interest in how FinTech affects the financial sector has motivated a large number of recent studies.

One interesting point in future research is constructing a direct FinTech index. At the time of writing, there is still no unified, standard, and comprehensive FinTech index available, thus, we used the digital financial inclusion index, which is the most comprehensive index compared to others and commonly used to reflect FinTech in the context of China. Having a direct and standard FinTech index will contribute to examining the influence of FinTech more accurately.

Another point is having a larger sample size. We included the data of 19 listed Chinese Commercial banks in Chapters 2 and 3 and 31 provinces in mainland China in Chapter 4 in our sample, which is limited. In order to reach more significant results, the bank data can be extended to non-listed commercial banks in China; and the provincial data for exploring the FinTech-growth nexus can be extended to the city and or county levels.

In addition, the argument can be conducted in some other contexts, such as European countries. Although China excels in the FinTech industry, institutions in Europe invest increasingly in disruptive technologies. While, up to now, there is still limited empirical evidence on the influence of FinTech on traditional banking and/or economic growth in Europe, which is particularly important for the future development of the financial industry and high-quality economic development in Europe. Meanwhile, as discussed in Chapter 4, the focus of FinTech in Europe is very different from that in China. Therefore, it is interesting to discuss different mechanisms of FinTech promoting financial and economic development in China and other countries in future research.

The outbreak of the Covid-19 pandemic has hit the global economy sharply, while it has provided an opportunity for FinTech development. The use of mobile banking and mobile wallets such as Apple Pay and google Pay, has been driven during the pandemic. As many SMEs have been hit hard, FinTech is expected to provide them with financial support to survive in these difficult times. Therefore, future contributions can be addressed to the effect of FinTech on traditional banking and economic development during and after the pandemic, and then to compare it with the effect before the pandemic.

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