Accounting & Finance

ACCOUNTING & FINANCE afaanz

RESEARCH ARTICLE OPEN ACCESS

Digital Gains: FinTech Development and Labour Share

Yuqiang Cao[1] | Meiting Lu[2] | Yaowen Shan[3] | Zhe Zhang[4] | Yanglan Zu[5]

[1]School of Accounting, Research Center for Cross-Board M&A and Innovation Strategy, Institute of Studies for the Greater Bay Area, Guangdong University of Foreign Studies, Guangzhou, China | [2]Macquarie Business School, Macquarie University, Sydney, New South Wales, Australia | [3]University of Technology Sydney, Sydney, New South Wales, Australia | [4]International School of Business Finance, Sun Yat-Sen University, Guangzhou, China | [5]College of Business, Government and Law, Flinders University, Bedford Park, South Australia, Australia

Correspondence: Meiting Lu (meiting.lu@mq.edu.au)

Received: 12 June 2024 | **Revised:** 27 April 2025 | **Accepted:** 29 April 2025

Funding: National Natural Science Foundation of China (grant number: 72072045), Guangdong Basic and Applied Basic Research Foundation (grant numbers: 2023A1515012701 and 2023A1515030075), and Guangdong Planning Office of Philosophy and Social Science (grant numbers: GD24CYJ20, GD25YYJ30, and GD23SJZ04). Yaowen Shan acknowledge the financial support from Australian Research Council.

Keywords: financing constraint | FinTech development | human capital structure | the labor share

ABSTRACT

Capital market development and technological innovation affect the labour income share and resource allocation, but the link between financial innovation and the labour share remains unclear. This paper examines the labour income share through the lens of financial innovation. Using the Bartik (1991) instrumental variable approach and a difference-in-differences estimation, we document a positive and casual relationship between local FinTech development and the labour income share among Chinese firms. Mechanism analyses suggest local FinTech development alleviates financing constraints, optimises resource allocation and improves the structure of human capital, leading to a higher labour income share of firms. The positive effects of local FinTech development are stronger for firms in industries or regions with inefficient resource allocation, for smaller non-state-owned enterprises and for firms with greater access to educational resources. Overall, our results highlight the role of FinTech development in improving capital allocation efficiency, shaping the distribution of labour and enhancing social welfare.

JEL Classification: G39, M41

1 | Introduction

Financial technology, commonly known as FinTech, is the innovative adaptation of technologies in capital markets. Chen et al. (2019) classify FinTech innovations into seven categories, that is, cybersecurity, mobile transactions, data analytics, blockchain, peer-to-peer, robo-advising and Internet of Things (IoT). These technologies have the potential to impact existing financial firms and challenge the established business models, which may transform the financial sector (Kanga et al. 2022) and essentially create a new ecosystem beyond the scope of the traditional financial system. There is a growing body of literature that examines the economic implications of FinTech development. For example, financing solutions enabled by FinTech provide an increasing number of banking options (Kendall 2017). FinTech firms may possess an information advantage with access to consumers' 'digital footprints', posing a threat to traditional financial intermediaries (Berg et al. 2020). In addition, FinTech applications may mitigate the challenges associated with corporate financing (Cheng et al. 2014) and increase firms' capacity for corporate innovation (Ding et al. 2022).

Despite the growing literature on FinTech applications, the relationship between FinTech development and the labour share of income, a crucial element in the socioeconomic context, is underexplored.[1] Labour share is the proportion of a firm's revenue or income allocated to labour, including wages, salaries and other benefits (Autor et al. 2020). A firm's investment in labour share reflects the proportion of value generated by the firm that is allocated to its workforce (Schneider 2011), typically through wages, salaries and other forms of compensation. This allocation is a key component of the firm's cost structure and is often seen as a measure of how much the firm values its human capital. A firm may prioritise investment in its workforce to enhance productivity and employee satisfaction, which in turn can improve overall performance. Alternatively, a firm can invest in non-labour factors by, for example, allocating its profits or returns to its shareholders.

This study focuses on the Chinese capital market, one of the largest capital markets in the world, and investigates whether and to what extent FinTech development affects the labour share of income. We examine the Chinese capital markets for two reasons. First, challenges arising from external financing for Chinese firms are particularly significant. The financial system in China was predominantly bank-centred (Allen et al. 2005) with a significant portion of corporate financing coming from the state-owned bank system where firms can struggle to access credit. As such, firms tend to either employ their internal resources as a form of financing (Fazzari et al. 1988; Song et al. 2011) or seek innovative financing options, both of which can increase firms' access to resources that are likely to be invested in their workforce, and this can change the labour share of income. Second, emerging trends in Chinese capital markets, such as FinTech innovations, may give rise to frictions that directly change the labour market and alter the labour income share (Petrosky-Nadeau and Wasmer 2013). Indeed, Liu et al. (2022) document that the growth of e-commerce in China leads to an expansion of employment that is accompanied by an increase in wages. However, recent studies also document potential bank risks associated with FinTech development (Ben Naceur et al. 2023; Elekdag et al. 2024). Therefore, the link between the level of FinTech development in China and the labour share of income remains unclear.

We posit that local FinTech development may increase the labour share of income for at least three reasons. First, FinTech transforms the financial services sector by providing alternative financing options (Neumeyer and Perri 2005; Benmelech et al. 2021) and fostering competition among financial institutions. This is expected to stimulate financial institutions' lending activities and increase firms' access to finance. Equipped with more financial resources, firms have the motivation to invest more in labour factors (Grossman and Rossi-Hansberg 2012; Stulz 2022) and have a higher labour share of income. Second, FinTech development facilitates business operations and also reduces information asymmetry among firms and across sectors. With access to more information, managers are expected to make sound decisions regarding factor allocation, potentially increasing labour investment. Third, FinTech development changes the workplace landscape (Hsu et al. 2014) and motivates firms to seek a talented workforce adept at emerging technologies (Liu et al. 2022) to upgrade human capital structure. As such, firms may invest in modernising human resource management practices and provide higher compensation packages to retain or attract highly skilled employees, leading to a higher labour share of income.

However, economic theories suggest that FinTech development may also play a negative role in affecting the labour share of income. First, FinTech innovations simplify work processes and improve efficiency through the adoption of intelligent systems and automation, potentially reducing firms' reliance on human labour (Gomber et al. 2018). By optimising inventory management, minimising waste and automating financial processes, firms can reduce the need for excessive labour and allocate resources towards value-added tasks. Therefore, the labour share of firms is expected to decline. Second, advances in FinTech motivate firms to seek employees with digital skills, which potentially leads to higher employee turnover. Accordingly, the associated costs that come with disruptions during such periods may erode the labour share of income for firms. The skill mismatch may also result in employee dissatisfaction, disengagement and reduced productivity (Claybourn 2011), impacting overall firm performance and profitability (Bernhardt et al. 2000). These challenges due to the changing roles and skill requirements in the FinTech era may decrease firms' labour share of income.

Given the above competing explanations, we examine the relationship between local FinTech development and the labour share of income using a sample of Chinese listed firms from 2003 to 2021. We use the number of FinTech firms in the prefecture-level city where a firm is headquartered to capture the level of local FinTech development. In particular, we search for various combinations of the following keywords: financial technology, cloud computing, big data, blockchain, artificial intelligence and the IoT, on the Tianyancha website to obtain information about FinTech firms. Using both the labour share measured as the share of industrial value added of the firm paid to employees and the natural logarithm of the labour share as dependent variables, we find consistent evidence of the positive role of local FinTech development in increasing the labour share of firms. The effect of FinTech is economically significant. One standard deviation increase in the level of FinTech development is associated with a 10.04% increase in the labour share. Our results are robust to alternative measures of local FinTech development and the labour share of income.

Although our baseline results point to a positive welfare effect of local FinTech development, one might doubt that local FinTech development may suffer from endogenous problems. For example, firms with a higher labour income share may possess greater demand and capability to foster local FinTech development, which may lead to simultaneity bias. Firms with a higher labour share of income may be located in the regions with a higher level of FinTech development, suggesting reverse causality. In addition, unobservable firm heterogeneity associated with both FinTech development and the labour share of income raises the concern of omitted variables.

We establish causality by adopting two identification strategies. Our first identification strategy is based on the Bartik (1991) instrumental variable (IV) approach. Specifically, we leverage the city-level FinTech variation and construct an IV by interacting each city's industry composition in 2016 with national FinTech trends. This city-specific IV captures exogenous FinTech variation, which is independent of local shocks and only driven by national trends. Cities with higher shares of industries that adopt FinTech innovations are expected to experience greater changes from national FinTech developments. The results estimated from the Bartik (1991) IV regressions support our hypothesis that local FinTech development has a positive socioeconomic effect and leads to a higher labour share.

Our second identification strategy is based on the differences-in-difference (DiD) analysis. On 31 December 2015, the State Council of China initiated a policy, the Plan for Developing Financial Inclusion (2016 to 2020). The policy recommends the integration of emerging information technologies, including big data, cloud computing and blockchain, to establish online financial service platforms. As the policy is set by the central government, we expect it to promote the adoption of FinTech applications across regions. Regions with limited FinTech advancement possess a comparatively lower level of technological integration and infrastructure than regions with more developed FinTech ecosystems. Therefore, we expect that the policy yields a more significant impact on firms situated in regions with weaker FinTech progress. Accordingly, we construct a DiD model to identify the causal relationship between local FinTech development and the labour income share. The results estimated from the DiD model support our hypothesis that local FinTech development has a positive socioeconomic effect, leading to a higher labour share. Further tests of the possible mechanisms through which FinTech development affects the labour share show that FinTech development provides firms with access to additional capital and alleviates firms' financing constraints. By taking advantage of diverse financing options, firms may potentially have lower financing costs, which narrows the difference between labour and capital and motivates them to invest in the labour factor. Moreover, FinTech advances may create forth new demands for human capital. Individuals hired by firms in the FinTech era are likely to possess digital knowledge and skills in line with emerging technologies. Firms are expected to offer them attractive compensation packages, including higher salaries. Accordingly, the labour share of income is higher. Heterogeneity analyses provide further insights into our findings. In particular, our results suggest that the positive effects of FinTech development on the labour share of income are stronger for firms operating in industries or regions with inefficient resource allocation, for smaller private firms and for firms that take advantage of greater access to educational resources.

This paper makes two main contributions. First, it adds to prior studies that explore the determinants of the labour share of income by focusing on the polarisation phenomenon in the labour market (Autor et al. 2006), technological change (Acemoglu and Autor 2011) and the relationship between countries (Karabarbounis and Neiman 2014). It also contributes to the recent studies in China that link the labour share of income with environmental regulation (Cui et al. 2023), bank competition (Lai, Chen, et al. 2023; Lai, Yang, et al. 2023) and corporate digital transformation (Li et al. 2023). However, FinTech development differs from these factors due to its transformative nature and the way it leverages technology to revolutionise financial services (Kanga et al. 2022) and deliver impacts that are beyond the financial industry. Through the scope of FinTech development, we depart from the existing evidence and show that local FinTech development may alleviate firms' financing constraints and improve their human capital structure, which reveals new channels for understanding the determinants of labour share in the FinTech era.

Second, this paper responds to Lagna and Ravishankar (2022)'s call for more research on FinTech development and adds to a growing body of literature on the consequences of FinTech development. For example, the risks associated with FinTech may spill over to traditional financial institutions, escalating systemic risk (Li et al. 2020). Multiple channels (i.e., artificial intelligence, cloud technology and data technology) enabled by FinTech development significantly enhance bank stability (Daud et al. 2022). In addition, FinTech intensifies the competition among banks (Stulz 2022) and stimulates firms' access to funds, thereby encouraging corporate R&D investment (Ding et al. 2022). This study goes beyond the economic impacts on the financial markets and examines the socioeconomic implications of FinTech development. Our results add to the literature by demonstrating that local FinTech development increases firms' labour share of income.

The remainder of the paper is organised as follows. Section 2 develops hypotheses. Section 3 outlines our sample and research design. Section 4 presents the main results. Sections 5 and 6 discuss possible mechanisms and heterogeneity analyses, respectively. Section 7 concludes the paper.

2 | Hypothesis Development

2.1 | Labour Share and Financial Market Development

Labour share, also known as labour share of income, represents the share of value added that is paid out to workers (Schneider 2011). Early theoretical studies highlight that labour share is associated with the allocation and distribution of economic output between labour and other factors of production, such as capital (Cobb and Douglas 1928; Douglas 1976). Despite the importance of addressing factor income shares (Atkinson 2009), the labour share has witnessed a decline worldwide (Grossman and Oberfield 2022), which has been attributed to various factors. For example, Kehrig and Vincent (2021) document that the declining labour share of income is attributed to a significant shift of value added towards the lower spectrum of the labour share distribution. Autor et al.'s (2020) analysis of 'superstar firms' shows that the declining labour share of income is largely driven by reallocation. Advances in information technology may also lower the price of investment goods and induce firms to favour capital over labour (Karabarbounis and Neiman 2014).

In the corporate context, firms use capital and labour to support production and turn to financial institutions to secure the funding needed for their working capital (Liu et al. 2021). Therefore, firms' access to resources in financial markets is expected to affect the distribution of labour share. For example, firms open capital accounts to raise capital overseas, which leads to a higher demand for skilled labour and aggravates wage inequality across sectors (Larrain 2015). Moreover, capital account liberalisation may change the relative bargaining power of firms and workers, which ultimately leads to a decline in the labour share (Furceri and Loungani 2018). As financial markets today integrate technology-driven solutions and become more sophisticated with FinTech advances, innovative business models are expected to bring forth novel ways for firms to access capital. This may further change economic dynamics and have a significant impact on the distribution of income between labour and capital factors. To this end, we discuss two opposing effects of regional FinTech development on firms' labour share of income.

2.2 | Local FinTech Development on the Labour Income Share: The Positive Role

There are at least three possible mechanisms that suggest that local FinTech development may have a positive effect on the labour share of firms. First, the development of FinTech presents opportunities to alleviate firms' financing constraints and increase the amount of capital held by firms, which increase the firm's capacity for investment in labour factors. Traditional financial markets pose challenges for firms in accessing funds (Neumeyer and Perri 2005; Benmelech et al. 2021). Therefore, under financing constraints, firms often prioritise capital investment over labour, primarily because capital assets can serve as collateral and generate additional financing capacity (Gan 2007; Grossman and Rossi-Hansberg 2012). In contrast, labour inputs lack collateralisable value, making them more vulnerable to cutbacks. As a result, firms facing liquidity shortages may reduce hiring or suppress wage growth, leading to an artificially low level of labour investment.

The rise of FinTech has fundamentally transformed the financial services landscape by introducing alternative financing channels that reduce firms' dependence on traditional banks. For example, peer-to-peer lending platforms bypass traditional financial institutions and attract borrowers with lower interest rates (Jiang et al. 2021), which can lead to heightened competition among financial institutions and propel banks to increase their lending activities with the aim of maintaining economies of scale (Stulz 2022). Firms can benefit from the increased rivalry among both traditional and emerging financing platforms and have access to a larger pool of capital with fewer financing constraints. As reliance on collateral-based lending diminishes, firms are better positioned to allocate resources more efficiently, enabling a disproportionate increase in labour investment relative to capital investment.

Moreover, the inherent flexibility and adaptability of the labour factor make it a priority in firms' investment decisions when financing becomes more accessible (Wang et al. 2017; Yang et al. 2022). Compared to capital investments (e.g., acquiring machinery or fixed assets), adjustments in labour, including hiring, wage increases and employee training, involve shorter implementation timelines. As a result, firms are more inclined to optimise labour input as the first step once financial constraints are eased.

Second, local FinTech development enables efficient information sharing and equips managers with the skills to make optimal factor allocation decisions, leading to a greater proportion of funds allocated to labour share. Specifically, when firms face high information asymmetry, they may struggle to allocate labour and non-labour factors efficiently, often deprioritising labour in their investment decisions. Nowadays, applications enabled by FinTech development emerge in every corner of business operations and help firms allocate their resources more efficiently. For example, blockchain technologies reduce delays and minimise errors across supply chain management (Prewett et al. 2020), which enhances the transparency and traceability of the information obtained by firms. The extent to which cross-sectional information is shared also increases as information acquisition costs associated with various business processes (e.g., supply chain operations, order processing and inventory management; Cachon and Fisher 2000) are lower with these evolving technologies. Moreover, innovations in digital payments (Bounie and Camara 2020) and retail payment systems (Arango et al. 2015) can enable firms to access real-time financial and business analytics data, which helps them to capture a clearer picture of not only their financial health but also the broader market. Big data analytics can further foster more efficient knowledge management (Rothberg and Erickson 2017), which helps firms to access large volumes of valuable information about labour market trends and insights into their industry.

With the advent of evolving technologies through local FinTech development, firms gain access to better information and a clearer understanding of their business operations and the broader market, which ideally enhances the efficiency of information sharing among firms and across industries and mitigates information asymmetry. This, in turn, can motivate managers to make more informed decisions regarding optimal factor allocation (Grossman and Rossi-Hansberg 2012). In particular, they may adjust their investments in both labour and non-labour factors, with the previously underemphasised labour factors receiving more attention and attracting greater funds.

Third, FinTech development may increase firms' share of labour income through its positive effect on the structure of human capital. As local FinTech development mitigates the inefficient allocation of resources and enables efficient information sharing across sectors, we expect that firms operating in this environment also have the motivation to modernise their human resource management practices by, for example, recruiting highly skilled employees with digital literacy. Firms may also seek to hire a talented workforce possessing analytical skills in various business areas (i.e., supply chain, marketing and innovation) to adapt to the ever-changing environment in the digital era (Leeflang et al. 2014). Employees' digital skill sets can enable firms to navigate opportunities and challenges in the modern FinTech ecosystem and enhance firms' competitiveness. As a result, firms may offer higher compensation packages to attract or retain manufacturing-oriented, high-tech and highly educated employees (Wu and Yang 2022), which are associated with higher labour share of income.

The above discussion leads to the following hypothesis:

H1a. *Local FinTech development increases firms' labour share of income.*

2.3 | Local FinTech Development on the Labour Income Share: The Negative Role

However, there are at least two mechanisms that suggest that local FinTech development may implicitly or explicitly reduce firms' labour share of income. First, advances in FinTech may change the workplace landscape (Hsu et al. 2014) and implicitly affect firms' labour share of income in a negative way. In

TABLE 1 | Summary statistics.

Variable	N	Mean	Std. Dev.	P25	P50	P75
Dependent variables						
Laborshare	23,651	16.254	8.435	10.228	15.015	20.790
LnLaborshare	23,651	−177.415	68.840	−217.219	−173.344	−133.763
Independent variable						
LnFinTech	23,651	3.115	2.473	1.099	2.708	4.477
Control variables						
Age	23,651	15.668	6.059	11.000	15.000	20.000
Size	23,651	22.220	1.421	21.195	22.044	23.065
Lev	23,651	0.509	0.205	0.362	0.513	0.651
Bsize	23,651	2.182	0.203	2.079	2.197	2.197
Tobin_q	23,651	1.801	1.156	1.124	1.398	1.989
Roa	23,651	0.028	0.067	0.010	0.030	0.057
Growth	23,651	0.052	0.351	−0.031	0.098	0.217

Note: This table presents the summary statistics of the variables used in the analysis. All variables are defined in Appendix A. All continuous variables are winsorised at 1% and 99%.

particular, firms may optimise business operations by adopting technologies, such as intelligent systems (Tan et al. 2008) and cloud manufacturing (Zhang et al. 2014), to automate repetitive and manual tasks. In addition, firms can reduce the time and effort required for tasks such as manual data entry by automating financial processes (Harrast and Wood 2022). We expect that simplified work processes may reduce firms' reliance on human labour and allow them to focus more on value-added tasks that are not labour intensive. Accordingly, firms' potential investment in labour may be lower, leading to a lower labour share of income.

Second, advances in FinTech are changing how financial services are structured, delivered and consumed (Gomber et al. 2018), which may have explicit implications for the workforce and the labour share of firms. In particular, empirical evidence on employment trends in China in the digital era (Liu et al. 2022) suggests that roles that used to be fulfilled by employees with traditional skills now require a blend of professional acumen and technology savvy. We expect that the shift towards more technology-centric roles will inevitably lead to a higher employee turnover. Moreover, the costs associated with employee turnover (e.g., recruiting, training and onboarding) during the transition period may erode the overall labour share of income for the firm. In addition, the skills mismatch may disrupt existing work cultures and relationships, potentially leading to employee dissatisfaction and disengagement (Claybourn 2011). As employees lack motivation and commitment to their work, their productivity and performance levels may decline, which may reduce firm performance and negatively impact revenue generation and profitability (Bernhardt et al. 2000). Taken together, we expect to see a decrease in the labour share of income within firms when they experience high levels of local FinTech development.

Based on the above discussion, we propose the following hypothesis:

H1b. *Local FinTech development reduces firms' labour share of income.*

3 | Sample and Research Design

3.1 | Sample Construction and Summary Statistics

We obtain information about the listed Chinese firms between 2003 and 2021 from the China Stock Market and Accounting Research (CSMAR) and RESSET datasets. We remove (i) insolvent firms; (ii) firms operating in the financial industry; (iii) observations with missing financial data. Continuous variables are winsorised at 1% and 99%. This yields a sample of 23,651 firm-year observations. Table 1 reports the summary statistics of the variables examined in this paper. The mean value for *Laborshare* (*LnLaborshare*) is 16.254 (−177.415). The 25th and 75th percentiles of *LnFinTech* is 1.099 and 4.477, respectively, suggesting that the level of local FinTech development varies significantly across regions in China.

3.2 | Research Design

We examine the relationship between local FinTech development and the labour share by estimating Model (1) with standard errors adjusted for clustering at the firm level:

$$\begin{aligned} Laborshare_{i,t} = \; & \alpha + \beta_1 LnFinTech_{m,t} + \gamma X_{i.t} + Firm\ FE \\ & + Year\ FE + \varepsilon_{i,t} \end{aligned} \tag{1}$$

where $Laborshare_{i,t}$ is the share of labour income of firm i in year. The labour share is the share of industrial value added of the firm paid for employees, measured as the share of industrial value added paid to employees (i.e., *cash paid to and for* *employees* divided by the sum of *operating income minus operating costs*, plus *depreciation of fixed assets* and *cash paid to and for employees*).[2] To ensure that labour income shares are normally distributed in terms of their values, we also use *Lnlaborshare*, the log-transformed form of *Laborshare*, as an additional dependent variable in our analyses.[3]

The variable of interest $LnFinTech_{m,t}$ presents the level of FinTech development in region *m* in year *t*, proxied by the number of FinTech firms at the city level. According to the definition of the Financial Stability Board, FinTech is a form of technology that incorporates finance and technology into financial services and can improve the efficiency of the traditional financial industry and effectively reduce operating costs through new technological means such as cloud computing, big data, blockchain and artificial intelligence. Based on this, following Phan et al. (2020), we identify information about FinTech firms on the Tianyancha website[4] by searching for several combinations of the following keywords: financial technology, cloud computing, big data, blockchain, artificial intelligence and the IoT. We review the collected information and remove the false positive search results.

In addition, we control for several variables in our regression models, including the age of the firm (*Age*), firm size (*Size*, the natural logarithm of total assets), leverage (*Lev*, total liabilities divided by total assets), board size (*Bsize*, the natural logarithm of the number of members on the board), Tobin's q (*Tobin_q*, Market capitalisation divided by total assets), firm growth (*Growth*, the growth rate of the firm's operating income) and return on assets (*Roa*, net profit divided by total assets) in Model (1). We also control for firm fixed effects and year fixed effects.

4 | Main Results

4.1 | Baseline Regression

Table 2 reports the regression results of the effect of local FinTech development on firms' labour share of income. Columns (1) and (2) show the regression results without control variables. Columns (3) and (4) report the regression results of Model (1), whereas Columns (5) and (6) present the regression results with additional city×year fixed effects[5]. The coefficients on *LnFinTech* in Table 2 are significantly positive at the 1% level in Columns (1) to (6), supporting our hypothesis that local FinTech development increases the labour share of income. The effect is also economically significant. Specifically, the results presented in Columns (3) and (4) suggest that a one standard deviation increase in the level of FinTech development is associated with a corresponding increase in the labour share of 10.04%.

4.2 | Identification Strategies

4.2.1 | The Bartik (1991) IV Approach

Our baseline results presented above may suffer from endogeneity issues, as both FinTech and labour share can be simultaneously influenced by various unobservable factors, potentially leading to biased estimates. To address this concern, we adopt the Bartik (1991) IV (also known as a shift-share instrument) approach, method, as our first identification strategy. In particular, we leverage the city-level variation in FinTech development and construct an instrumental variable by interacting the industry distribution of each city with national FinTech trends (Goldsmith-Pinkham et al. 2020).

Our reasoning is that initial industry distribution in each city, prior to the widespread adoption of FinTech, indicates how national trends in FinTech affect local development. Cities with a higher share of industries are more likely to adopt FinTech innovations and are expected to experience more significant changes due to national FinTech developments (Wu et al. 2024). Specifically, we use the industry composition of cities in 2016 as the baseline year. We construct the Bartik instrument by combining the baseline-year city-level industry shares with national growth rates in FinTech. This creates a city-specific instrument that captures exogenous variation in FinTech developments, which is independent of local shocks and driven purely by national trends.

The Bartik IV for city *i* in year *t*, denoted as $Region\_Bartik\_IV_{i,t}$ is calculated as follows:

$$Region\_Bartik\_IV_{i,t} = \sum_j \left(\frac{LnFinTech_{i,j,2016}}{TotalLnFinTech_{i,2016}} \right) \times NationalFinTechGrowth_{j,t}$$

where $LnFinTech_{i,j,2016}$ is the LnFinTech in $industry_j$ in $city_i$ in the baseline year 2016, and $NationalFinTechGrowth_{j,t}$ represents the national growth in FinTech for $industry_j$ over time. The weight is the industry share in each city based on the employment structure in 2016.

Using this instrument, we estimate a two-stage least squares (2SLS) regression where the endogenous variable $LnFinTech_{i,t}$ is instrumented by the $Region\_Bartik\_IV_{i,t}$. Table 3 presents the results of this 2SLS estimation. The coefficients on *Region_Bartik_IV* in the first-stage regressions are significant at the 1% level, indicating the Bartik IV is strongly associated with the endogenous variable and is consistent with our prediction. The coefficients on *LnFinTech* in the second-stage regressions are significantly positive at the 1% level, which reinforces our main findings that local FinTech development increases firms' labour share of income.

4.2.2 | The DiD Estimation

Our second identification strategy is the DiD estimation. We use the Plan for Developing Financial Inclusion 2016 to 2020 (hereafter: the policy) to construct a DiD model. The State Council of China issued the policy on December 31st, 2015, advocating the use of emerging information technologies, such as big data, cloud computing and blockchain, to establish online financial service platforms. This policy, enacted by the central government, serves as an exogenous shock to stimulate the development of FinTech applications adopted by local financial institutions.

TABLE 2 | Effect of local FinTech development on the labour share of income.

	(1)	(2)	(3)	(4)	(5)	(6)
	Laborshare	***LnLaborshare***	***Laborshare***	***LnLaborshare***	***Laborshare***	***LnLaborshare***
LnFinTech	0.601***	4.241***	0.660***	4.710***	0.821***	5.908***
	(3.78)	(3.29)	(4.13)	(3.67)	(3.46)	(3.04)
Age			0.001	0.432	0.003	0.892
			(0.00)	(0.27)	(0.01)	(0.52)
Size			−0.081	−0.795	−0.200	−1.894
			(−0.37)	(−0.44)	(−0.80)	(−0.94)
Lev			−0.809	−3.941	−0.778	−4.035
			(−1.13)	(−0.68)	(−0.99)	(−0.64)
Bsize			1.342**	13.239***	1.639***	14.793***
			(2.54)	(3.04)	(2.76)	(3.18)
Tobin_q			0.166**	0.597	0.143	0.339
			(2.02)	(0.89)	(1.64)	(0.49)
Roa			−14.083***	−110.551***	−13.934***	−107.341***
			(−10.09)	(−9.70)	(−9.41)	(−8.96)
Growth			−1.825***	−13.531***	−2.056***	−15.452***
			(−9.12)	(−7.80)	(−9.83)	(−8.87)
Constant	14.368***	−190.707***	13.649**	−205.378***	15.200**	−194.564***
	(29.07)	(−47.57)	(2.33)	(−4.42)	(2.29)	(−3.80)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City × Year	No	No	No	No	Yes	Yes
N	23,554	23,554	23,554	23,554	22,078	22,078
R-squared	0.658	0.668	0.676	0.684	0.683	0.697

Note: This table presents the effect of local FinTech development on the labour share of income. All variables are defined in Appendix A. All continuous variables are winsorised at the 1% and 99% levels. The numbers reported in parentheses are t-statistics based on standard errors clustered at the firm level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

We expect it to promote the adoption of FinTech applications across regions for at least three reasons. First, the policy aims to foster innovation in financial products and services by actively encouraging financial inclusion providers to leverage modern information technologies to reduce transaction costs, expand service reach and enhance both the breadth and depth of financial inclusion (Yang and Zhang 2022). Second, the policy emphasises the development of financial infrastructure, advocating for the use of advanced technologies to improve operational efficiency. By integrating internet-based technologies, financial inclusion providers can lower the costs of financial transactions and extend their services to a wider range of underserved populations, thus increasing the reach and effectiveness of inclusive financial services (Niu et al. 2022). Third, the policy seeks to strengthen the legal and regulatory framework for financial inclusion. It promotes the adoption of internet and modern information technologies by financial service providers, which not only reduces costs but also increases access to financial services, ultimately deepening the scope of financial inclusion across regions and sectors (Hua and Huang 2021; Fu and Yi 2023).

We expect that regions with weaker FinTech development have a lower level of technology adoption and infrastructure compared to regions with more advanced FinTech ecosystems. Therefore, the policy should have a greater impact on financial institutions in regions with weaker FinTech development. This provides a unique setting for constructing a DD model in our setting and helps identify the causality between local FinTech development and the labour income share (Huang 2022). Following Vig (2013), we use the median value of local FinTech development in 2015 as a reference point and divide cities in our sample into two groups, that is, high and low FinTech development. The two groups are referred to as the control group and the treatment group, respectively. We employ *Laborshare* and *LnLaborshare* as dependent variables

TABLE 3 | Bartik (1991) IV approach.

	(1)	(2)	(3)
	LnFinTech	*Laborshare*	*Lnlaborshare*
LnFinTech		2.586***	21.218***
		(3.50)	(3.46)
Region_Bartik_IV	0.093***		
	(5.54)		
Age	0.082***	−0.145**	−1.255**
	(31.62)	(−2.33)	(−2.44)
Size	0.672***	−1.949***	−17.286***
	(53.23)	(−3.86)	(−4.13)
Lev	−1.411***	1.459	13.844
	(−16.89)	(1.31)	(1.50)
Bsize	−0.744***	0.362	4.554
	(−10.30)	(0.58)	(0.87)
Tobin_q	0.180***	0.100	0.039
	(12.99)	(0.67)	(0.03)
Roa	−1.547***	−9.382***	−65.122***
	(−5.89)	(−5.88)	(−4.93)
Growth	−0.202***	−0.644***	−2.154
	(−4.57)	(−2.78)	(−1.12)
Constant	−11.050***	52.360***	145.157**
	(−37.62)	(6.25)	(2.09)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	23,651	23,651	23,651
R-squared	0.207		

Note: This table presents the results of the Bartik (1991) IV approach. We use the industry composition of cities in 2016 as the baseline. *Region_Bartik_IV* is constructed by combining each city's industry distribution in the baseline year with the national growth rates in *FinTech*. Column (1) reports the results of the first-stage regression, whereas Columns (2) and (3) report the results of the second-stage regression. All variables are defined in Appendix A. All continuous variables are winsorised at the 1% and 99% levels. The numbers reported in parentheses are t-statistics based on standard errors clustered at the firm level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

in our DiD analysis. We also use *DFinTech* as an additional dependent variable to validate that the policy increases the local FinTech adoption.[6]

The DiD regression is estimated as follows:

$$Laborshare_{i,t}\ \left(DFinTech_{m,t}\right) = \alpha + \beta Treat_m \times Post_t + \gamma X_{i.t} + \lambda_m + \delta_t + \varphi_i + \varepsilon, \quad (2)$$

where $Treat_{mi,t} \times post_{i,t}$ presents the treatment group, $Treat_{mi,t} \times post_{i,t}$ is one for the periods after 2016, and zero otherwise. The coefficient on $Treat_{mi,t} \times post_{i,t}$ captures the impact of the policy. Given that the policy is implemented at the city level, we also incorporate city fixed effects into our model and cluster standard errors at the city level.

The estimation results of the DiD regressions are reported from Columns (1) to (3) of Table 4. When *DFinTech* is used as the dependent variable in Column (1) of Table 4, the coefficient on the interaction term $Treat_{mi,t} \times post_{i,t}$ is 1.496 and statistically significant. This validates our expectation that the policy substantially increases local FinTech adoption among firms. When the two labour share variables (*Laborshare* and *LnLaborshare*) are used as the dependent variables in Columns (2) and (3) of Table 4, the coefficients on the interaction term are also positive. This is consistent with our baseline results and indicates that the growth rate of FinTech

TABLE 4 | DiD estimation.

	(1)	(2)	(3)	(4)	(5)	(6)
	DFinTech	***Laborshare***	***LnLaborshare***	***DFinTech***	***Laborshare***	***LnLaborshare***
Treat×Post	1.496***	0.824***	3.696*			
	(4.64)	(2.75)	(1.66)			
*Treat×Pre3_*				−0.112	−0.004	0.074
				(−0.35)	(−0.01)	(0.03)
Treat×Pre2				0.164	−0.488	−2.461
				(0.42)	(−1.51)	(−0.97)
Treat×Current				0.061	0.421	1.632
				(0.13)	(1.41)	(0.65)
Treat×Post1				1.538***	0.413	0.760
				(2.80)	(1.14)	(0.25)
Treat×Post2				1.533***	1.028**	5.375*
				(2.73)	(2.48)	(1.68)
Treat×Post3				1.710***	1.049**	5.692*
				(2.65)	(2.42)	(1.76)
*Treat×Post4_*				2.138***	0.885**	3.803
				(4.55)	(2.10)	(1.12)
Age	0.005	0.170	1.177	0.003	0.170	1.173
	(0.11)	(0.82)	(0.71)	(0.06)	(0.82)	(0.71)
Size	0.009	−0.079	−0.335	0.009	−0.079	−0.335
	(0.30)	(−0.38)	(−0.21)	(0.28)	(−0.38)	(−0.21)
Lev	−0.002	−1.316	−9.595	−0.004	−1.320	−9.611
	(−0.01)	(−1.63)	(−1.32)	(−0.03)	(−1.64)	(−1.32)
Bsize	0.000	1.152**	12.237***	0.005	1.146**	12.200***
	(0.00)	(2.48)	(3.06)	(0.04)	(2.47)	(3.05)
Tobin_q	−0.019	0.195***	1.003	−0.014	0.195***	1.003
	(−1.08)	(2.60)	(1.63)	(−0.75)	(2.60)	(1.63)
Roa	0.492*	−15.347***	−124.441***	0.456	−15.366***	−124.546***
	(1.66)	(−10.06)	(−9.95)	(1.53)	(−10.07)	(−9.95)
Growth	−0.048	−1.622***	−12.609***	−0.043	−1.622***	−12.607***
	(−1.19)	(−7.81)	(−6.94)	(−1.08)	(−7.78)	(−6.93)
Constant	1.809*	13.238***	−210.412***	1.859	13.274***	−210.181***
	(1.68)	(2.78)	(−5.71)	(1.61)	(2.78)	(−5.73)
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	20,616	20,616	20,616	20,616	20,616	20,616
R-squared	0.399	0.748	0.751	0.405	0.748	0.751

Note: This table presents the results of the DiD estimation. Specifically, we use the Plan for Developing Financial Inclusion 2016 to 2020 (hereafter: the policy, announced on December 31st, 2015) to construct a DiD model. We follow Vig (2013) and use the median value for local FinTech development in 2015 as a reference point. We divide cities in our sample into two groups, that is, high and low FinTech development, and label them as the control group and the treatment group, respectively. Therefore, *Treat* is coded as one when a firm is located in a prefecture-level city where the level of FinTech development is less than the median in 2015, and zero otherwise. *Post* is coded as one for years 2016 or after, and zero otherwise. Accordingly, *Pre3_* is coded as one for years 2013 and earlier, whereas *Pre2* presents the year 2014. *Current* presents the year 2016. *Post1*, *Post2* and *Post3* present the years 2017, 2018 and 2019, respectively, and *Post4_* is coded as one for the years 2020 and beyond. All variables are defined in Appendix A. All continuous variables are winsorised at the 1% and 99% levels. The numbers reported in parentheses are t-statistics based on standard errors clustered at the city level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

development level in cities with low FinTech development level has increased.

Next, we adopt an event study approach and set the year before the policy implementation, 2015, as the baseline period to test the parallel assumption. *Pre3_* is coded as one for years 2013 and earlier, whereas *Pre2* presents the year 2014. *Current* presents the year 2016. *Post1*, *Post2* and *Post3* present the years 2017, 2018 and 2019, respectively, and *Post4_* is coded as one for the years 2020 and beyond. Columns (4–6) of Table 4 show that the coefficients on interaction terms with *Pre3_* and *Pre2* are not significantly different from zero. This indicates that the difference in labour income shares between the two groups before the policy implementation is not significant, which satisfies the parallel trend hypothesis of a DiD estimation.

4.3 | Robustness Tests

In this section, we re-estimate Model (1) with alternative variables to measure local Fintech development and the labour share of income. First, we use the Digital Financial Inclusion Index of China compiled by the Peking University Digital Finance Center and Ant Financial Group as an alternative variable of interest to measure the level of regional FinTech development. In particular, this index covers 31 provinces, 337 cities and 1754 counties in China, reflecting the degree to which different regions have adopted FinTech. Table 5 Panel A shows that the coefficients on the alternative measures of local FinTech development are positive and statistically significant, which is consistent with our main results.

Second, according to the Industry Labor Cost Survey and Analysis Methods published by the Chinese Ministry of Human Resources and Social Security in 2004, the labour income should reflect the relation between the labour input and the total output of a firm. As such, we re-calculate the labour share (*Laborshare1*) as the proportion of total employee compensation to total operating income, where total employee compensation is measured by *cash paid to and for employees*. *LnLaborshare1* is the natural logarithm of *Laborshare1*. In addition, Solow (1957) defines the labour share of income as the increase in factor cost. Following this definition, we calculate *Laborshare2* as the sum of cash paid to and for employees plus employee compensation payable at the end of the period minus employee compensation payable at the beginning of the period, divided by the sum of operating income minus operating cost plus the labour income plus depreciation of fixed assets. *LnLaborshare2* is the natural logarithm of *Laborshare2*. Table 5 Panel B shows the results of our regressions. The coefficients on *LnFinTech* are positive and statistically significant from Columns (1) to (4), suggesting that local FinTech development increases the labour share, which is consistent with our baseline results.

Third, we include two additional control variables at the regional level: regional GDP and regional tax revenue. The economic conditions at the regional level, such as regional GDP and regional fiscal revenues, may to some extent reflect the association between FinTech development and local economic conditions and play a confounding role in changes in labour income shares (Li et al. 2009). As shown in Panel C of Table 5, the coefficients on *LnFinTech* continue to be positive and statistically significant from Columns (1) to (2), suggesting that local FinTech development increases labour shares, consistent with our baseline results. This suggests that our main findings remain robust after controlling for regional differences and are not affected by changes in regional economic conditions.

Fourth, considering that Fintech applications in China explosively grew after 2013 (Ding et al. 2022), we use 2013 to 2021 as an alternative sample in our robustness test. The coefficients on *LnFinTech* remain positive and statistically significant from Columns (1) to (2) in Panel D of Table 5. In particular, the coefficient on *LnFinTech* is 0.482 and 3.260, respectively. This evidence indicates that local FinTech development increases labour shares, which is consistent with our baseline results.

5 | Possible Mechanisms

Our findings so far highlight that local FinTech development increases firms' labour share of income. However, what are the possible mechanisms that could explain the link between FinTech and the labour share? We first focus on firms' financial constraints. Traditional financial markets make it difficult for firms to access finance (e.g., Benmelech et al. 2021). With the rise of FinTech, peer-to-peer lending circumvents traditional channels by providing borrowers with more favourable interest rates (Jiang et al. 2021). To remain competitive and take advantage of economies of scale, banks strive to expand their lending operations (Stulz 2022). Therefore, we expect that FinTech can equip firms with diverse financing avenues and stimulate conventional financial institutions to become more willing to lend, thereby alleviating firms' constraints in obtaining funding. Following Hadlock and Pierce (2010), we construct the KZ index and the FC index to capture firms' financing constraints. In particular, firms with a higher KZ Index (FC Index) score are more likely to experience financing difficulties, while a lower score suggests a healthier financial position. The coefficients on local FinTech development (*LnFinTech*) are negative and statistically significant, at least at the 10% level, in Columns (1) and (2) of Table 6, which suggests that FinTech provides firms with additional sources of capital and potentially simplifies the process of securing loans, which eases firms' financing constraints. Consequently, with enhanced access to capital, firms may be stimulated to invest more in the labour factor, and thus have a higher labour share of income.

The second mechanism centres on firms' allocation of the labour and capital factor. Given that knowledge management enabled by big data analytics (Rothberg and Erickson 2017) may facilitate firms' acquisition of information about labour market trends and insights into their industry, firms are expected to experience less information asymmetry. Accordingly, managers are expected to make informed factor allocation decisions (Grossman and Rossi-Hansberg 2012). Under such circumstances, firms are expected to have optimised the allocation of the labour and capital factors. Moreover, having access to more financing options with lower financing costs may also lead to a smaller relative price disparity between labour and capital. Therefore, firms may be motivated to invest more in labour factors, which leads to a higher labour share of income. Accordingly, we use labour

TABLE 5 | Robustness checks.

Panel A: An alternative independent variable

	(1)	(2)
	Laborshare	***LnLaborshare***
FinTech	0.035***	0.359***
	(3.11)	(3.86)
Age	−0.280	−1.030
	(−0.95)	(−0.51)
Size	0.672**	4.848**
	(2.34)	(2.19)
Lev	−1.929**	−10.121
	(−2.08)	(−1.42)
Bsize	0.920	8.460
	(1.40)	(1.62)
Tobin_q	0.095	−0.054
	(1.04)	(−0.07)
Roa	−19.304***	−139.183***
	(−11.63)	(−10.62)
Growth	−2.355***	−18.276***
	(−10.26)	(−9.94)
Constant	−0.052	−337.668***
	(−0.01)	(−5.52)
Firm FE	Yes	Yes
Year FE	Yes	Yes
N	13,920	13,920
R-squared	0.786	0.800

Panel B: Alternative dependent variables

	(1)	(2)	(3)	(4)
	Laborshare1	***LnLaborshare1***	***Laborshare2***	***LnLaborshare2***
LnFinTech	18.400*	4.425**	0.818***	4.550***
	(1.84)	(2.52)	(3.97)	(3.34)
Age	3.241	−0.322	−0.057	−0.341
	(0.19)	(−0.09)	(−0.22)	(−0.22)
Size	−1.484	−15.707***	−0.048	−1.377
	(−0.14)	(−7.42)	(−0.15)	(−0.71)
Lev	208.695***	−17.561**	0.500	4.259
	(4.58)	(−2.43)	(0.56)	(0.72)
Bsize	11.419	8.860*	1.404**	12.861***
	(0.28)	(1.65)	(2.16)	(2.89)

(Continues)

Panel B: Alternative dependent variables

	(1)	(2)	(3)	(4)
	Laborshare1	***LnLaborshare1***	***Laborshare2***	***LnLaborshare2***
Tobin_q	4.676	3.017***	0.332***	1.275*
	(0.68)	(3.70)	(3.11)	(1.88)
Roa	−280.421***	−131.852***	−16.020***	−112.691***
	(−2.72)	(−10.06)	(−8.77)	(−10.07)
Growth	−89.349***	−42.803***	−2.320***	−14.309***
	(−5.68)	(−24.49)	(−8.45)	(−8.74)
Constant	−185.066	92.881	14.569*	−168.271***
	(−0.50)	(1.30)	(1.81)	(−3.48)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	23,542	23,495	23,546	23,546
R-squared	0.009	0.724	0.644	0.687

Panel C: Additional regional control variables

	(1)	(2)
	Laborshare	***Lnlaborshare***
Lnfintech	0.650***	4.528***
	(3.97)	(3.44)
Age	−0.015	0.362
	(−0.07)	(0.23)
Size	−0.068	−0.741
	(−0.31)	(−0.41)
Lev	−0.777	−4.156
	(−1.07)	(−0.71)
Bsize	1.413***	14.021***
	(2.65)	(3.18)
Tobin_q	0.178**	0.704
	(2.14)	(1.04)
Roa	−13.957***	−109.618***
	(−9.86)	(−9.49)
Growth	−1.831***	−13.486***
	(−8.95)	(−7.64)
GDP	−0.000	−0.000
	(−0.94)	(−0.52)
Fiscal_revenue	0.000	0.000
	(1.06)	(0.75)

(Continues)

TABLE 5 | (Continued)

Panel C: Additional regional control variables		
	(1)	**(2)**
	Laborshare	***Lnlaborshare***
Constant	13.565**	−206.538***
	(2.32)	(−4.51)
Firm FE	Yes	Yes
Year FE	Yes	Yes
N	23,090	23,090
R-squared	0.675	0.685

Panel D: Alternative sample period		
	(1)	**(2)**
	Laborshare	***Lnlaborshare***
Lnfintech	0.482**	3.260**
	(2.14)	(2.05)
Age	−0.347	−1.737
	(−1.38)	(−1.02)
Size	0.481	3.046
	(1.51)	(1.28)
Lev	−1.544	−8.590
	(−1.46)	(−1.06)
Bsize	1.623**	13.556***
	(2.47)	(2.70)
Tobin_q	−0.112	−1.655**
	(−1.02)	(−2.01)
Roa	−18.730***	−136.166***
	(−10.86)	(−10.58)
Growth	−2.545***	−18.747***
	(−9.77)	(−9.18)
Constant	9.290	−234.989***
	(1.12)	(−4.02)
Firm FE	Yes	Yes
Year FE	Yes	Yes
N	11,696	11,696
R-squared	0.793	0.809

Note: This table presents the results of the robustness tests. Panel A reports the regression results where we use the Digital Financial Inclusion Index of China as an alternative independent variable to capture the level of local FinTech development (*FinTech*). Panel B reports the results where two alternative dependent variables to measure the labour share of income are used in regressions. Specifically, we follow the Industry Labor Cost Survey and Analysis Methods published by the Chinese Ministry of Human Resources and Social Security in 2004 and measure *Laborshare1* as the proportion of total employee compensation to total operating income, where total employee compensation is measured by cash paid to and for employees. *LnLaborshare1* is the natural logarithm of *Laborshare1*. Moreover, we follow Solow (1957) and define *Laborshare2* as the sum of cash paid to and for employees plus employee compensation payable at the end of the period minus employee compensation payable at the beginning of the period, divided by the sum of operating income minus operating cost plus the labour income plus depreciation of fixed assets. *LnLaborshare2* is the natural logarithm of *Laborshare2*. All variables are defined in Appendix A. All continuous variables are winsorised at the 1% and 99% levels. The numbers reported in parentheses are *t*-statistics based on standard errors clustered at the firm level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

TABLE 6 | Possible mechanisms.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	KZ Index	***FC Index***	***Laborintensive***	***Salary***	***Capital_ intensity***	***Capital_ expenditure***	***Degree***	***Degreeincrease***
LnFinTech	−0.085***	−0.007*	0.104***	3.867*	−0.009***	−1.178	0.002***	0.001***
	(−3.08)	(−1.71)	(2.78)	(1.84)	(−3.05)	(−1.03)	(2.73)	(2.94)
Age	−0.021	−0.005	0.025	−0.373	−0.005	−0.417	0.002**	−0.000
	(−0.50)	(−0.91)	(0.66)	(−0.24)	(−1.14)	(−0.73)	(2.04)	(−0.48)
Size	−0.277***	−0.002	0.006	7.664***	−0.016***	1.731	−0.000	0.001
	(−8.86)	(−0.27)	(0.06)	(4.93)	(−3.77)	(1.02)	(−0.15)	(1.01)
Lev	6.870***	−0.055***	0.501**	3.760	0.027*	−18.419	−0.002	−0.007
	(48.99)	(−4.02)	(2.22)	(1.44)	(1.74)	(−1.04)	(−0.40)	(−1.25)
Bsize	−0.131	0.002	−0.181	−4.103	−0.007	7.807	−0.001	0.004
	(−1.25)	(0.19)	(−1.08)	(−0.90)	(−0.64)	(1.01)	(−0.21)	(0.99)
Tobin_q	0.438***	−0.014***	−0.046***	0.800*	−0.001	−0.103	−0.000	−0.000
	(21.35)	(−6.51)	(−2.68)	(1.65)	(−0.61)	(−0.68)	(−0.47)	(−0.45)
Roa	−8.128***	0.052**	1.251***	8.821**	−0.205***	−21.022	0.003	−0.008
	(−23.79)	(2.28)	(4.51)	(2.14)	(−8.04)	(−0.95)	(0.47)	(−1.07)
Growth	−0.403***	0.011***	0.015	−0.892	0.007**	5.925	0.001	0.000
	(−10.38)	(3.78)	(0.26)	(−1.53)	(2.52)	(1.04)	(0.91)	(0.03)
Constant	5.548***	3.875***	−0.257	−157.651***	0.738***	−33.621	0.055**	−0.020
	(5.79)	(22.88)	(−0.10)	(−3.64)	(6.72)	(−1.00)	(2.11)	(−0.88)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	22,106	23,540	23,497	23,546	23,554	23,534	23,425	20,120
R-squared	0.806	0.919	0.010	0.749	0.741	−0.033	0.907	0.825

Note: This table presents the results of the mechanisms tests. Columns (1) and (2) report the results focusing on firms' financing constraints measured by the *KZ Index* and *FC Index*. In particular, firms with a higher *KZ* (*FC*) *Index* are more likely to experience financing difficulties. Columns (3) and (4) report the results focusing on firms' allocation of the labour and capital factor. Specifically, we use labour intensity (*Laborintensive*) and changes in average employee wages and other welfare expenditures (*Salary*) to proxy the price disparity between labour and capital. Columns (5) and (6) report the results for capital intensity (*Capital_intensity*) and capital expenditure (*Capital_expenditure*). Capital intensity is the ratio of fixed assets to total assets. Capital expenditure is the ratio of cash paid out to the construction of fixed assets, intangible assets, and other long-term assets over depreciation and amortisation. Columns (7) and (8) report the results focusing on employees' education level, measured by the proportion of employees with bachelor's degree and above (*Degree*) and the natural logarithm of the increase in the number of employees with a bachelor's degree and above (*DegreeIncrease*). All variables are defined in Appendix A. All continuous variables are winsorised at the 1% and 99% levels. The numbers reported in parentheses are t-statistics based on standard errors clustered at the firm level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

intensity (*Laborintensive*) and changes in average employee wages and other welfare expenditures (*Salary*) to proxy for the price disparity between labour and capital. The positive and statistically significant coefficients on LnFinTech in Columns (3) and (4) of Table 6 indicate that FinTech enhances firms' labour intensity and boosts employee income. This evidence also supports our prediction that the adjustments in factor allocation serve as an important channel through which FinTech development increases the labour income share.

It is important to note that the above results imply that FinTech, by easing financial constraints, disproportionately affects labour rather than capital. However, seminal work documents evidence that the relaxation of financial constraints can fund physical capital and boost capital spending, as evidenced by firm-level capital intensity and expenditure. To address this concern, we examine whether FinTech would impact labour share relative to physical capital to a greater extent when funding is more widely available. We measure capital intensity as the ratio of fixed assets to total assets, and capital expenditure as the ratio of cash paid out to the construction of tangible, intangible and other long-term assets to depreciation and amortisation. The results in Columns (5) and (6) confirm the greater impact of FinTech on labour share compared to physical capital. The coefficient on FinTech is insignificant for capital expenditure and negatively significant for capital intensity.

TABLE 7 | Heterogeneity analyses.

Panel A: Credit resources	Industry competition				Bank concentration			
	Laborshare		*LnLaborshare*		*Laborshare*		*LnLaborshare*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High	Low	High	Low	Low	High	Low	High
LnFinTech	0.348	0.875***	2.673	5.778***	0.537**	0.451*	3.510**	2.102
	(1.48)	(4.00)	(1.36)	(3.34)	(2.27)	(1.71)	(2.04)	(0.98)
Age	0.401	−0.292*	3.782	−2.113	−0.063	0.140	−0.270	1.996
	(1.25)	(−1.70)	(1.59)	(−1.59)	(−0.21)	(0.37)	(−0.12)	(0.77)
Size	−0.534*	0.639*	−4.025*	4.636	0.259	−0.176	1.402	−0.704
	(−1.91)	(1.90)	(−1.76)	(1.55)	(0.90)	(−0.48)	(0.57)	(−0.24)
Lev	0.142	−1.498	2.508	−8.868	−1.259	−0.823	−4.465	−6.617
	(0.14)	(−1.49)	(0.30)	(−1.08)	(−1.23)	(−0.77)	(−0.55)	(−0.73)
Bsize	0.391	1.841**	6.474	16.479***	2.207***	0.079	18.647***	3.898
	(0.51)	(2.56)	(1.01)	(2.81)	(3.25)	(0.10)	(3.16)	(0.60)
Tobin_q	−0.054	0.362***	−0.706	1.834*	0.231**	0.081	1.203	−0.220
	(−0.48)	(3.04)	(−0.75)	(1.86)	(2.27)	(0.61)	(1.45)	(−0.20)
Roa	−12.137***	−16.824***	−99.893***	−124.401***	−15.066***	−13.304***	−115.138***	−108.414***
	(−6.26)	(−8.82)	(−6.15)	(−7.96)	(−8.30)	(−5.91)	(−7.62)	(−6.03)
Growth	−1.961***	−1.575***	−15.178***	−10.879***	−1.540***	−2.208***	−10.898***	−17.444***
	(−7.54)	(−5.54)	(−6.74)	(−4.18)	(−5.69)	(−7.28)	(−4.44)	(−6.88)
Constant	20.000***	0.362	−168.382***	−298.183***	5.943	17.009*	−249.630***	−201.679***
	(2.61)	(0.04)	(−2.78)	(−4.19)	(0.78)	(1.75)	(−4.03)	(−2.73)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	11,925	11,376	11,925	11,376	12,473	10,464	12,473	10,464
R-squared	0.675	0.739	0.672	0.747	0.668	0.700	0.683	0.707

Panel B: The ownership of firms	Firm size				Ownership			
	Laborshare		*LnLaborshare*		*Laborshare*		*LnLaborshare*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Small	Large	Small	Large	Public	Private	Public	Private
LnFinTech	0.740***	0.448*	5.145***	2.932	0.271	0.963***	1.534	7.483***
	(3.37)	(1.90)	(2.97)	(1.60)	(1.27)	(3.87)	(0.91)	(3.69)
Age	−0.239	−0.049	−1.691	0.942	0.384*	−0.836**	3.541**	−5.778**
	(−1.17)	(−0.19)	(−1.26)	(0.48)	(1.69)	(−2.07)	(2.00)	(−2.13)
Size	−0.794**	0.649**	−4.972*	6.127**	0.039	−0.198	0.196	−1.984
	(−2.24)	(2.18)	(−1.80)	(2.40)	(0.12)	(−0.63)	(0.07)	(−0.76)

(Continues)

Panel B: The ownership of firms

	Firm size				Ownership			
	Laborshare		*LnLaborshare*		*Laborshare*		*LnLaborshare*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Small	Large	Small	Large	Public	Private	Public	Private
Lev	−0.974	−0.430	−7.349	3.479	−0.640	−0.654	0.074	−3.734
	(−1.09)	(−0.40)	(−1.05)	(0.36)	(−0.66)	(−0.59)	(0.01)	(−0.43)
Bsize	1.170	1.054	11.867*	9.927*	1.766**	0.216	16.513***	3.543
	(1.59)	(1.51)	(1.90)	(1.76)	(2.57)	(0.27)	(2.93)	(0.53)
Tobin_q	−0.062	0.250**	−0.906	1.947**	0.323***	0.048	1.699*	−0.448
	(−0.69)	(2.02)	(−1.22)	(2.02)	(2.72)	(0.43)	(1.73)	(−0.50)
Roa	−11.902***	−18.969***	−85.200***	−169.872***	−12.138***	−16.785***	−96.784***	−129.764***
	(−7.36)	(−7.93)	(−6.61)	(−8.73)	(−6.20)	(−8.72)	(−5.78)	(−8.71)
Growth	−1.524***	−2.301***	−9.337***	−20.699***	−1.918***	−1.817***	−15.336***	−13.420***
	(−6.01)	(−8.16)	(−4.32)	(−8.99)	(−7.16)	(−6.48)	(−6.23)	(−6.02)
Constant	34.326***	−2.444	−67.137	−375.170***	4.364	31.869***	−282.177***	−60.211
	(4.21)	(−0.32)	(−1.07)	(−6.10)	(0.53)	(3.33)	(−4.24)	(−0.83)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	11,657	11,719	11,657	11,719	13,225	10,246	13,225	10,246
R-squared	0.647	0.771	0.633	0.791	0.713	0.674	0.738	0.660

Panel C: Educational resources

	Region						Talent intensity			
	Laborshare			*LnLaborshare*			*Laborshare*		*LnLaborshare*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Western	Eastern	Central	Western	Eastern	Central	Low	High	Low	High
LnFinTech	0.377	0.507**	0.862**	0.293	3.522*	5.521*	0.285	0.748***	1.409	5.043**
	(1.00)	(2.18)	(2.17)	(0.10)	(1.96)	(1.76)	(1.22)	(2.61)	(0.72)	(2.24)
Age	−0.924	0.166	−0.292	−5.701	1.680	−2.106	−0.140	0.131	−0.243	1.379
	(−0.98)	(0.74)	(−0.79)	(−0.79)	(1.08)	(−0.70)	(−0.32)	(0.63)	(−0.08)	(0.80)
Size	−0.640	−0.019	0.895*	−5.731	0.054	6.746*	−0.282	0.160	−1.818	0.502
	(−1.51)	(−0.07)	(1.96)	(−1.50)	(0.02)	(1.73)	(−0.88)	(0.53)	(−0.66)	(0.20)
Lev	−1.244	−0.715	−0.583	−8.949	0.507	−9.015	0.136	−2.605**	2.965	−15.014*
	(−0.88)	(−0.76)	(−0.36)	(−0.78)	(0.07)	(−0.65)	(0.14)	(−2.33)	(0.38)	(−1.65)
Bsize	2.348**	0.323	2.519**	18.856**	4.955	26.416**	1.082	0.884	12.940**	8.024
	(2.24)	(0.47)	(2.15)	(2.22)	(0.92)	(2.27)	(1.46)	(1.31)	(2.09)	(1.39)
Tobin_q	0.138	0.110	0.351*	0.082	0.186	2.680	0.088	0.159	0.112	0.385
	(0.77)	(1.11)	(1.91)	(0.06)	(0.23)	(1.50)	(0.79)	(1.45)	(0.12)	(0.42)

(Continues)

TABLE 7 | (Continued)

Panel C: Educational resources

	Region						Talent intensity			
	Laborshare			***LnLaborshare***			***Laborshare***		***LnLaborshare***	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
	Western	**Eastern**	**Central**	**Western**	**Eastern**	**Central**	**Low**	**High**	**Low**	**High**
Roa	−13.29***	−16.35***	−12.34***	−109.12***	−121.09***	−110.43***	−13.01***	−17.22***	−106.46***	−124.417**
	(−4.91)	(−8.86)	(−3.62)	(−5.04)	(−8.28)	(−3.55)	(−6.89)	(−8.38)	(−7.17)	(−6.93)
Growth	−1.089***	−2.359***	−1.253**	−7.506**	−17.856***	−9.609*	−1.877***	−1.786***	−14.174***	−12.521***
	(−2.75)	(−9.45)	(−2.51)	(−2.16)	(−8.84)	(−1.81)	(−7.14)	(−5.87)	(−6.29)	(−4.62)
Constant	38.474**	12.971*	−7.374	−6.406	−219.36***	−368.15***	21.724**	7.728	−164.133**	−234.07***
	(2.28)	(1.80)	(−0.66)	(−0.05)	(−3.85)	(−3.96)	(2.26)	(1.03)	(−2.17)	(−3.80)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5790	14,015	3736	5790	14,015	37,36	13,126	10,399	13,126	10,399
R-squared	0.606	0.710	0.679	0.625	0.719	0.685	0.662	0.720	0.669	0.727

Note: This table reports the heterogeneity analyses. Panel A reports the results focusing on the availability of local credit resources. From Columns (1) to (4), we divide firms into high and low groups based on the Herfindahl–Hirschman Index of firms' industry competition level. From Columns (5) and (8), we divide firms into high and low groups based on bank intensity, that is, the ratio of total bank branches to total population. Panel B reports the results focusing on firm size and ownership. From Columns (1) to (4), we divide firms to small and large groups based on the firm size. From Columns (5) and (8), we divide firms into public and private groups based on the firm ownership. Panel C reports the results focusing on firms' access to educational resources. From Columns (1) to (6), we divide firms into west, east and central regions based on firms' locations. From Columns (7) and (10), we divide firms into low and high groups based on talent intensity. All variables are defined in Appendix A. All continuous variables are winsorised at the 1% and 99% levels. The numbers reported in parentheses are t-statistics based on standard errors clustered at the firm level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

The third mechanism we examine is the education attainment of employees. FinTech innovation introduces new demands on human capital, requiring a combination of individuals with digital expertise (Leeflang et al. 2014; Wu and Yang 2022). We expect that employees with knowledge and skills related to new technologies in the FinTech era are more likely to have higher education levels. Accordingly, these individuals may help firms identify and navigate opportunities and challenges in the FinTech era, which may ultimately enhance firms' competitiveness. Specifically, we use the proportion of employees with a bachelor's degree or higher (*Degree*) as a proxy for the education attainment of employees. The natural logarithm of the increase in the number of employees with a bachelor's degree and above (*Indegree*) is used as an additional variable to proxy the increase in employees' education level. The coefficients on both proxies are positive and statistically significant at the 1% level in Columns (5) and (6) of Table 6, suggesting that FinTech development encourages the hiring of highly educated and knowledgeable individuals, which develops the human capital structure of firms.

6 | Heterogeneity Analyses

6.1 | Credit Resources

The labour share of income can be influenced by both micro and macro factors. For example, Karabarbounis and Neiman 2014) show that advances in information technology lead to a decline in the labour share of income. Reallocation may also drive the declining labour share of 'superstar firms' (Autor et al. 2020). Given that prior research suggests that various factors are responsible for the variations in the labour share across countries and sectors, we acknowledge that there may be variations across firms in our sample. Therefore, in this section, we explore heterogeneity to provide further evidence on whether and to what extent micro and macro factors alter the relationship between local FinTech development and firm labour share.

First, we first examine firms' industry competition and their access to credit resources. Firms operating in competitive industries may seek to reduce information asymmetry and obtain lower-cost external finance to enhance their competitiveness (Bolton and Scharfstein 1990). In contrast, firms in less competitive industries may fail to secure external finance due to distortions in resource allocation (Brandt et al. 2020), making them more likely to be affected by local FinTech development. In addition, firms located in areas with inefficient credit markets may have difficulty accessing banks for external financing (Liu et al. 2022). Thus, these disadvantaged firms are more likely to be in financing distress and affected by local FinTech development.

We use two measures to capture the availability of local credit resources, namely the Herfindahl–Hirschman index of firms' industry competition level and banking intensity (the ratio of total bank branches to total population) (Liu et al. 2022). The grouping criterion is the median value if the firm's industry competition and local bank intensity. Table 7 Panel A presents the regression results. Overall, FinTech development has a more significant impact on the labour income share of financially disadvantaged firms that experience resource mismatch. This further validates the notion that FinTech can help alleviate firms' financing constraints and reduce the information asymmetry between banks and firms, which motivates firms to invest more in the labour factor.

6.2 | Firm Size and Ownership

State-owned enterprises (SOEs) have a unique advantage in China's credit markets because bonds issued by SOEs have higher credit ratings (Dong et al. 2021). However, small and medium-sized enterprises (SMEs), particularly those that are privately owned, face difficulties in obtaining financing. FinTech can improve traditional financial services by integrating innovative technologies, which reduces information asymmetry between banks and firms. In addition, we expect that FinTech development may facilitate financial institutions' evaluation of the risks borne by SMEs through advanced technologies. As a result, SMEs obtain a higher degree of support SMEs receive in terms of external funds and have a higher labour share of income.

We divide our sample based on firm size and ownership. The results are reported in Table 7 Panel B. The coefficients on *LnFinTech* in Columns (1) and (3) are 0.740 and 5.745, respectively. Moreover, the coefficients on *LnFinTech* in Columns (6) and (8) are 0.963 and 7.483, respectively. These findings are consistent with the notion that local FinTech development exerts a more significant influence on the labour income share within SMEs compared to larger and public firms.

6.3 | Educational Resources

Knowledge spillovers vary across different regions in China. Specifically, major cities and provinces in central and eastern China, such as Beijing, Shanghai, Guangdong, Zhejiang and Jiangsu, are home to a higher concentration of prestigious universities and colleges. These regions have been at the forefront of educational development and investment, with numerous academic institutions attracting students from across the country and internationally. Indeed, prior evidence suggests that the central and eastern regions of China are expected to possess a larger pool of high-quality talents (Zhang et al. 2012), which may serve as a backup for firms to optimise the human capital structure of local firms. Accordingly, we expect that FinTech development has a greater impact on the labour income share of firms in the regions with access to more abundant educational resources.

We divide our sample into three subsamples: Eastern, Central and Western regions. We also divide the full sample into two subsamples based on the median number of undergraduate colleges and universities at the province level. Table 7 Panel C shows that the positive effect of FinTech development on firms' labour income share is more pronounced in the central and eastern regions, which are rich in talent. This is consistent with the fact that China's central and eastern regions have a higher number of colleges and universities, thereby attracting more high-quality talents.

7 | Conclusions

Using a sample of Chinese listed firms between 2003 and 2021, we find that local FinTech development increases the labour income share. Our identification strategies include the Bartik (1991) IV approach and the DiD estimation. Our tests of possible mechanisms suggest that local FinTech development increases the labour income share by alleviating firms' financing constraints, reducing the relative price of labour and capital and refining the human capital structure. Furthermore, the positive effect of FinTech development is more pronounced for firms in regions or industries with inefficient resource allocation, for smaller private firms and for firms with greater access to educational resources.

This paper has significant policy implications. For example, our findings suggest that firms can leverage the innovative technologies and data-driven approaches made possible by FinTech development, thereby improving the lending process and expanding the pool of capital they can access. As such, policymakers should encourage the adoption and integration of FinTech solutions across various industries, which can be achieved through creating a supportive regulatory environment and providing incentives to firms that invest in FinTech.

Our results also suggest that FinTech may allow firms to optimise the allocation of factors. Specifically, the technological advances associated with financial innovation better allocate resources such as capital, talent and expertise. Therefore, policymakers should focus on further enhancing the human capital structure of firms by investing in education and training programmes that develop digital skills and technological literacy that adapts to the emerging trend of capital markets. Moreover, underserved segments, such as SMEs in disadvantaged areas, have relatively limited access to traditional financing, let alone innovative financing options. Policymakers should explore ways to leverage FinTech to address these challenges, such as promoting peer-to-peer lending platforms, crowdfunding and other alternative financing options that can increase the availability of credit to SMEs.

Acknowledgements

We appreciate the constructive suggestions from Martin Bugeja, Chris Patel and Grant Richardson. We also thank the seminar participants at Guangdong University of Foreign Studies, Macquarie University and the University of Technology Sydney. Yuqiang Cao acknowledges the financial support from the National Natural Science Foundation of China (grant number: 72072045), Guangdong Basic and Applied Basic Research Foundation (grant numbers: 2023A1515012701 and 2023A1515030075), and Guangdong Planning Office of Philosophy and Social Science (grant numbers: GD24CYJ20 and GD23SJZ04). Yaowen Shan acknowledge the financial support from Australian Research Council. Open access publishing facilitated by Macquarie University, as part of the Wiley - Macquarie University agreement via the Council of Australian University Librarians.

Data Availability Statement

Data available on request from the authors.

Endnotes

[1]The labour share of income and the labour share are used interchangeably throughout this paper.

[2]*Laborshare* = *cash paid to and for employees*/(*operating income*—*operating costs* + *depreciation of fixed assets* + *cash paid to and for employees*) × 100.

[3]*Lnlaborshare* = 100 × log(*Laborshare*/(100—*Laborshare*)).

[4]Tianyancha is a leading Chinese platform providing comprehensive company data and business information. It provides access to detailed company records, including company profiles, financials, legal filings, and industry analysis.

[5]Changes in the combination of city and year levels can confound the results. Including the interaction of city and year fixed effects helps control for the effects of these confounding effects, allowing the model to more accurately estimate the impact of each variable. However, incorporating these interaction terms introduces additional controls and covariances, which leads to a slight reduction in the sample size.

[6]We aim to examine whether regions with relatively low levels of FinTech development prior to the policy implementation experience significant improvements afterward. As fintech development exhibits inertia over time, using the level of FinTech development as the dependent variable would lead to model specification bias. To mitigate this issue, we use the change in the level of fintech development, that is, the logarithmic growth rate of the number of local fintech companies, as the dependent variable. The change in fintech development (*DFinTech*) is divided by 10 for presentation purposes.

References

Acemoglu, D., and D. Autor. 2011. "Skills, Tasks and Technologies: Implications for Employment and Earnings." In *Handbook of Labor Economics*, vol. 4, 1043–1171. Elsevier.

Allen, F., J. Qian, and M. Qian. 2005. "Law, Finance, and Economic Growth in China." *Journal of Financial Economics* 77, no. 1: 57–116.

Arango, C., K. P. Huynh, and L. Sabetti. 2015. "Consumer Payment Choice: Merchant Card Acceptance Versus Pricing Incentives." *Journal of Banking & Finance* 55: 130–141.

Atkinson, A. B. 2009. "Factor Shares: The Principal Problem of Political Economy?" *Oxford Review of Economic Policy* 25, no. 1: 3–16.

Autor, D., D. Dorn, L. F. Katz, C. Patterson, and J. Van Reenen. 2020. "The Fall of the Labor Share and the Rise of Superstar Firms." *Quarterly Journal of Economics* 135, no. 2: 645–709.

Autor, D. H., L. F. Katz, and M. S. Kearney. 2006. "The Polarization of the US Labor Market." *American Economic Review* 96, no. 2: 189–194.

Bartik, T. J. 1991. *Who Benefits From State and Local Economic Development Policies?* WE Upjohn Institute for Employment Research.

Ben Naceur, S., B. Candelon, S. A. Elekdag, and D. Emrullahu. 2023. *Is FinTech Eating the Bank's Lunch?* IMF Working Paper No. 2023/239. Is FinTech Eating the Bank's Lunch?. imf.org.

Benmelech, E., N. Bergman, and A. Seru. 2021. "Financing Labor." *Review of Finance* 25, no. 5: 1365–1393.

Berg, T., V. Burg, A. Gombović, and M. Puri. 2020. "On the Rise of Fintechs: Credit Scoring Using Digital Footprints." *Review of Financial Studies* 33, no. 7: 2845–2897.

Bernhardt, K. L., N. Donthu, and P. A. Kennett. 2000. "A Longitudinal Analysis of Satisfaction and Profitability." *Journal of Business Research* 47, no. 2: 161–171.

Bolton, P., and D. S. Scharfstein. 1990. "A Theory of Predation Based on Agency Problems in Financial Contracting." *American Economic Review* 80: 93–106.

Bounie, D., and Y. Camara. 2020. "Card-Sales Response to Merchant Contactless Payment Acceptance." *Journal of Banking & Finance* 119: 105938.

Brandt, L., G. Kambourov, and K. Storesletten. 2020. "Barriers to Entry and Regional Economic Growth in China."

Cachon, G. P., and M. Fisher. 2000. "Supply Chain Inventory Management and the Value of Shared Information." *Management Science* 46, no. 8: 1032–1048.

Chen, M. A., Q. Wu, and B. Yang. 2019. "How Valuable Is FinTech Innovation?" *Review of Financial Studies* 32, no. 5: 2062–2106.

Cheng, B., I. Ioannou, and G. Serafeim. 2014. "Corporate Social Responsibility and Access to Finance." *Strategic Management Journal* 35, no. 1: 1–23.

Claybourn, M. 2011. "Relationships Between Moral Disengagement, Work Characteristics and Workplace Harassment." *Journal of Business Ethics* 100, no. 2: 283–301.

Cobb, C. W., and P. H. Douglas. 1928. "A Theory of Production" *The American economic review* 18, no 1 :139-165.

Cui, G., Y. Zhang, J. Ma, and W. Yao. 2023. "Does Environmental Regulation Affect the Labor Income Share of Manufacturing Enterprises? Evidence From China." *Economic Modelling* 123: 106251.

Daud, S. N. M., A. Khalid, and W. N. W. Azman-Saini. 2022. "FinTech and Financial Stability: Threat or Opportunity?" *Finance Research Letters* 47: 102667.

Ding, N., L. Gu, and Y. Peng. 2022. "Fintech, Financial Constraints and Innovation: Evidence From China." *Journal of Corporate Finance* 73: 102194.

Dong, Y., Q. Hou, and C. Ni. 2021. "Implicit Government Guarantees and Credit Ratings." *Journal of Corporate Finance* 69: 102046.

Douglas, P. H. 1976. "The Cobb-Douglas Production Function Once Again: Its History, Its Testing, and Some New Empirical Values." *Journal of Political Economy* 84, no. 5: 903–915.

Elekdag, S. A., E. Drilona, and S. B. Naceur. 2024. *Does FinTech Increase Bank Risk Taking?* IMF Working Paper No. 2024/017. Does FinTech Increase Bank Risk Taking?. imf.org.

Fazzari, S., R. G. Hubbard, and B. Petersen. 1988. "Investment, Financing Decisions, and Tax Policy." *American Economic Review* 78, no. 2: 200–205.

Fu, Y., and Z. Yi. 2023. "Multi-Province Comparisons of Digital Financial Inclusion Performance in China: A Group Ranking Method With Preference Analysis." *China Economic Review* 80: 102014.

Furceri, D., and P. Loungani. 2018. "The Distributional Effects of Capital Account Liberalization." *Journal of Development Economics* 130: 127–144.

Gan, J. 2007. "Collateral, Debt Capacity, and Corporate Investment: Evidence From a Natural Experiment." *Journal of Financial Economics* 85, no. 3: 709–734.

Goldsmith-Pinkham, P., I. Sorkin, and H. Swift. 2020. "Bartik Instruments: What, When, Why, and How." *American Economic Review* 110, no. 8: 2586–2624.

Gomber, P., R. J. Kauffman, C. Parker, and B. W. Weber. 2018. "On the Fintech Revolution: Interpreting the Forces of Innovation, Disruption, and Transformation in Financial Services." *Journal of Management Information Systems* 35, no. 1: 220–265.

Grossman, G. M., and E. Oberfield. 2022. "The Elusive Explanation for the Declining Labor Share." *Annual Review of Economics* 14: 93–124.

Grossman, G. M., and E. Rossi-Hansberg. 2012. "Task Trade Between Similar Countries." *Econometrica* 80, no. 2: 593–629.

Hadlock, C. J., and J. R. Pierce. 2010. “New Evidence on Measuring Financial Constraints: Moving Beyond the KZ Index.” *Review of Financial Studies* 23, no. 5: 1909–1940.

Harrast, S. A., and D. A. Wood. 2022. *The Status of Robotic Process Automation*, 103. Routledge Handbook of Accounting Information Systems.

Hsu, P. H., X. Tian, and Y. Xu. 2014. “Financial Development and Innovation: Cross-Country Evidence.” *Journal of Financial Economics* 112, no. 1: 116–135.

Hua, X., and Y. Huang. 2021. “Understanding China's Fintech Sector: Development, Impacts and Risks.” *European Journal of Finance* 27, no. 4–5: 321–333.

Huang, S. 2022. “Does FinTech Improve the Investment Efficiency of Enterprises? Evidence From China's Small and Medium-Sized Enterprises.” *Economic Analysis and Policy* 74: 571–586.

Jiang, J., L. Liao, Z. Wang, and X. Zhang. 2021. “Government Affiliation and Peer-To-Peer Lending Platforms in China.” *Journal of Empirical Finance* 62: 87–106.

Kanga, D., C. Oughton, L. Harris, and V. Murinde. 2022. “The Diffusion of Fintech, Financial Inclusion and Income Per Capita.” *European Journal of Finance* 28, no. 1: 108–136.

Karabarbounis, L., and B. Neiman. 2014. “The Global Decline of the Labor Share.” *Quarterly Journal of Economics* 129, no. 1: 61–103.

Kehrig, M., and N. Vincent. 2021. “The Micro-Level Anatomy of the Labor Share Decline.” *Quarterly Journal of Economics* 136, no. 2: 1031–1087.

Kendall, J. 2017. *Fintech Companies Could Give Billions of People More Banking Options*. Harvard Business Review.

Lagna, A., and M. N. Ravishankar. 2022. “Making the World a Better Place With Fintech Research.” *Information Systems Journal* 32, no. 1: 61–102.

Lai, S., L. Chen, Q. S. Wang, and H. D. Anderson. 2023a. “Bank Competition and Corporate Employment: Evidence From the Geographic Distribution of Bank Branches in China.” *Journal of Banking and Finance* 154: 1–24.

Lai, S., L. Yang, Q. Wang, and H. D. Anderson. 2023b. “Judicial Independence and Corporate Innovation: Evidence From the Establishment of Circuit Courts.” *Journal of Corporate Finance* 80: 102424.

Larrain, M. 2015. “Capital Account Opening and Wage Inequality.” *Review of Financial Studies* 28, no. 6: 1555–1587.

Leeflang, P. S., P. C. Verhoef, P. Dahlström, and T. Freundt. 2014. “Challenges and Solutions for Marketing in a Digital Era.” *European Management Journal* 32, no. 1: 1–12.

Li, C., P. Huo, Z. Wang, W. Zhang, F. Liang, and A. Mardani. 2023. “Digitalization Generates Equality? Enterprises' Digital Transformation, Financing Constraints, and Labor Share in China.” *Journal of Business Research* 163: 113924.

Li, D. D., L. Linlin, and W. Hongling. 2009. “Changes in the Labor Share of GDP: A U-Shaped Curve.” *Social Sciences in China* 30, no. 4: 131–153.

Li, J., J. Li, X. Zhu, Y. Yao, and B. Casu. 2020. “Risk Spillovers Between FinTech and Traditional Financial Institutions: Evidence From the US.” *International Review of Financial Analysis* 71: 101544.

Liu, N., X. Gu, and C. K. Lei. 2022. “The Equilibrium Effects of Digital Technology on Banking, Production, and Employment.” *Finance Research Letters* 49: 103196.

Liu, Z., M. M. Spiegel, and J. Zhang. 2021. “Optimal Capital Account Liberalization in China.” *Journal of Monetary Economics* 117: 1041–1061.

Neumeyer, P. A., and F. Perri. 2005. “Business Cycles in Emerging Economies: The Role of Interest Rates.” *Journal of Monetary Economics* 52, no. 2: 345–380.

Niu, G., X. Jin, Q. Wang, and Y. Zhou. 2022. “Broadband Infrastructure and Digital Financial Inclusion in Rural China.” *China Economic Review* 76: 101853.

Petrosky-Nadeau, N., and E. Wasmer. 2013. “The Cyclical Volatility of Labor Markets Under Frictional Financial Markets.” *American Economic Journal: Macroeconomics* 5, no. 1: 193–221.

Phan, D. H. B., P. K. Narayan, R. E. Rahman, and A. R. Hutabarat. 2020. “Do Financial Technology Firms Influence Bank Performance?” *Pacific-Basin Finance Journal* 62: 101210.

Prewett, K. W., G. L. Prescott, and K. Phillips. 2020. “Blockchain Adoption Is Inevitable—Barriers and Risks Remain.” *Journal of Corporate Accounting and Finance* 31, no. 2: 21–28.

Rothberg, H. N., and G. S. Erickson. 2017. “Big Data Systems: Knowledge Transfer or Intelligence Insights?” *Journal of Knowledge Management* 21, no. 1: 92–112.

Schneider, D. 2011. *The Labor Share: A Review of Theory and Evidence*. SFB 649 Discussion Papers, (2011-069).

Solow, R. M. 1957. “Technical Change and the Aggregate Production Function.” *Review of Economics and Statistics* 39, no. 3: 312–320.

Song, Z., K. Storesletten, and F. Zilibotti. 2011. “Growing Like China.” *American Economic Review* 101, no. 1: 196–233.

Stulz, R. M. 2022. “FinTech, BigTech, and the Future of Banks.” *Journal of Applied Corporate Finance* 34, no. 1: 106–117.

Tan, W., W. Shen, L. Xu, B. Zhou, and L. Li. 2008. “A Business Process Intelligence System for Enterprise Process Performance Management.” *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)* 38, no. 6: 745–756.

Vig, V. 2013. “Access to Collateral and Corporate Debt Structure: Evidence From a Natural Experiment.” *Journal of Finance* 68, no. 3: 881–928.

Wang, H., Y. Cao, Q. Yang, and Z. Yang. 2017. “Does the Financialization of Non-Financial Enterprises Promote or Inhibit Corporate Innovation.” *Nankai Business Review* 20, no. 1: 155–166.

Wu, B., and W. Yang. 2022. “Empirical Test of the Impact of the Digital Economy on China's Employment Structure.” *Finance Research Letters* 49: 103047.

Wu, F., Y. Hu, and M. Shen. 2024. “The Color of FinTech: FinTech and Corporate Green Transformation in China.” *International Review of Financial Analysis* 94: 103254.

Yang, J., Y. Jiang, H. Chen, and S. Gan. 2022. “Digital Finance and Chinese Corporate Labor Investment Efficiency: The Perspective of Financing Constraints and Human Capital Structure.” *Frontiers in Psychology* 13: 962806.

Yang, T., and X. Zhang. 2022. “FinTech Adoption and Financial Inclusion: Evidence From Household Consumption in China.” *Journal of Banking & Finance* 145: 106668.

Zhang, L., Y. Luo, F. Tao, et al. 2014. “Cloud Manufacturing: A New Manufacturing Paradigm.” *Enterprise Information Systems* 8, no. 2: 167–187.

Zhang, R., K. Sun, M. S. Delgado, and S. C. Kumbhakar. 2012. “Productivity in China's High Technology Industry: Regional Heterogeneity and R&D.” *Technological Forecasting and Social Change* 79, no. 1: 127–141.

Appendix A

Variable definitions.

Variable	Definition
Dependent variables	
Laborshare	The share of industrial value added paid to employees (i.e., cash paid to and for employees divided by the sum of operating income minus operating costs, plus depreciation of fixed assets and cash paid to and for employees, multiplied by 100)
LnLaborshare	The log-transformed form of *Laborshare, measured as* $100 \times \log(Laborshare/(100—Laborshare))$
Independent variable	
LnFinTech	The level of FinTech development, proxied by the number of FinTech firms in the firm's prefecture-level city
Control variables	
Age	The age of the firm
Size	The natural logarithm of total assets
Lev	Total liabilities divided by total assets
Bsize	The natural logarithm of the number of members on the board
Tobin_q	Market capitalisation divided by total assets
Growth	The growth rate of the firm's operating income
Roa	Net profit divided by total assets
Mechanism variables	
KZ	$-0.091 \times$ Cash flow from operating activities/total assets—$0.062 \times$ an indicator of cash dividend payment $+ 0.021 \times$ long-term liabilities/total assets—$0.044 \times$ ln(total assets) $+ 0.102 \times$ industry sales growth rate $-0.035 \times$ company sales growth rate
FC	The absolute value of SA index, where SA index is equal to $-0.737 \times$ firm size $+ 0.043 \times$ firm size$^2 -$ $0.04 \times$ firm age
Laborintensive	Employee compensation divided by operating income
Salary	Changes in average employee wages and other welfare expenditures
Degree	The proportion of employees with a bachelor's degree and above
Degreeincrease	Natural logarithm of the increase in the number of employees with bachelor's degree and above