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Is digital finance always beneficial to accounting information transparency? Evidence from China

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ABSTRACT

Using a sample of Chinese listed firms over 2011–2020, this study examines the impact of digital finance on accounting information transparency. Our findings reveal an inverted U-shaped relationship between digital finance and accounting information transparency, suggesting that digital finance within certain limits increases accounting information transparency by optimising information acquisition and processing, but excessive digital finance leads to information overload and impairs accounting information transparency. Our findings are robust to a variety of sensitivity tests and are still valid after using two-stage “shift-share” instrumental variable procedures, propensity score matching method and firm-level fixed effect regression to control for the endogeneity issue. Lastly, MD&A and annual reporting disclosure timeliness are two influential channels by which digital finance affects accounting information transparency, and further the inverted U-shaped relationship is more pronounced for firms in provinces with lower marketisation indexes (CEO-chairman duality) than for their counterparts.

KEYWORDS

Digital finance; accounting information transparency; the inverted U-shaped relationship; information overload

1. Introduction

In recent years, the way of information dissemination has experienced unprecedented changes. Digital technology has been integrated into people’s daily lives and has penetrated into every corner of industrial transformation. Digital finance refers to a new financial model that integrates financial activities with emerging technologies (artificial intelligence, block-chain technology, cloud computing, big data and the Internet technology; Goldstein et al., 2019; Gomber et al., 2017; Y. Huang & Huang, 2018). Digital finance in a broad sense includes both the Internet finance and Fintech (Ji et al., 2022), which improves the experiences of customers in terms of speeds, conveniences and multi-channel accessibilities (Lee & Shin, 2018). To date, digital finance has become a traditional financial markets’ changer, rather than just an eye-catching hype (Lee &

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Shin, 2018). Thus, digital finance has attracted increasing attention from scholars, regulators and the public.

Transparency, which is viewed as an important consequence of digital finance, can play a key role in well-functioning financial markets and the efficiency of investment decisions (Wurgler, 2000). Prior literature finds that ownership structure (Eng & Mak, 2003; Xiao et al., 2004), internal governance mechanisms (Fama & Jensen, 1983; Forker, 1992; Leftwich et al., 1981) and external governance mechanisms (Bushman et al., 2004; Costello et al., 2019) affect accounting information transparency. Nevertheless, to our knowledge and literature in hand, previous studies have provided little evidence about whether digital finance affects accounting information transparency. In response, we aim to focus on the Chinese context to examine whether digital finance affects accounting information transparency.

Drawing on the theory of information asymmetry (Akerlof, 1978; Durnev et al., 2009; M. H. Miller & Rock, 1985), incremental information is beneficial for alleviating information asymmetry and improving information transparency between enterprises and investors (Dhaliwal et al., 2011). On the one hand, digital finance enriches the quantity and diversity of available information due to its more convenient and cheaper access channels (Hiltz & Turoff, 1985). In reality, information in digital forms facilitates the process of information processing and reduces the costs of information analysis (Gomber et al., 2017). On the other hand, excessive digitalisation may lead to information overload, which makes information recipients fail to extract value-added knowledge from massive available information (Edmunds & Morris, 2000; Eppler & Mengis, 2004). Thus, we predict an inverted U-shaped relationship between digital finance and accounting information transparency.

Our empirical analyses are conducted on the basis of the Chinese context for several reasons. First, in recent years, the Chinese capital market has attracted close attention from the public and scholars. Second, China is one of few countries at the forefront of developing digital finance. According to the CB Insights, in 2016, 12.7 billion dollars have been invested into the Fintech industry in the world, among which 4.6 billion dollars are invested in Chinese Fintech companies (Ji et al., 2022). Moreover, according to the statistics of the Chinese Ministry of Industry and Information Technology, China's 5G network coverage has reached 96% by 2022. Specifically, more and more financial data are stored and utilised in digital form, and mobile payment has replaced cash to a great extent. Thus, China's development of digital finance is advanced in the world, which facilitates researchers to tap more fully into digital finance. Third, the Chinese capital market is less mature and information transparency has been criticised for a long time, so the Chinese context can provide researchers with a unique setting in which scholars can observe the significant variations in information transparency from technical progresses like digital finance. Lastly but not least, China is one of few contexts where the data on digital finance are available and vary across different provinces (regional heterogeneity).

Using a sample of 15,931 firm-year observations from the Chinese stock market over 2011–2020, we examine the impact of digital finance on accounting information transparency. Our findings reveal several aspects as below: First, there is a significantly inverted U-shaped relationship between digital finance and accounting information transparency, suggesting that digital finance increases accounting

information transparency by optimising information acquisition and processing, but excessive digital finance leads to information overload and is harmful for accounting information transparency. Second, our findings are robust to sensitivity tests using alternative proxies for digital finance and accounting information transparency. Third, our conclusions are still valid after using two-stage 'shift-share' instrumental variable (IV) regression procedures, propensity score matching approach and firm-level fixed effect regression method to address the endogeneity issue. Fourth, MD&A (management discussion and analysis) and annual reporting disclosure timeliness are two influential channels by which digital finance affects accounting information transparency. Lastly, the inverted U-shaped relationship between digital finance and accounting information transparency is more pronounced for firms in provinces with lower marketisation indexes (with CEO-chairman duality).

Our study makes several contributions to the existing literature as below. First, our study is one of few studies, if it is not the first, to examine whether digital finance affects accounting information transparency. Prior studies find that transparency is affected by ownership structure (Eng & Mak, 2003; Xiao et al., 2004) and governance mechanisms (Bushman et al., 2004; Costello et al., 2019; Fama & Jensen, 1983; Forker, 1992; Jaggi & Low, 2000; Leftwich et al., 1981). However, previous studies have provided little evidence about whether digital finance (technologies) affects firm-level accounting information transparency. In this regard, our study explores digital finance as a novel insight and adds to the existing literature on the determinants of accounting information transparency.

Second, our study enriches prior literature on economic consequences of digital finance. Previous studies argue that digital finance can affect social, regulatory, technological and managerial aspects (Chiu & Koepl, 2019; Clemons & Row, 1992; Wigand, 1997; Zhu, 2019). Nevertheless, empirical evidence is still relatively rare. Fortunately, the data on the degree of province-level digital finance (Peking University Digital Financial Inclusion Index) are available in China, which provides an appropriate setting for scholars to investigate the impacts of digital finance on accounting information transparency. Thus, our findings about an inverted U-shaped relation between digital finance and accounting information transparency lend important supplements for prior literature.

Lastly, our study dialectically validates the effect of digital finance on accounting information transparency is non-linear (an inverted U-shaped relationship), echoing the arguments that technology is a double-edged sword (Davis et al., 2017; Goldstein et al., 2019). Digital finance can optimise data acquisition/processing and improve accounting information transparency, but when the degree of digital finance and information availability exceeds information users' understanding abilities and data processing capacities, information overload may be harmful for investor to make decisions. As a result, the inverted U-shaped relation between digital finance and accounting information transparency can help strengthen our understanding about the potential consequences of digital finance.

The remainder of the article is organised as follows: [Section 2](#) introduces institutional background and reviews prior literature. [Section 3](#) develops testable hypothesis. [Section 4](#) includes the sample, data, models and variables. [Section 5](#) reports descriptive statistics,

empirical findings and robustness checks. [Section 6](#) reports endogeneity and additional tests. The final section summarises.

2. Institutional background and prior literature

2.1. Institutional background

Digital finance originates from traditional financial institutions' dabbling in digital technologies. Specifically, banks seize the emerging opportunity to launch an integrated e-banking service system including mobile banking, internet banking and telephone banking (Thakor, 2020). Today, the world has witnessed that digital finance has expanded from physical bank branches and the accessibility of credit services to a wider range of business areas (e.g. payments, deposits, loans, insurance, credit services and securities). From 2010 to 2015, more than USD 50 billion has been invested in Fintech globally (Skan et al., 2016). Currently, digital finance as a continuously disruptive innovation has shaken up traditional financial markets (Lee & Shin, 2018). Against this context, digital technology in the financial field explores broader coverage and more diverse usage scenarios.

The current financial service providers are being challenged by new competitions from digital finance (Gomber et al., 2017). According to PwC (2016), 83% of financial institutions feel to be challenged by Fintech startups (Lee & Shin, 2018). Due to the inexorable march of digital finance, financial institutions choose to develop Fintech technologies or partner with Fintech firms strategically (Takeda & Ito, 2021). Banks have recognised opportunities of financial business transformation driven by digital finance and offer added value services by the new financial ecosystem (Anagnostopoulos, 2018). In reality, digital finance mirrors the trend of financial industry digitalisation (Gomber et al., 2017). Innovativeness and potentials of digital finance exert significant effects on the whole financial service industry (Ferreira et al., 2015). Fintech like big data and cloud data storage continues to mature new possibilities of simplification, adaptability and individualisation (Dapp, 2016).

In China, digital finance has developed significantly and mobile payment (e.g. online credits, third-party payments) has become an alternative to electronic payment and cash (Stern et al., 2017),; which are ahead of most developed countries. Over 2011–2020, digital finance in China has grown by leaps and bounds with an average annual growth rate of 29.1% (Guo et al., 2020), which leads to significant time-series variations in digital finance.

2.2. Prior literature on digital finance

Digital finance includes Internet finance and other emerging Fintech (Ji et al., 2022). Digital finance enables firms to gain business information more timely, which improves the quality and quantity of information (Gomber et al., 2017), alleviates opportunistic activities (Demertzis et al., 2018), reduces coordination costs (Clemons & Row, 1992; Wigand, 1997), and promotes transaction (market) effectiveness. Chiu and Koepl (2019) find that block-chain improves transaction speed, reduces transaction costs, and brings out extra gains for debt market. Zhu (2019) validates that big data increases stock price informativeness by lowering information acquisition costs. With the help of AI

technology, financial-services firms personalise customer service and provide customer-centred and more efficient financial services to customers (Lui & Lamb, 2018). Also, Fintech lenders can process mortgage applications faster without excessive default (Fuster et al., 2019).

Moreover, Fintech companies can provide more micro-finance (Bollinger & Yao, 2018). Due to its conveniences and low marginal costs, digital finance expands the coverage of traditional finance and covers the 'long tail' of financial demands (Jagtiani & Lemieux, 2019). Tang (2019) regards P2P lending services as the supplement for bank lending in the context of small loans.

However, digital finance brings out more challenges (uncertainties) for financial markets. Davis et al. (2017) find that financial risks increase in credit losses and money laundering areas after adopting Fintech technologies. Also, regulations on Fintech firms is relatively weaker than those on traditional financial institutions (Goldstein et al., 2019), leading to firms' exploiting regulatory loopholes. Foley et al. (2019) find that 46% of Bitcoin transactions are related to illicit activities. Thus, it is important to explore how to use digital finance technologies under appropriate regulations.

2.3. Prior literature on accounting information transparency

Transparency refers to 'the availability of firm specific information to those outside publicly traded firms', and thus is determined by information dissemination (Bushman et al., 2004). Accounting information transparency can alleviate information asymmetry among investors (Barth & Schipper, 2008) and improve investment efficiency (Durnev et al., 2009). Prior studies have explored the determinants of (accounting information) transparency. Specifically, institutional ownership (Xiao et al., 2004) and government ownership (Eng & Mak, 2003) promote firm-level information disclosure, but a lower managerial ownership is associated with a higher degree of information disclosure (Eng & Mak, 2003). Moreover, independent directors are associated with a higher extent of willingness to disclose information voluntarily (Fama & Jensen, 1983; Forker, 1992; Leftwich et al., 1981).

As for external governance, Bushman et al. (2004) find that macro-level factors at the country level can affect corporate transparency, and specifically, information is more transparent for firms in countries with a higher level of judicial efficiency and a more active and well-developed market. Jaggi and Low (2000) reveal that, compared with firms from code law countries, firms from common law countries have higher levels of corporate transparency. Besides, strict regulations are found to be positively associated with the transparency of banks (Costello et al., 2019).

Another branch of prior studies find that accounting information transparency plays the mitigating role in information asymmetry (Leuz & Verrecchia, 2000). Accounting information transparency is related to higher industry growth rates (Francis et al., 2009), lower financing cost (Bhattacharya et al., 2003; Bushman & Smith, 2001; Leuz & Verrecchia, 2000), more optional investment access (Beatty et al., 2010), higher investment efficiency (Barth et al., 2013; Biddle & Hilary, 2006; Durnev et al., 2009; McNichols & Stubben, 2008), more analyst coverage (Lang & Lundholm, 1996), larger trading volume (B. P. Miller, 2010), higher liquidity

(Diamond & Verrecchia, 1991) and more informative stock prices (Francis et al., 2009).

3. Hypothesis development

3.1. *The impact of digital finance: from macro level to micro level*

Drawing on the theory of technology diffusion (Eaton & Kortum, 1996; Geroski, 2000; Kantor & Whalley, 2019; Keller, 2002), technology has mobility to some extent, and thus new technology can diffuse due to its inherent positive externalities (Loch & Huberman, 1999). That is, follow-up groups can reactively adopt new technology, and then new technology can be utilised more frequently and is adopted by an increasing proportion of firms, organisations and individuals (Geroski, 2000).

Technology diffusion is more likely to firstly occur within an administrative jurisdiction and countries tend to diffuse technology internally rather than across borders (Eaton & Kortum, 1996, 1999). Even in a country, technological knowledge is regional in essence (Keller, 2002). Skiti (2020) finds that institutional entry restrictions lead to a decrease in technological diffusion across state borders. Gong (2020) validates that the diffusion of agricultural technology between provinces is more difficult than inside province because provincial extension system can facilitate technology diffusion within its own area. Thus, we use province (prefecture)-level *Digital Financial Inclusion Index* to measure the average digital financial technology of enterprises within a region.

On the one hand, the degree of digital finance in a region can create an ecological environment in which digital finance within firms in the same region is likely to affect each other. When a discrepancy between the firm's digital finance and region-level digital finance exists, the firm has to accelerate to adopt digital finance technology and adapt to the local ecological environment about digital finance; Or else, this discrepancy may negatively affect the firm. To sum up, referring to the technology diffusion theory, the extent of digital finance in a region can affect the firm's degree of digital finance, and further exert crucial influence on accounting information transparency.

On the other hand, digital finance index at the region level is condensed from daily behaviours and operation activities about billions of individuals and millions of enterprises. In reality, the Peking University Digital Financial Inclusion Index is construed *based on the usage of Alipay, mobile payments, digital credit and other digital finance by natural persons and small/micro businesses* (Guo et al., 2020). Thus, digital finance index, which reflects the extent of digital finance development at the region level, can approximately and roughly capture the average digital finance at the firm level.

To sum up, referring to the theory of technology diffusion, digital financial technology reflects a process from the micro level to the macro level, and then maps to the micro level. Thus, digital financial technology at the macro level can affect micro-level corporate behaviours to some extent.

3.2. *The positive effect of digital finance on accounting information transparency*

Information asymmetry refers to 'a condition wherein one party in a relationship has more or better information than another' (Akerlof, 1978). In reality, information asymmetry

exists between the public and the firm's decision makers (Durnev et al., 2009; M. H. Miller & Rock, 1985). Dhaliwal et al. (2011) find that value-relevant incremental information mitigates firm-investor information asymmetry. However, the lack of a well-developed communication infrastructure impedes information flow, exacerbates information asymmetry, and eventually leads to information opacity (Bushman et al., 2004). As such, digital finance can play a governance role to accelerate information dissemination, and further increase information transparency (Demertzis et al., 2018; Zhu, 2019).

Digital finance can exert positive effects on accounting information transparency by increasing the amount of useful information and promoting information processing. First, digital finance can increase available information, relieve information asymmetry, and enhance information transparency. Wooten et al. (2020) find that the usage of digital platforms in the auction landscape brings more available data and more valuable information for users. Digital technology enriches the quantity and diversity of available information (Bawden & Robinson, 2020; Hiltz & Turoff, 1985), and further digital finance reduces the cost of collecting information by replacing unstructured paper-based records with structured digital data. Thus, information users can obtain accurate information about corporate operations at lower costs (Buchak et al., 2018). Moreover, information in the digital form can be processed and analysed more conveniently and cheaper, and further mutually authenticated information increases information transparency. Thus, digital finance can optimise data acquisition, mining and analysis, which help electronic transactions and improve the efficiency (Ji et al., 2022). In reality, big data and machine learning can 'paint a fuller and more accurate picture about people's financial lives and creditworthiness' (Jagtiani & Lemieux, 2019), and further block chain decreases transaction costs and increases transaction speed for creditors (Chiu & Koepl, 2019).

3.3. Information overload and the inverse impact of digital finance on accounting information transparency

However, digital finance is like a double-edged sword. In the digital technology era, the volume of information increases at an unprecedented speed (Hiltz & Turoff, 1985) and is becoming more diverse (Bawden & Robinson, 2020). Digital information breaks the constraints of time and space, broadens the contact point and communication circle, and increases liquidity and uncertainty (Benselin & Ragsdell, 2016). Thus, users have to handle with thousands of bits of information every moment, which is far beyond their process ability (Renjith, 2017; Yan, 2021), makes users spend more time to digest complex information (Chen et al., 2011; Denning, 2006) and thus exacerbates information overload (Edmunds & Morris, 2000; Eppler & Mengis, 2004).¹ Sevinc and D'Ambra (2010) define information overload as '*the volume of information received by the individual surpasses their ability to process it*'. Information overload means a symptom of failing to extract needed knowledge from an immense quantity of information (Nelson, 1994), or to '*create high quality or value added information from the large amounts of information available*' (Jones et al., 2004; Simpson & Prusak, 1995).

¹Referring to the information overload theory, overabundance of available information is a generally accepted source of information overload (Nelson, 1994; Tushman & Nadler, 1978). Malhotra (1982) find that respondents experience information overload when they are provided with more than 10 brands, which reduces recognising correctness. Information overload also makes users ignore important details (Tungare & Perez-Quinones, 2009), and further leads to negative work environment and kills productivity (Dean & Webb, 2012).

First, increasingly complicated information system creates system feature overload (Pennington & Tuttle, 2007), and thus crowds out the availability when information system offers excessive features than the user's demands (Karr-Wisniewski & Lu, 2010; Thompson et al., 2005). System feature overload is a salient aspect of technology overload, which is positively associated with information overload (Fu et al., 2020). Along with the development of digital technology, to meet the user's needs and new IT governance demands, information system must constantly add or upgrade functionality (Zhang et al., 2016). Thus, information users can't comprehend technological innovations easily, feel challenged to adapt to new functions or interfaces (Pothos et al., 2021), and thus perceive a system feature overload (Zhang et al., 2016). As a result, complex information systems lead to system feature overload, which increases information overload.

Second, for information receivers, higher information loads result in information overload. The effectiveness of the receiver's 'information filters' determines how well they can use information. However, when information overload occurs, neither non-experts nor experts can take advantage of newly added massive amount of information to improve decision making (Paredes, 2003). In reality, information overload reduces decision quality and consistency even when information receivers adopt accelerating information processing (Pennington & Tuttle, 2007).

Lastly, accountants and managers as accounting information providers are also constrained by inadequate technology education. Even though accounting students have recognised the importance of IT-related lessons, they demonstrate less enthusiasm about technology-related courses than traditional accounting curricula (Kearns, 2010). Moreover, curricula about accounting information system are adequately covered by about 25% accounting programs in the U.S., suggesting a discrepancy between teaching and expectations for productive capacity (Apostolou et al., 2014). As a result, accountants are less likely to be conversant with digital technology, which increases the risks of making mistakes when they use digital accounting information, and then leads to more biases in accounting information. What's more, accountants may use information overload to bury stakeholders in an overabundance of irrelevant data to cover up some specific misconducts (Paredes, 2003).

3.4. The inverted U-shaped relationship between digital finance and accounting information transparency

When the degree of digital finance reaches a critical mass value, information emerges endlessly, which triggers information overload. As such, noises disturb information processing capacity because exponential growth in the amount of information does not bring out the linear increase in information quality (Kirsh, 2000). Thus, with the increase in the amount of information, the signal-to-noise ratio decreases, and errors increase. When limited attention is met with the vast amount of information, users may be sidetracked by less relevant information instead of focusing on the most pertinent information (Saxena & Lamest, 2018). As a result, the limits of information processing lead to the downside of information (Hirshleifer & Teoh, 2003; Klapp, 1986), and thus noises affect information users' judgements and exert a negative impact on accounting information transparency. That is, information overload means that *the relation between information input and decision output shows an inverted U-shaped curve, and*

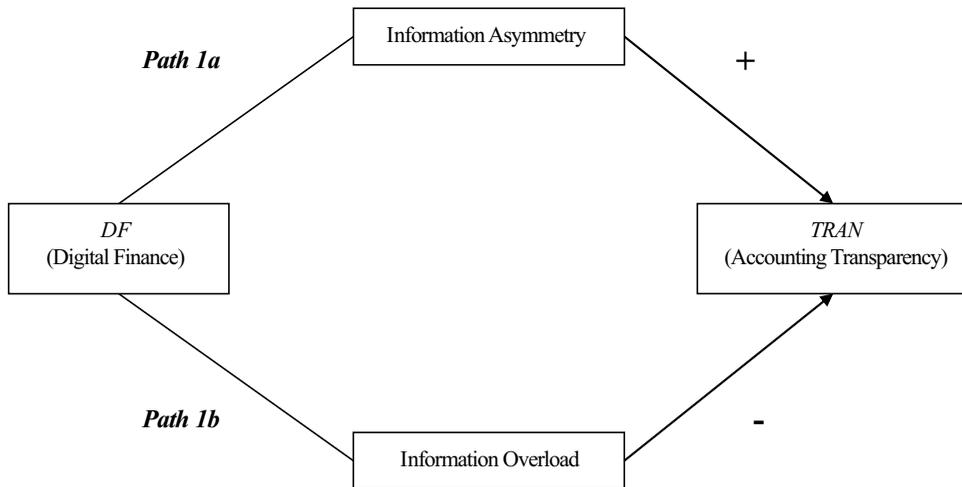


Figure 1. The logic framework about hypothesis 1.

the inflection point is determined by human information processing capacity' (Driver & Streufert, 1969; Roetzel, 2019; Schroder et al., 1967).²

To sum up, in the range from zero to the inflection point, a higher degree of digital finance enriches available information, improves (optimises) information processing, and collectively increases accounting information transparency. However, after the degree of digital finance exceeds the inflection point, information overload makes accounting information be more opaque. Based on above discussions, we formulate Hypothesis 1 (H1) in an alternative form as below:

H1: *Ceteris paribus, there exists an inverted U-shaped relationship between digital finance and accounting information transparency.*

As shown in Figure 1, digital finance increases valuable information, mitigates information asymmetry, reduces gathering (processing) costs, and thus is beneficial for accounting information transparency. However, like a double-edged sword, excessive usage of digital finance may lead to information overload and harm accounting information transparency. Thus, H1 predicts an inverted U-shaped relation between digital finance and accounting information transparency.

4. Research design

4.1. Sample and data source

The initial sample includes all Chinese A-share listed firms over 2011–2020. The sample period begins from 2011 because the data on digital finance (i.e. the Peking University

²With regard to digital finance, it is easier for auditors to save time in processing information and discovering various relations between numbers. However, when information is digitised endlessly, the volume of information proliferates and auditors have to spend more time to identify useful information. External audit is strictly limited by time, resources and budget (Roetzel, 2019), so auditors are unable to use all the information and distinguish critical information from interference information, which harm accounting information transparency (Libby et al., 2002).

Digital Financial Inclusion Index) cannot be obtained until 2011. Then, we select the research sample based on several criteria as below: First, we delete firm-year observations pertaining to banking, insurance and other financial industries. Second, we delete ST and *ST firms (Ma et al., 2010). Lastly, we delete firm-years observations with missing information or data on digital finance, accounting information transparency and firm-specific control variables. As a result, the final research sample includes 15,931 firm-year observations, covering 2,623 unique firms. To mitigate the effect of extreme firm-year observations, all continuous variables are winsorised at the 1% and 99% of their original values.

Data sources are reported as below (see Appendix 1 in detail): First, the data on digital finance is obtained and hand-collected from the Peking University Digital Financial Inclusion Index. Second, the data on accounting information transparency is calculated based on original information in CSMAR (China Stock Market and Accounting Research). Third, the data on control variables is obtained from the CSMAR. Lastly, the data on instrumental variable is calculated based on original information in Urban Statistical Yearbook of China and CNRDS (Chinese Research Data Services).

4.2. Regression model specification for hypothesis 1 (H1)

To test H1 that predicts an inverted U-shaped relationship between digital finance and accounting information transparency, we construct the OLS Model (1) to link accounting information transparency (*TRAN*) to digital finance (*DF*), the square term of digital finance (DF^2) and other determinants:

$$TRAN = a_0 + a_1DF + a_2DF^2 + a_{3-14}Controls + Year \text{ and } Industry \text{ Fixed Effects} + \varepsilon \quad \text{Model (1)}$$

In Model (1), the dependent variable is accounting information transparency (labelled as *TRAN*), a comprehensive index on the basis of earnings aggressiveness (*EA*) and earnings smoothing (*ES*) (Bhattacharya et al., 2003). The main independent variable is digital finance (*DF*) and the square term of digital finance (DF^2). The data on digital finance (*DF*) is obtained from *Peking University Digital Financial Inclusion Index*, which has been employed in China-based studies (Guo et al., 2020).

In Model (1), if the coefficient on *DF* (α_1) is significantly positive and the coefficient on DF^2 (α_2) is significantly negative simultaneously, H1 is supported by empirical evidence.

To identify the incremental effect of digital finance on accounting information transparency, we incorporate a set of control variables into Model (1). First, we incorporate blockholder ownership (*FIRST*), the ratio of independent directors (*INDR*) and board size (*BOARD*) into Model (1) to control for the impacts of corporate governance mechanisms on accounting information transparency.

Second, firm size (*SIZE*), financial leverage (*LEV*), returns on total assets (*ROA*), operating cash flow ratio (*OCF*), the ratio of capital expenditure (*CAP*), book-to-market ratio (*BTM*), a firm's age from its foundation (*FIRMAGE*) and an indicator for state-owned enterprise (*STATE*) are included to address the effects of firm-specific financial characteristics on accounting information transparency.

Third, we include Marketization index (*MKT*) to control for the impact of macro-level factors on accounting information transparency.

Lastly, we include a set of year and industry dummies to control for industry and year fixed effects. All variables are defined in [Appendix 1](#) for details.

4.3. Accounting information transparency

In our study, accounting information transparency is measured based on earnings aggressiveness (EA) and earnings smoothing (ES) (Bhattacharya et al., 2003):

$$TRAN_{i,t} = [\text{Deciles}(EA_{i,t}) + \text{Deciles}(ES_{i,t})]/2 \quad \text{Model (2)}$$

In Model (2), Deciles (.) is the value assigned to the decile in which EA or ES appears.

EA is calculated on the basis of Models (3) and (4):

$$EA_{i,t} = ACC_{i,t}/ASSET_{i,t-1} \quad \text{Model (3)}$$

$$ACC_{i,t} = \Delta CA_{i,t} - \Delta CL_{i,t} - \Delta CASH_{i,t} + \Delta STD_{i,t} - DEP_{i,t} + \Delta TP_{i,t} \quad \text{Model (4)}$$

In Models (3) and (4), for firm i and year t ($t-1$), $ASSET_{i,t-1}$ denotes total assets at the beginning of the year, and $ACC_{i,t}$ denotes the total accruals, $\Delta CA_{i,t}$ denotes the change in total current assets, $\Delta CL_{i,t}$ denotes the change in total current liabilities, $\Delta CASH_{i,t}$ denotes the change in cash holding, $\Delta STD_{i,t}$ denotes the change in current portion of long-term debt, $DEP_{i,t}$ denotes depreciation and amortisation expense in the year, $\Delta TP_{i,t}$ denotes the change in income taxes payable.

And ES is calculated on the basis of Model (5):

$$ES_{i,t} = \frac{SD\left(\frac{OCF_{i,t-3}}{ASSET_{i,t-4}}, \frac{OCF_{i,t-2}}{ASSET_{i,t-3}}, \frac{OCF_{i,t-1}}{ASSET_{i,t-2}}, \frac{OCF_{i,t}}{ASSET_{i,t-1}}\right)}{SD\left(\frac{NI_{i,t-3}}{ASSET_{i,t-4}}, \frac{NI_{i,t-2}}{ASSET_{i,t-3}}, \frac{NI_{i,t-1}}{ASSET_{i,t-2}}, \frac{NI_{i,t}}{ASSET_{i,t-1}}\right)} \quad \text{Model (5)}$$

In Model (5), $OCF_{i,t}$ denotes cash flow from operations and $NI_{i,t}$ denotes net income.

4.4. Digital finance and Peking University digital financial inclusion index

In our study, the Peking University Digital Financial Inclusion Index of China is employed as the proxy for digital finance. The Peking University Digital Financial Inclusion Index of China, which is compiled by the Institute of Digital Finance at Peking University and the Shanghai Finance Institute, is based on the original information from the Ant Financial Services (Guo et al., 2020). This Index gauges the degree of digital finance and has been frequently used in China-based studies. This index includes 33 sub-index categories, covering payment, credit, monetary funds and other topics from three major aspects (breadth of coverage, depth of use, and digital support services). At the current stage, this index covers around 31 provinces (municipalities, autonomous regions) and 337 prefecture-level cities during the period of 2011–2020, and some county-level data has been supplemented since 2014.³

³The Peking University Digital Financial Inclusion Index adopts a methodology from micro level to macro level based on the usage of Alipay, mobile payments, digital credit and other digital finance by natural persons and small and micro businesses (Guo et al., 2020), so it can roughly capture the average digital finance at the firm level.

5. Empirical results

5.1. Descriptive statistics

Table 1 reports the results of descriptive statistics. The mean value of *TRAN* is 5.5087, indicating the current status about accounting information transparency of Chinese listed firms. The mean value of *DF* (the main independent variable) is 2.3539, meaning that the average degree (index) of digital finance is 235.39. Also, the value of standard deviation (S. D) of *DF* (0.9750) reveals that the degree of digital finance varies by a large margin across different provinces in China.

As for control variables, on average and approximately: First, with regard to variables about corporate governance, blockholder ownership (*FIRST*) is 34.80%, the ratio of independent directors (*INDR*) is 37.52%, and the board of directors (*BOARD*) consists of 8.56 directors ($e^{2.1473}$). Second, regarding firm-specific financial characteristics, firm size (*SIZE*) is 5.86 billion RMB ($e^{22.4912}$), financial leverage (*LEV*) is 47.67%, returns on total assets (*ROA*) is 3.39%, operating cash flow ratio (*OCF*) is 5.07%, the ratio of capital expenditure (*CAP*) is 4.84%, book-to-market ratio (*BTM*) is 0.6027, firm age (*FIRMAGE*) is 17 years ($e^{2.8603}$), and the ultimate owner in 42.94% of firms is local government or a state-owned enterprise (*STATE*). Lastly, the marketisation index at the province level (*MKT*) is 9.3519.

5.2. Pearson correlation analyses

Table 2 reports the results of Pearson correlation analysis. The correlation coefficient between *DF* and *TRAN* is positive but insignificant, implying no significant linear relation between digital finance and accounting information transparency and suggesting a nonlinear relation between digital finance and accounting information transparency. Moreover, *TRAN* is significantly negatively (positively) correlated to *BOARD*, *SIZE*, *LEV*, *ROA*, *BTM*, *FIRMAGE* and *STATE* (*OCF*, *CAP* and *MKT*), implying the necessity of including these variables as control variables. Furthermore, most correlations among control variables are less than 0.5, implying no serious multicollinearity after including them into regression models simultaneously (Belsley, 1991; Belsley et al., 1980).

5.3. Multivariate tests of H1

Table 3 reports the regression results of H1, which predicts an inverted U-shaped relationship between digital finance (*DF*) and accounting information transparency (*TRAN*). All reported t-statistics are based on standard errors adjusted for clustering at both firm and year level (Petersen, 2009).

In Panel A of **Table 3**, the coefficient on the linear term of digital finance index (*DF*) is positive and significant at the 1% level (0.8783 with $t = 3.46$). Moreover, the coefficient on DF^2 is negative and significant at the 1% level (-0.1293 with $t = -3.78$). Above findings collectively suggest that: (1) In the range from zero to the inflection point, digital finance increases accounting information transparency. (2) After exceeding the inflection point, accounting information transparency decreases along with the increase in digital finance. Clearly, the relation between digital finance and accounting information transparency embodies an inverted U-shaped relationship, and thus lends important support to H1.

Referring to Lind and Mehlum (2010), digital finance should exert significantly positive (*negative*) effect on accounting information transparency below (*above*) the inflection point. Figure 2 illustrates the estimated relation between digital finance (*DF*) and accounting information transparency (*TRAN*). The data range is $[min(DF), max(DF)]$, and the inflection (turning) point is 3.3973, which is quite close to $max(DF)$ and falls within the estimated range of [2.5097, 4.2727] (95% Fieller interval).⁴ In Panel B of Table 3, the slope of the left (right) side of the inverted U-shaped curve at the inflection point is positive (negative) and significant, further validating the inverted U-shaped relationship between digital finance and accounting information transparency and lending additional support to H1.

As for control variables, the coefficients on blockholder ownership (*FIRST*), board size (*BOARD*), operating cash flow ratio (*OCF*) and the ratio of capital expenditure (*CAP*) are significantly positive, suggesting that these factors can significantly increase accounting information transparency. However, the coefficients on firm size (*SIZE*), financial leverage (*LEV*), returns on total assets (*ROA*), book-to-market ratio (*BTM*) and state-owned enterprises (*STATE*) are significantly negative, implying these determinants can negatively affect accounting information transparency.

Panel C of Table 3 uses the left subsample and the right subsample (based on the inflection point) to conduct additional tests. For the left subsample in Column (1) of Panel C, the coefficient on *DF* is significantly positive. Also, for the right subsample in Column (2) of Panel C, the coefficient on *DF* is negative and significant. These findings, taken together, provide further support for H1.

5.4. Robustness checks using digital finance at the prefecture level

Panel A of Table 4 adopts prefecture-level index of digital finance (*DF_P*) to re-test H1. In Panel A of Table 4, the coefficients on *DF_P* and *DF_P*² are significantly positive and significantly negative, respectively, lending important support for H1.

5.5. Robustness checks using the weighted average digital finance index

For the firms with cross-regional operation, we construct a weighted average digital finance index (*DF_WA*) based on the proportion of 'sales revenue from each province to the firm's total sales revenue' and digital finance index at the province level.⁵ Specifically, *DF_WA* is measured as:

$$DF_WA = \sum_{t=1}^n \frac{SALE_t}{TSALE} \times DF_t \quad \text{Model (6)}$$

⁴The inflection value for digital finance is 3.3973, suggesting that 13,321 (2,610) observations are located on the left (right) of the inflection point. Thus, for the majority of firm-year observations, digital finance has a positive impact on accounting information transparency. Instead, only for a small proportion of firm-year observations, excessive digital finance may inversely affect accounting information transparency. The possible reason for the asymmetric number of observations lies in the unbalanced development of digital finance across different provinces in China. Along with the development of digital finance (index), the inflection point is constantly changing, and accordingly, the number of observations in the left subsample and the right subsample around the inflection point gradually tends to balance.

⁵The WIND database only provides the firm's sales revenue in top five provinces. Against this context, when the firm's sales revenue at the province level is not disclosed or the firm's sales revenue in other regions outside top five provinces, we use digital finance index of the firm's registered province as a substitute.

Table 1. Descriptive statistics.

Variable	N	Mean	S. D.	Min	Q1	Median	Q3	Max
TRAN	15,931	5.5087	2.0961	1.0000	4.0000	5.5000	7.0000	10.0000
DF	15,931	2.3539	0.9750	0.3268	1.6665	2.3536	3.1085	4.3193
DF ²	15,931	6.4912	4.6187	0.1068	2.7772	5.5394	9.6628	18.6564
FIRST	15,931	0.3480	0.1510	0.0872	0.2285	0.3274	0.4509	0.7409
INDR	15,931	0.3752	0.0545	0.3333	0.3333	0.3571	0.4286	0.5714
BOARD	15,931	2.1473	0.2000	1.6094	1.9459	2.1972	2.1972	2.7081
SIZE	15,931	22.4912	1.3497	19.9096	21.5217	22.3067	23.3021	26.2090
LEV	15,931	0.4767	0.2023	0.0498	0.3239	0.4832	0.6277	0.8918
ROA	15,931	0.0339	0.0601	-0.2361	0.0114	0.0318	0.0613	0.2178
OCF	15,931	0.0507	0.0815	-0.2054	0.0073	0.0490	0.0940	0.3166
CAP	15,931	0.0484	0.0456	0.0002	0.0149	0.0352	0.0684	0.2220
BTM	15,931	0.6027	0.2734	0.0863	0.3853	0.5858	0.8133	1.1830
FIRMAGE	15,931	2.8603	0.3476	1.7918	2.6391	2.8904	3.0910	3.4965
STATE	15,931	0.4294	0.4950	0.0000	0.0000	0.0000	1.0000	1.0000
MKT	15,931	9.3519	1.5676	4.5870	8.5530	9.6390	10.4900	11.9340

Note: All the variables are defined in [Appendix 1](#).

DF_WA denotes a weighted average digital finance index; $SALE_t$ is sales revenue from province t ; $TSALE$ refers to the firm's total sales revenue; DF_t denotes digital finance index in province t .

As shown in Panel B of [Table 4](#), for the full sample, the coefficients on DF_WA and DF_WA^2 are significantly positive and significantly negative, additionally validating H1.

5.6. Robustness checks using earning aggressiveness

More aggressive earnings reflect biased and optimistic management of earnings (Bhattacharya et al., 2003), and thus are associated with more opaque earnings under the assumption that managers tend to overstate rather than understate earnings. [Table 5](#) uses the negative value of earnings aggressiveness as the dependent variable (EA) to re-test H1. As shown, the coefficient on DF is positive and significant at the 1% level and the coefficient of DF^2 is negative and significant at 1% level, validating H1 again.

5.7. Robustness checks using the reduced sample

In China, digital finance in four municipalities, which have economic and political particularity, is different from that in other provinces. In response, Panel A of [Table 6](#) deletes firm-year observations belonging to four municipalities, and the findings support H1 again.

5.8. Robustness checks after including regional economic development

Regional economic development positively affects digital finance, consistent with prior literature (Hu et al., 2021; Imam & Kpodar, 2016; Liu et al., 2021). Nevertheless, digital finance is not completely equivalent to local economic development. In reality, technical factors such as broadband infrastructure (Niu et al., 2022), artificial intelligence (Mhlanga, 2020) and financial literacy (Shen et al., 2018) can also affect the development of digital finance. To address whether our findings are driven by the resemblance of digital finance and regional economic development, we include GDP (per capita GDP in a province) as

Table 2. Pearson correlation matrix.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) TRAN	1.0000														
(2) DF	0.0100	1.0000													
(3) DF ²	0.0079	0.9723***	1.0000												
(4) FIRST	0.0077	-0.0735***	-0.0703***	1.0000											
(5) INDR	0.0064	0.0699***	0.0721***	0.0482***	1.0000										
(6) BOARD	-0.0391***	-0.0999***	-0.0917***	0.0333***	-0.5063***	1.0000									
(7) SIZE	-0.1540***	0.2786**	0.2842***	0.2425***	0.0497***	0.2365***	1.0000								
(8) LEV	-0.1710***	0.0947***	0.1142***	0.0742***	0.0139*	0.1208***	0.5033***	1.0000							
(9) ROA	-0.0893***	-0.1151***	-0.1167***	0.1187***	-0.0198**	0.0296***	0.0071	-0.3675***	1.0000						
(10) OCF	0.0225***	0.0495**	0.0477**	0.0780**	-0.0120	0.0379***	0.0524***	-0.1724***	0.3892***	1.0000					
(11) CAP	0.1417***	-0.1321**	-0.1104***	0.0118	-0.0310***	0.0409***	-0.0646***	-0.1293***	0.1545***	0.2123***	1.0000				
(12) BTM	-0.1288***	0.1322**	0.1759***	0.1370***	-0.0087	0.1798***	0.6354***	0.4699***	-0.2329***	-0.1143***	-0.0952***	1.0000			
(13) FIRMAGE	-0.0928***	0.3581***	0.3526***	-0.0951***	-0.0123	0.0387***	0.2187***	0.2583***	-0.1191***	-0.0139*	-0.1920***	0.2085***	1.0000		
(14) STATE	-0.1276***	-0.0864**	-0.0719**	0.2660***	-0.0352***	0.2439***	0.3340***	0.2640***	-0.0699***	-0.0146*	-0.0881***	0.3404***	0.2085***	1.0000	
(15) MKT	0.0341***	0.4657***	0.4564***	-0.4657***	0.0256***	-0.1080***	0.0110	-0.0472***	0.0283***	0.0180**	-0.0264***	-0.0593***	0.0638***	-0.1859***	1.0000

Note: ***, ** and * represent the 1, 5, and 10% levels of significance respectively, for a two-tailed test. All variables are defined in Appendix 1.

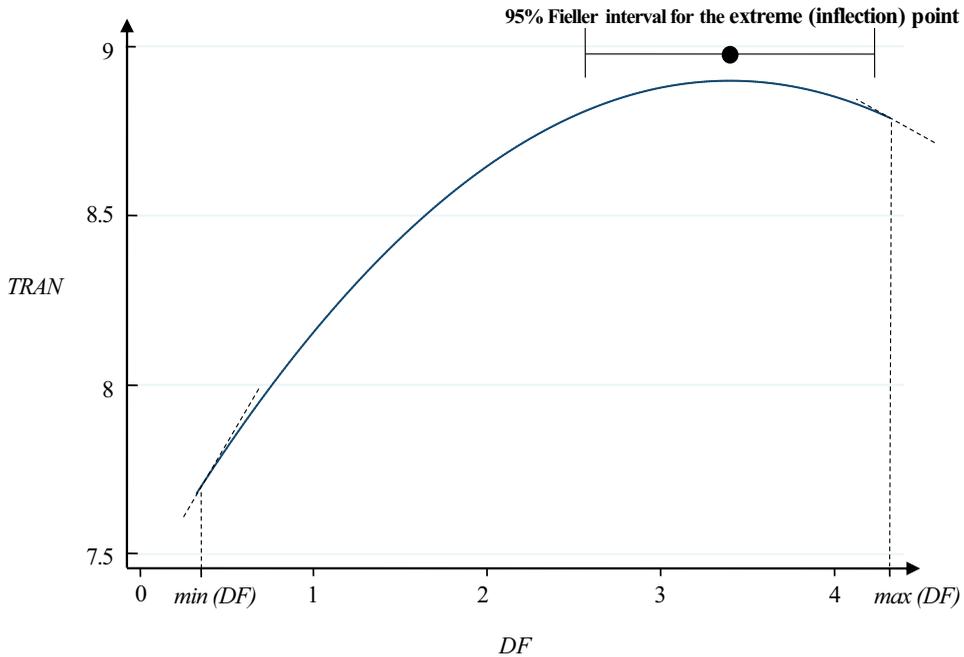


Figure 2. The inverted U-shaped relationship between digital finance and accounting information transparency.

a control variable into the regression models to conduct robustness checks. As shown in Panel B of Table 6, our findings are qualitatively similar to those in Table 3.

6. Endogeneity discussions and additional tests

6.1. Endogeneity tests using two-stage “shift-share” instrumental variable regression procedures

Table 7 uses two-stage instrumental variable regression procedure to mitigate the potential endogeneity. In doing so, it is crucial to obtain the appropriate instrumental variable. Referring to Q. Huang et al. (2019) and Bai and Yu (2021), we adopt the ‘shift-share’ instrumental variable, measured as ‘the number of post offices per million people in 1984 at the province level \times the number of Internet ports nationwide (unit: hundred million)’. Specifically, the number of post offices per million people in 1984 at the province level is the ‘share’, which is associated with individual characteristics. Moreover, the number of Internet ports nationwide is the ‘shift’ part, which varies over time.

The exogeneity of the shift-share IV is mainly determined by the ‘Share’ (Goldsmith-Pinkham et al., 2020). First, post offices are important infrastructures in the early dial-up digital network stage, which are likely to affect regional development of digitalisation technologies. More post offices in the early years may imply a higher demand for regional information usage. Second, the Internet ports are essential access hardware in digital technologies. Thus, the number of Internet ports nationwide reflects a rough time-varying level of Internet developing in China. As such, the number of post offices in 1984

Table 3. The influence of digital finance on accounting information transparency.

Panel A: Regression result of accounting information transparency on digital finance and other determinants				
Variable	Dependent variable : <i>TRAN</i>			
	Coefficient	t-value		
DF	0.8783***	3.46		
DF ²	-0.1293***	-3.78		
FIRST	0.8672***	4.54		
INDR	0.5316	1.22		
BOARD	0.3339**	2.41		
SIZE	-0.0567*	-1.84		
LEV	-2.2821***	-4.75		
ROA	-8.3305***	-11.38		
OCF	1.3258***	2.75		
CAP	7.2400***	7.31		
BTM	-0.8070***	-4.51		
FIRMAGE	-0.2949	-1.57		
STATE	-0.2972**	-2.49		
MKT	-0.0321	-1.60		
Constant	7.4064***	10.84		
Year fixed effects		Yes		
Industry fixed effects		Yes		
N		15,931		
Adjusted R ²		0.113		
F- (p-value)		50.05 (<.0001)		
Panel B: Further tests about the inverted U-shaped relationship between digital finance and accounting information transparency				
Indicator	Results			
Tests about the presence of an inverted U-shaped relationship	t-value = 2.20 (p-value = 0.021)			
Extreme (inflection) point	3.3973			
95% Fieller interval for extreme point	[2.5097, 4.2727]			
Slope and t-value on both sides of the inverted U-shaped relationship	Lower bound: Slope = 0.7938, t-value = 3.40 Upper bound: Slope = -0.2384, t-value = -2.04			
Panel C. Regression results using the left sample and the right subsample				
Variable	Dependent variable : <i>TRAN</i>			
	(1)		(2)	
	The left subsample		The right subsample	
	Coefficient	t-value	Coefficient	t-value
DF	0.3040**	2.40	-6.5493***	-25.26
Control variables	Yes		Yes	
Constant	7.4350***	10.02	29.6508***	10.00
Year fixed effects	Yes		Yes	
Industry fixed effects	Yes		Yes	
N	13,321		2,610	
Adjusted R ²	0.117		0.119	
F- (p-value)	43.51 (<.0001)		2.91 (<.0001)	

Note: ***, ** and * represent the 1, 5, and 10% levels of significance respectively, for a two-tailed test. All reported t-statistics are based on the robust standard errors clustering at both year and firm level. All variables are defined in Appendix 1.

Table 4. Robustness checks using alternative proxies for digital finance.

Panel A: Robustness checks using the degree of digital finance at the prefecture level		
Variable	Dependent variable : <i>TRAN</i>	
	Coefficient	t-value
DF_P	0.8445**	2.48
DF_P ²	-0.1328**	-2.44
FIRST	0.8686***	4.50
INDR	0.4901	1.13
BOARD	0.3397**	2.46
SIZE	-0.0573*	-1.85
LEV	-2.3008***	-4.77
ROA	-8.3273***	-11.48
OCF	1.3353***	2.77
CAP	7.2138***	7.33
BTM	-0.7914***	-4.41
FIRMAGE	-0.2923	-1.54
STATE	-0.2968**	-2.49
MKT	-0.0186	-0.92
Constant	7.2115***	9.90
Year and industry fixed effects		Yes
<i>N</i>		15,931
Adjusted <i>R</i> ²		0.113
F- (p-value)		49.77 (<.0001)
Panel B: Robustness checks using the weighted average digital finance index		
Variable	Dependent variable : <i>TRAN</i>	
	Coefficient	t-value
DF_WA	0.8156**	2.12
DF_WA ²	-0.1514**	-2.50
FIRST	0.7537***	3.72
INDR	0.9310*	1.74
BOARD	0.4655**	2.42
SIZE	-0.0550	-1.43
LEV	-2.0834***	-5.21
ROA	-8.4102***	-12.26
OCF	0.9925**	2.13
CAP	7.6149***	7.63
BTM	-0.7756***	-3.49
FIRMAGE	-0.1941	-0.90
STATE	-0.1622	-1.27
MKT	-0.0048	-0.22
Constant	6.2895***	5.61
Year and industry fixed effects		Yes
<i>N</i>		9,587
Adjusted <i>R</i> ²		0.104
F- (p-value)		28.34 (<.0001)

Note: ***, ** and * represent the 1, 5, and 10% levels of significance respectively, for a two-tailed test. All reported t-statistics are based on the robust standard errors clustering at both year and firm level.

(‘Share’) belongs to historical data about forty years ago, which is relatively exogenous and does not directly affect the current accounting information transparency.⁶

⁶Maybe one may address the concerns about whether the number of post offices per million people in 1984 is related to economic development and education quality, which may further affect accounting (information) quality. In response, we conduct two sets of additional tests (untabulated for brevity, but the results are available upon request; similarly hereinafter): (1) GDP₂₀₂₀ as the dependent variable, the coefficients on the number of post offices per million inhabitants (*SHARE*), five-year-lagged *SHARE* (*LS_SHARE*), ten-year-lagged *SHARE* (*L10_SHARE*), twenty-year-lagged *SHARE* (*L20_SHARE*), and the number of post offices per million inhabitants in 1984 (*SHARE*₁₉₈₄) are insignificant, implying no significant relation between post offices and economic development. (2) Education quality (*EDU*) as the

Table 5. Robustness checks using earning aggressiveness as an alternative proxy for accounting information transparency.

Variable	Dependent variable : EA	
	Coefficient	t-value
DF	0.1033***	4.83
DF ²	-0.0151***	-5.82
FIRST	0.0903***	5.08
INDR	0.0930***	2.94
BOARD	0.0294**	2.56
SIZE	-0.0150***	-3.76
LEV	-0.1479***	-2.84
ROA	-0.4482***	-7.60
OCF	0.0692**	2.17
CAP	0.7117***	7.38
BTM	0.0233	1.23
FIRMAGE	-0.0274**	-2.33
STATE	-0.0071	-0.84
MKT	-0.0028	-1.44
Constant	0.4488***	6.54
Year and industry fixed effects		Yes
N		15,931
Adjusted R ²		0.150
F- (p-value)		57.00 (<.0001)

Note: ***, ** and * represent the 1, 5, and 10% levels of significance respectively, for a two-tailed test. All reported t-statistics are based on the robust standard errors clustering at both year and firm level. All variables are defined in [Appendix 1](#).

Referring to prior studies (Bai & Yu, 2021; Callen & Fang, 2015; Cao et al., 2021; Hilary & Hui, 2009; Q. Huang et al., 2019), the lagged variables are often employed as instrument variable. Hilary and Hui (2009) and Callen and Fang (2015) use three-year-lagged religious population to serve as the instrumental variable for main independent variable (religious population). Cao et al. (2021) employ the post office in the Ming Dynasty and the number of telephones per 10,000 people at the city level in 1984 as two instrument variables for e-commerce city pilot. Moreover, 'the number of post offices (fixed-line telephone) per million people in 1984 at the province level \times the number of Internet ports nationwide' (the lagged variables) is also explored as the 'Shift-share' instrumental variable (Bai & Yu, 2021; Q. Huang et al., 2019). As a matter of fact, the demand for postal services affects the location of post office (Goddard & Pye, 1977). Thus, post service was not only run for profit, and in some cases, post offices would continue to operate in remote villages (Howe, 2007). Hodgson (2018) finds that larger towns (cities) do not have significantly more post offices than smaller towns (villages), suggesting an insignificant impact of post offices on economic development.

The results of the first stage regression are reported in Column (1) of [Table 7](#). As expected, *IV* is significantly positively related with *DF* (2.0816 with $t = 3.09$). Column (2) of [Table 7](#) displays the results of the second stage regression using the fitted value of *DF**

dependent variable, all the coefficients on *SHARE*, *L5_SHARE*, *L10_SHARE*, *L20_SHARE* and *SHARE*₁₉₈₄ are insignificant, suggesting that the number of post offices per million inhabitants does not significantly affect education quality. To sum up, the relation between post offices per million people and economic development (education quality) is insignificant, and thus 'the number of post offices per million people in 1984' does not influence accounting information transparency by the channel of economic development (education quality). Thus, the 'shift-share' *IV* satisfies the exogeneity requirement and can serve as a relatively appropriate instrument variable.

Table 6. Robustness checks using the reduced sample and considering regional economic development.

Panel A: Robustness checks using the reduced sample excluding four municipalities		
Variable	Dependent variable : <i>TRAN</i>	
	Coefficient	t-value
DF	0.6331**	2.06
DF ²	-0.1572***	-3.46
Control variables	Yes	
Constant	7.2575***	12.87
Year and industry fixed effects	Yes	
N	12,545	
Adjusted R ²	0.109	
F- (p-value)	36.80 (<.0001)	

Panel B: Robustness checks after including regional economic development		
Variable	Dependent variable : <i>TRAN</i>	
	Coefficient	t-value
DF	0.7920***	2.66
DF ²	-0.1371***	-3.81
Control variables	Yes	
GDP	0.0146	0.74
Constant	7.4025***	10.84
Year and industry fixed effects	Yes	
N	15,931	
Adjusted R ²	0.113	
F- (p-value)	48.93 (<.0001)	

Note: ***, ** and * represent the 1, 5, and 10% levels of significance respectively, for a two-tailed test. All reported t-statistics are based on the robust standard errors clustering at both year and firm level. All variables are defined in [Appendix 1](#).

and DF^{*2} as the main independent variables. Results in Column (2) of [Table 7](#) for the full sample validate H1.

6.2. Endogeneity tests using the propensity score matching approach

Next, [Table 8](#) uses the propensity score matching approach to mitigate the endogeneity issue and reduce the probability of estimation error. Referring to prior literature (Ogawa et al., 2021; Yang et al. 2022), we construct a dummy variable of DF_DUM , equalling 1 if DF is greater than the inflection point of the inverted U-shape relation ($DF > 3.3973$) and 0 otherwise ($DF < 3.3973$). For the treatment group ($DF_DUM = 1$), digital finance has a negative impact on accounting information transparency; However, for the control group ($DF_DUM = 0$), digital finance has a positive effect on accounting information transparency. In the first stage regression, we abide by the one-to-one principle and adopt '±0.001' as the threshold to match each firm-year observation in the treatment group ($DF_DUM = 1$) to only one firm-year observation in the control group, by which the unbalanced distributions between two subsamples can be mitigated to some extent. In Panel A of [Table 8](#), a set of control variables and industry fixed effect are chosen to conduct the first-stage matching process. In Panel B of [Table 8](#), all the differences in covariates between the treatment group and the control group are insignificant after conducting PSM procedures, suggesting that all the covariates can pass through the balance tests.

Table 7. Endogeneity tests using two-stage “shift-share” instrumental variable regression procedure.

Variable	(1)		(2)	
	The first stage		The second stage	
	Dependent variable: <i>DF</i>		Dependent variable: <i>TRAN</i>	
	Coefficient	t-value	Coefficient	t-value
IV	2.0816***	3.09		
DF*			0.9232***	4.74
DF* ²			-0.1432***	-5.39
FIRST	0.0043***	4.00	0.9226***	4.98
INDR	0.0194*	1.82	0.2604	0.57
BOARD	-0.0020	-1.12	0.2625*	1.84
SIZE	0.0004	1.11	-0.0726**	-2.22
LEV	0.0121**	2.34	-2.2354***	-4.13
ROA	-0.0278**	-2.15	-8.5361***	-11.95
OCF	-0.0042	-0.56	1.4125***	2.61
CAP	0.0271	1.63	7.0543***	6.06
BTM	-0.0113***	-2.93	-0.7044***	-3.45
FIRMAGE	-0.0015	-1.58	-0.2103	-1.05
STATE	-0.0001	0.63	-0.3004**	-2.30
MKT	-0.0213***	-2.63	-0.0346	-1.62
Constant	1.8234***	21.78	7.2003***	10.15
Year fixed effects	Yes		Yes	
Industry fixed effects	Yes		Yes	
Province fixed effects	Yes		No	
<i>N</i>	13,976		13,976	
Adjusted <i>R</i> ²	0.996		0.110	
F-(p-value)	75311.63 (<.0001)		45.60 (<.0001)	

Note: ***, ** and * represent the 1, 5, and 10% levels of significance respectively, for a two-tailed test. All reported t-statistics are based on the robust standard errors clustering at both year and firm level. All variables are defined in Appendix 1.

For the second stage regression, as Panel C of Table 8 shows, the coefficient on *DF* is significantly positive at the 1% level (2.8320 with $t = 3.78$) and the coefficient on DF^2 is significantly negative at the 1% level (-0.4136 with $t = -4.10$), validating H1.

6.3. Endogeneity tests using firm-level fixed effect regression approach

In Table 9, we further employ firm-level fixed effect regression approach to mitigate the influence of omitted variables on regression results. For the full sample in Table 9, the coefficient on *DF* is significantly positive at the 1% level (1.7390 with $t = 3.98$) and the coefficient on DF^2 is significantly negative at the 1% level (-0.1970 with $t = -4.38$), indicating an inverted U-relation between digital finance and accounting information transparency and verifying H1.

6.4. Additional tests using various samples to exclude the potential impacts of extreme observations

To exclude the possibilities that our findings are driven by extreme observations, we conduct four additional tests. First, Panel A of Table 10 takes 25% sample to the right and 25% sample to the left of the inflection point. As shown in Column (1) of Panel A, the

Table 8. Endogeneity tests using the propensity score matching approach.

Panel A: The first stage of the propensity score matching approach						
Variable	Dependent variable : <i>DF_DUM</i>					
	Coefficient			z-value		
FIRST	-0.3925**			-1.97		
INDR	0.1433			0.24		
BOARD	-0.9937***			-5.81		
SIZE	0.2588***			8.55		
LEV	-0.3066			-1.60		
ROA	-4.5318***			-8.68		
OCF	3.5755***			9.14		
CAP	-0.2774			-0.41		
BTM	2.3141***			16.26		
FIRMAGE	2.0144***			19.79		
STATE	-0.5109***			-7.56		
MKT	1.4379***			41.94		
Constant	-26.1971***			-29.77		
Year and industry fixed effects				Yes		
N				15,923		
LR- χ^2				5315.20		
Pseudo R^2				0.3741		
Log likelihood				-4445.70		
Panel B: Results of covariate balance tests before and after conducting the propensity score matching procedures						
Variable	Full sample			Matched sample		
	(1) <i>DF_DUM</i> = 1 [N = 2,610]	(2) <i>DF_DUM</i> = 0 [N = 13,321]	(3) t-tests [(1)-(2)]	(4) <i>DF_DUM</i> = 1 [N = 1,412]	(5) <i>DF_DUM</i> = 0 [N = 1,412]	(6) t-tests [(4)- (5)]
FIRST	0.333	0.351	-5.58***	0.340	0.342	-0.39
INDR	0.382	0.374	7.03***	0.379	0.378	0.44
BOARD	2.119	2.153	-7.82***	2.130	2.132	-0.21
SIZE	23.003	22.391	21.47***	22.861	22.785	1.46
LEV	0.517	0.469	11.19***	0.506	0.498	1.21
ROA	0.022	0.036	-11.32***	0.027	0.029	-0.82
OCF	0.059	0.049	5.57***	0.057	0.058	-0.40
CAP	0.045	0.049	-4.17***	0.046	0.046	-0.33
BTM	0.701	0.583	20.32***	0.653	0.645	0.77
FIRMAGE	3.033	2.827	28.41***	2.976	2.977	-0.14
STATE	0.370	0.441	-6.68***	0.402	0.400	0.08
MKT	10.704	9.086	52.16***	10.239	10.274	-1.09
Panel C: The second stage of the propensity score matching approach						
Variable	Dependent variable : <i>TRAN</i>					
	Coefficient			t-value		
DF	2.8320***			3.78		
DF ²	-0.4136***			-4.10		
FIRST	0.5335			1.62		
INDR	0.1421			0.25		
BOARD	0.0712			0.37		
SIZE	-0.0383			-0.87		
LEV	-2.0983***			-3.73		
ROA	-9.5753***			-12.04		
OCF	1.6215**			2.20		
CAP	6.0567***			4.66		
BTM	-1.1608***			-4.32		
FIRMAGE	-0.4161**			-2.46		
STATE	-0.1355			-1.31		
MKT	-0.0567			-1.26		
Constant	6.9245***			5.11		
Year fixed effects				Yes		
Industry fixed effects				Yes		
N				2,824		
Adjusted R^2				0.112		
F- (p-value)				10.95 (<.0001)		

Note: ***, ** and * represent the 1, 5, and 10% levels of significance respectively, for a two-tailed test. All reported t-statistics are based on the robust standard errors clustering at both year and firm level. All variables are defined in Appendix 1.

Table 9. Endogeneity tests using firm-level fixed effects regression approach.

Variable	Dependent variable : <i>TRAN</i>	
	Coefficient	t-value
DF	1.7390***	3.98
DF ²	-0.1970***	-4.38
FIRST	1.6336***	3.43
INDR	0.2995	0.44
BOARD	-0.0570	-0.26
SIZE	-0.4316***	-4.20
LEV	-1.2392*	-1.77
ROA	-8.4407***	-19.20
OCF	0.3064	0.82
CAP	8.6275***	10.23
BTM	-0.0970	-0.33
FIRMAGE	-2.9573***	-3.70
STATE	-0.2151	-1.13
MKT	0.0570	0.90
Constant	25.5506***	10.04
Year fixed effects		Yes
Firm fixed effects		Yes
N		15,931
Adjusted R ²		0.307
F- (p-value)		2.76 (<.0001)

Note: ***, ** and * represent the 1, 5, and 10% levels of significance respectively, for a two-tailed test. All reported t-statistics are based on the robust standard errors clustering at both year and firm level. All variables are defined in [Appendix 1](#).

coefficient on *DF* is significantly positive for the left subsample (0.5005 with t-value = 1.69), suggesting that digital finance increases accounting information transparency. Moreover, in Column (2) of Panel A, for the right subsample, the coefficient on *DF* is significantly negative (-2.0953 with t-value = -6.22), indicating that excessive digital finance has a negative impact on accounting information transparency.

Second, Panel B of [Table 10](#) takes 10% sample to the right (left) of the inflection point. As shown, the coefficient on *DF* is significantly positive for the left subsample (0.6010 with t-value = 10.51), suggesting that digital finance increases accounting information transparency. Moreover, for the right subsample, the coefficient on *DF* is significantly negative (-15.1307 with t-value = -33.59), indicating that excessive digital finance has a negative impact on accounting information transparency.

Lastly, in Panel C of [Table 10](#), all continuous variables are winsorised at the 5% and 95% levels to re-test H1. As shown, H1 is still supported by empirical evidence. Similarly, after all continuous variables are winsorised at the 10% (90%) level, results in Panel D of [Table 10](#) validate H1 again.

6.5. Additional tests about the mediating effects of MD&A and annual reporting disclosure timeliness

In H1, we argue that digital finance can increase available information and upgrade accounting information transparency in the range from zero to the inflection point, but after digital finance exceeds the inflection point, accounting information becomes more opaque due to information overload. Referring to Caserio et al.

Table 10. Additional tests using various samples to exclude the potential impacts of extreme observations.

Panel A: Additional tests using 25% sample to the right and 25% sample to the left of the inflection point				
Variable	Dependent variable : <i>TRAN</i>			
	(1)		(2)	
	25% sample on the left side		25% sample on the right side	
	Coefficient	t-value	Coefficient	t-value
DF	0.5005*	1.69	-2.0953***	-6.22
Control variables	Yes		Yes	
Year and industry fixed effects	Yes		Yes	
<i>N</i>	3,792		1,000	
Adjusted <i>R</i> ²	0.081		0.122	
Panel B: Additional tests after using 10% sample to the right and 10% sample to the left of the inflection point				
Variable	Dependent variable : <i>TRAN</i>			
	(1)		(2)	
	10% sample on the left side		10% sample on the right side	
	Coefficient	t-value	Coefficient	t-value
DF	0.6010***	10.51	-15.1307***	-33.59
Control variables	Yes		Yes	
Year and industry fixed effects	Yes		Yes	
<i>N</i>	742		284	
Adjusted <i>R</i> ²	0.148		0.122	
Panel C: Additional tests after winsorising all continuous variables at 5% and 95% levels				
Variable	Dependent variable : <i>TRAN</i>			
	Coefficient	t-value		
DF	1.0197***	4.27		
DF ²	-0.1665***	-4.59		
Control variables and Constant	Yes			
Year and industry fixed effects		Yes		
<i>N</i>		15,931		
Adjusted <i>R</i> ²		0.100		
Panel D: Additional tests after winsorising all continuous variables at 10% and 90% levels				
Variable	Dependent variable : <i>TRAN</i>			
	Coefficient	t-value		
DF	1.0265***	4.16		
DF ²	-0.1702***	-3.78		
Control variables and Constant	Yes			
Year and industry fixed effects		Yes		
<i>N</i>		Yes		
Adjusted <i>R</i> ²		15,931		
F- (p-value)		0.078		

Note: ***, ** and * represent the 1, 5, and 10% levels of significance respectively, for a two-tailed test. All reported t-statistics are based on the robust standard errors clustering at both year and firm level. All variables are defined in [Appendix 1](#).

(2019) and Hanley and Hoberg (2010), we use MD&A as the proxy for information contents, and then investigate the mediating role of MD&A in the relation between digital finance and accounting information transparency. MD&A is measured as the natural logarithm of total vocabulary in MD&A (management discussion and analysis).

Table 11. Additional tests about the mediating effects of MD&A and annual reporting disclosure timeliness.

Panel A: Additional tests about the mediating effects of MD&A				
Variable	(1)		(2)	
	Dependent variable : MD&A		Dependent variable : TRAN	
	Coefficient	t-value	Coefficient	t-value
DF	0.0734**	2.21	0.0625	0.74
DF ²	-0.2345**	-2.30	0.4079*	1.78
MD&A			0.1742***	4.19
Control variables	Yes		Yes	
Constant	7.5412***	29.80	6.4769***	10.59
Year fixed effects	Yes		Yes	
Industry fixed effects	Yes		Yes	
N	15,931		15,931	
Adjusted R ²	0.189		0.106	
F- (p-value)	89.73 (<.0001)		43.06 (<.0001)	
Sobel Z		-3.14***		
Mediation Ratio		11.72%		

Panel B: Additional tests about the mediating effect of and annual reporting disclosure timeliness (TIME)				
Variable	(1)		(2)	
	Dependent variable : TIME		Dependent variable : TRAN	
	Coefficient	t-value	Coefficient	t-value
DF	1.0254*	1.68	0.3185***	3.22
DF ²	-0.6102*	-1.67	-0.1253**	-2.05
TIME			0.0020*	1.73
Control variables	Yes		Yes	
Constant	57.0381***	18.13	8.8961***	16.62
Year fixed effects	Yes		Yes	
Industry fixed effects	Yes		Yes	
N	15,931		15,931	
Adjusted R ²	0.157		0.106	
F- (p-value)	79.37 (<.0001)		43.06 (<.0001)	
Sobel Z		1.72*		
Mediation Ratio		6.41%		

Note: ***, ** and * represent the 1, 5, and 10% levels of significance respectively, for a two-tailed test. All reported t-statistics are based on the robust standard errors clustering at both year and firm level.

For MD&A as the dependent variable in Column (1) of Panel A of Table 11, we can observe the inverted U-shaped relationship between digital finance and MD&A, accompanying with a significantly positive coefficient on *DF* and a significantly negative coefficient on *DF*². Moreover, after using *TRAN* as the dependent variable and incorporating *DF*, *DF*² and *MD&A* and *DF*×*MD&A* into Column (2) of Panel A of Table 11, the coefficients on *DF*, *DF*² and *MD&A* is positive, significantly positive and significantly positive, respectively. More importantly, the value of Sobel Z is significant, and the mediating ratio is 11.72%. The above results suggest that digital finance has an impact on accounting information transparency through the channels of MD&A and other increased information contents, and the impact pattern exhibits an inverted U-shaped feature.

Both the information amount and timeliness are equally important to accounting information transparency. Thus, referring to Dyer and McHugh (1975), Whittred (1980) and Whittred and Zimmer (1984), we further test the mediating role of annual reporting disclosure timeliness (*TIME*) in the relation between digital finance and accounting

Table 12. Subsample tests considering marketisation index and CEO-chairman duality.

Panel A: Subsample tests considering marketisation index				
Dependent variable: <i>TRAN</i>				
Variable	(1)		(2)	
	High-MKT subsample		Low-MKT subsample	
	Coefficient	t-value	Coefficient	t-value
DF	0.1369	0.25	1.3741***	4.77
DF ²	-0.0030	-0.04	-0.2282***	-3.96
Control variables	Yes		Yes	
Constant	6.8677***	7.26	7.4311***	7.93
Year fixed effects	Yes		Yes	
Industry fixed effects	Yes		Yes	
<i>N</i>	8,810		7,121	
Adjusted <i>R</i> ²	0.116		0.118	
F-(p-value)	29.89 (<.0001)		24.97 (<.0001)	
Chow test		2.63***		
Coefficient test (<i>DF</i>)		5.07**		
Coefficient test (<i>DF</i> ²)		5.66**		

Panel B: Subsample tests considering CEO-chairman duality				
Dependent variable: <i>TRAN</i>				
Variable	(1)		(2)	
	<i>DUAL</i> = 0		<i>DUAL</i> = 1	
	Coefficient	t-value	Coefficient	t-value
DF	0.6839**	2.26	1.6350***	2.71
DF ²	-0.0867**	-2.08	-0.2833***	-3.61
Control variables	Yes		Yes	
Constant	6.9805***	7.87	8.5520***	6.93
Year fixed effects	Yes		Yes	
Industry fixed effects	Yes		Yes	
<i>N</i>	12,048		3,684	
Adjusted <i>R</i> ²	0.106		0.137	
F-(p-value)	35.51 (<.0001)		14.64 (<.0001)	
Chow test		7.75***		
Coefficient test (<i>DF</i>)		2.91**		
Coefficient test (<i>DF</i> ²)		5.22**		

Note: ***, ** and * represent the 1, 5, and 10% levels of significance respectively, for a two-tailed test. All reported t-statistics are based on the robust standard errors clustering at both year and firm level. All variables are defined in Appendix 1.

information transparency. *TIME* is defined as the negative value of the time lag of annual reporting disclosure.

For *TIME* as the dependent variable in Column (1) of Panel B of Table 11, there exists an inverted U-shaped relationship between digital finance and annual reporting disclosure timeliness, along with a significantly positive coefficient on *DF* and a significantly negative coefficient on *DF*². Moreover, after using *TRAN* as the dependent variable and incorporating *DF*, *DF*² and *TIME* into Column (2) of Panel B of Table 11, the coefficients on *DF* and *DF*² and *TIME* are significantly positive, significantly negative and significantly positive, respectively. More importantly, the value of Sobel *Z* is 1.72, and the mediating ratio is 6.41%. The above results suggest that digital finance affects accounting information transparency by the channels of annual reporting disclosure timeliness, and the impact pattern exhibits an inverted U-shaped feature.

6.6. Subsample tests considering marketization index and CEO duality

A well-developed market is beneficial for corporate transparency (Bushman et al., 2004). Digital financial services break through the geographical limitations and can fully reflect the inclusive characteristics, which enable less developed regions to benefit more from digital finance. In response, according to the mean value of the Marketization Index, we partition the sample into the high-*MKT* subsample and the low-*MKT* subsample for cross-sectional analyses.

As shown in Panel A of Table 12, the coefficients on *DF* and DF^2 are both significant for the low-*MKT* subsample, but not for the high-*MKT* subsample. Moreover, the differences between two subsamples are significant (F-statistics) and the differences in the coefficients on *DF* and DF^2 are both significant (t-tests). Above results collectively reveal that the inverted U-shaped relationship between digital finance and accounting information transparency is more pronounced for low-*MKT* subsample than for high-*MKT* subsample, suggesting that the degree of marketisation weakens the impacts of digital finance on accounting information transparency and reflects the inclusiveness of digital finance.

The CEO-chairman's role separation can improve monitoring quality and create the pressures for better information disclosure (Fama & Jensen, 1983; Forker, 1992). In response, we divide the full sample into two subsamples on the basis of CEO-chairman duality. In Panel B of Table 12, the inverted U-shaped relationship between digital finance and accounting information transparency exists for both the non-*DUAL* subsample and the *DUAL* subsample, but the absolute values of the magnitude of the coefficients on *DF* and DF^2 are significantly greater for the *DUAL* subsample than for the non-*DUAL* subsample. Also, Chow test between two subsamples is significant, and further t-statistics (for the coefficient difference) about *DF* and DF^2 between two subsamples are both significant. Above results, taken together, suggest that the inverted U-shaped effect of digital finance on accounting information transparency is more pronounced for the *DUAL* subsample than for the non-*DUAL* subsample.

7. Conclusions

Our findings reveal an inverted U-shaped relationship between digital finance and accounting information transparency. Moreover, the inverted U-shaped relation only stands for firms with CEO-chairman duality and firms in provinces with lower marketisation indexes.

Our findings have several managerial implications as below. First, digital finance brings out great convenience and information availability, but digital finance may lead to information overload, information cocoons and digital divide (Schultz & Vandenbosch, 1998). In reality, as our findings reveal, digital finance only promotes accounting information transparency within a specific range, but excessive digital finance impairs accounting information transparency. In this regard, regulators and the public should take use of the advantages and restrain the shortcomings of digital finance.

Second, firms in provinces with lower marketisation indexes and firms with CEO-chairman duality should pay close attention to the inverted U-shaped relationship between digital finance and accounting information transparency. Especially, due to information overload, the downside of excessive digital finance on accounting

information transparency may be enlarged in firms with CEO-chairman duality and firms in regions with lower marketisation indexes.

Lastly, due to an inverted U-shaped relation between digital finance and accounting information transparency, here comes a crucial question about to what extent digital finance should be regulated. Regulations always lag behind practices, and in reality, Fintech firms lack due regulations (Goldstein et al., 2019). As a result, information cocoons and digital divide are undermining the function of resource allocation efficiency of the capital market. In response, it is time for regulatory bodies to formulate and consummate regulations for digital financial service providers.

Our study has two limitations that can be addressed in future research. First, the Peking University Digital Financial Inclusion Index only provides province- (prefecture-) level indexes of digital finance, and thus our findings may undergo the challenges from cross-sectional self-correlation problems. In this regard, future research can further obtain firm-level data on digital finance to validate our findings. Second, it is a pending question about whether our findings based on the Chinese context can be generalised to other contexts. Thus, future research can employ the international setting to address the effects of digital finance on accounting information transparency.

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Appendix 1: Variable definition

Table A1. Variable definition.

Variable	Definition	Data Source
Variables for main tests		
TRAN	= Accounting information transparency, calculated on the basis of earnings aggressiveness (EA) and earnings smoothing (ES) (Bhattacharya et al., 2003).	Calculated
DF	= The degree of digital finance at the province level, measured as the PekingUniversity Digital Financial Inclusion Index at the province level divided 100.	<i>The PekingUniversity Digital Financial Inclusion Index</i>
DF ²	= The square term of the degree of digital finance at the province level (the PekingUniversity Digital Financial Inclusion Index at the province level divided 100).	<i>The PekingUniversity Digital Financial Inclusion Index</i>
FIRST	= Blockholder ownership, measured as the percentage of common shares held by the largest shareholder.	CSMAR
INDR	= The ratio of independent directors, measured as the number of independent directors scaled by the total number of directors in the boardroom.	CSMAR
BOARD	= Board size, measured as the natural logarithm of directors in the boardroom.	CSMAR
SIZE	= Firm size, measured as the natural logarithm of total assets.	CSMAR
LEV	= Financial leverage, measured as the ratio of liabilities (including long-term loan, short-term loan, bonds, and notes payable) to total assets.	CSMAR
ROA	= Returns on total assets, measured as net profits scaled by total assets.	CSMAR
OCF	= The ratio of cash flow, measured as the amount of cash flow from operational activities to total assets at the beginning of the year.	CSMAR
CAP	Capital expenditures, measured as the ratio of capital expenditures to total assets.	CSMAR
BTM	Book-to-market ratio, measured as book value of total assets scaled by the market value of total assets.	CSMAR
FIRIMAGE	= The natural logarithm of the number of years since a firm is founded.	CSMAR
STATE	= A dummy variable, equalling 1 for state-owned enterprises and 0 otherwise.	CSMAR
MKT	Marketisation index, which capture the degree of marketisation at the province level.	Wang et al. (2021)
Variables for robustness checks, endogeneity tests and additional tests		
DF_P	= The degree of digital finance at the prefecture level, measured as the PekingUniversity Digital Financial Inclusion Index at the prefecture level divided 100.	<i>The PekingUniversity Digital Financial Inclusion Index</i>
DF_P ²	= The square term of the degree of digital finance at the prefecture level (the PekingUniversity Digital Financial Inclusion Index at the prefecture level divided 100).	<i>The PekingUniversity Digital Financial Inclusion Index</i>
EA	= Earnings Aggressiveness, calculated based on Bhattacharya et al. (2003).	Calculated
IV	= Post offices per million population at the province level in 1984×the number of Internet ports of China	<i>Urban Statistical Yearbook Of China & CNRDS</i>
DUAL	= A dummy variable for CEO-chairman duality, equalling 1 if the CEO and the chairman of the board are the same person and 0 otherwise.	CSMAR
GDP	= per capita GDP in a province	CSMAR
DF_WA	= A weighted average digital finance index based on the proportion of 'sales revenue from each province to the firm's total sales revenue' and digital finance index at the province level.	Calculated
MD&A	= the natural logarithm of total vocabulary in MD&A (management discussion and analysis)	CSMAR
TIME	= the negative value of the time lag of annual reporting disclosure	CSMAR

Note: CSMAR, China Stock Market and Accounting Research; CNRDS, Chinese Research Data Services.