Internet of things adoption, earnings management, and resource allocation efficiency

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ABSTRACT
This study aims at addressing the economic consequences of the adoption of the Internet of Things (IoT) in China. As the fundamental technology for the next-generation information technology, IoT is supposed to have the most profound and comprehensive influence on both business operation and accounting information environment. By using a difference-in-differences method, our findings focusing on earnings management activities in China-listed firms around the adoption of IoT confirm the conjecture that such technology effectively deters accrual-based and real earnings management. The results are also robust to dynamic analysis, instrumental variable approach, PSM analysis, placebo tests and other robustness tests. Furthermore, we also document that the reduction in real earnings management due to IoT adoption has positive implications on the capital market, financing and investment activities and long-term operational efficiency. Taken together, we reveal the promising prospects of IoT adoption on corporate accounting information and establish the association between information technology and efficiency of resource allocation.

KEYWORDS
Information technology; Internet of Things (IoT); earnings management; resource allocation efficiency

1. Introduction

The industrial-scale adoption of the Internet of Things (IoT), a critical underlying pillar of new-generation information technology, has become a cornerstone for the information industry’s broader development. Meanwhile, for the manufacturing sector, IoT’s adoption promoted smart manufacturing and the implementation of ‘Industry 4.0’ and similar initiatives. On 10 September 2017, Luo Wen, Vice Minister of the Ministry of Industry and Information Technology of China, said at the World Internet of Things Wuxi Summit: ‘The market size of the Internet of Things in 2018 will exceed 100 billion U.S. dollars. By 2021, the number of connected devices will reach 28 billion, of which 16 billion are related to the Internet of Things’.\textsuperscript{1} IoT may introduce unprecedented transformation of a firm’s
production and operation processes and internal information environment (G. Wang et al., 2016). It also has a strong ‘value-adding’ effect for firm value (Addo-Tenkorang & Helo, 2016). However, the literature on cases of IoT adoption is limited (Appelbaum et al., 2017; Gepp et al., 2018; Vasarhelyi et al., 2015), and the empirical evidence about firm-level behavioural changes is remarkably scant.

The economic consequence of information technology adoption is also an important research topic (Dedrick et al., 2003; Dehning & Richardson, 2002). Early studies on cases of information technology adoption, such as enterprise resource planning, accounting information systems, customer relationship management, and supply chain management, revealed that information technology led to macroeconomic growth (Wu & Xie, 1999; Xu & Mao, 2004) and increase in firm value (Dedrick et al., 2003; Kobelsky et al., 2008). However, studies have also documented the ‘productivity paradox’ (Carr, 2003; Dehning & Richardson, 2002): due to the computer industry’s limited scale, measurement errors in information technology indicators, unpredictability of short-term technological effects (Triplett, 1999), risks related insufficient capabilities in implementing technologies, and technologies’ inherent control risks (Brown-Liburd et al., 2015; Han et al., 2016; H. W. Kim & Kankanhalli, 2009), the relationship between information technology adoption and macro or microeconomic performance may be insignificant (Lim et al., 2011). IoT adoption, which represents the new-generation information technology, may have two categories of firm-level effects: (1) Direct effects on business operation, that is, IoT adoption can improve resource allocation in production and operation processes and enhance the monitoring of the material flow process and key assets (Zhong et al., 2016). (2) Indirect effects through information, as IoT adoption can strengthen information integration, improve information transfer efficiency (Hendricks et al., 2007; Melville et al., 2004), and improve the internal information environment (Bendoly et al., 2009; Dorantes et al., 2013). Compared with previous information technology systems, IoT accompanied with an integral information technology solution, improves firm information efficiency further down the organisation, enabling unprecedented transformations in production, operation, and management processes (Addo-Tenkorang & Helo, 2016; G. Wang et al., 2016), and beyond the capability of any single information technology system. A single information technology system targets a given part of information and cannot profoundly affect or change business processes. Given these differences, examining the economic outcomes of IoT adoption has theoretical and practical implications, not simply repeating studies on economic outcomes of a single information technology system.

Specifically, this study aimed to explore the microeconomic outcomes of IoT adoption by observing firm-level earnings management behaviours. Accounting involves recording and reflecting economic events. As IoT can shape production and operation processes (Addo-Tenkorang & Helo, 2016; G. Wang et al., 2016), it may affect the information asymmetry in financial reporting process and earnings quality (Cohen et al., 2008; P. Dechow et al., 2010; Jensen & Meckling, 1976; Jones, 1991; Roychowdhury, 2006) and have a profound impact on accounting behaviours (Appelbaum et al., 2017; Gepp et al., 2018; Vasarhelyi et al., 2015; Warren et al., 2015). Earnings quality is regarded as a function of both information efficiency and operations, and aggressive earnings management undermines earnings quality. Accrual earnings management results in an ‘untrue’ representation of real business operations, while real earnings management aims to alter such
operations. Therefore, earnings management relates to both direct effects at the business level, and indirect effects at the information level, of IoT adoption. On the one hand, the automation process and integrated operation mode enabled by IoT helps to reduce abnormal management decision-making, alleviate the accounting information’s ‘distortion’ of real economic activities, restrict discretionary accounting information (Addo-Tenkorang & Helo, 2016; G. Wang et al., 2016; Zhong et al., 2016), and provide direct and thus more reliable evidence for professional accounting judgment, thereby deterring earnings manipulation. On the other hand, IoT can provide more efficient information flow (Bendoly et al., 2009; Dorantes et al., 2013), help optimise contract arrangement (Laux & Laux, 2009; Rajgopal et al., 2008), and improve internal control quality (Y. Chen et al., 2014; Morris, 2011), thus reduce firms’ motivations in earnings manipulation. Notably, the shift from traditional to intelligent manufacturing realised by IoT adoption has altered the underlying mechanism of earnings management, thereby leading to systematic changes in related behaviours.

IoT-enabled new generation information technology has become a strategic emerging industry in China’s development agenda. China, as a world-leading adopter of IoT, offers an opportunity for this study. Drawing on the methods of Morris (2011) and Dorantes et al. (2013), we constructed the indicator for IoT adoption based on ‘IoT’ announcements issued by listed companies from 2009 to 2016. Then, we employ the staggered difference-in-differences approach to examine how IoT adoption has affected earnings management behaviours and resource allocation. The results show that compared with firms that have not adopted IoT, those that adopted IoT experienced significant reduction in accrual, real, and total earnings management. Furthermore, we check the robustness of our findings by multiple techniques, such as propensity score matching (PSM), dynamic difference-in-differences, and instrumental variable approach to confirm that IoT adoption leads to lower firm-level earnings management. The mechanism involved can be inferred from tests showing that the main effects are significant only in groups with a decreasing proportion of production personnel, lower levels of asset impairment, lower agency costs, and fewer internal control deficiencies, all of which can be attributed to IoT’s direct and indirect effects.

Furthermore, this study investigated how the earnings management reduction after adopting IoT could affect resource allocation efficiency. On the one hand, reducing earnings management can deter managerial incentives to conceal bad news and increase stock price information content (Hutton et al., 2009), thereby enhancing resource allocation efficiency in the capital market (Jiang et al., 2018; H. Wang et al., 2015; Xu et al., 2012, 2013). On the other hand, it can improve investment efficiency (Li, 2009; H. Liu et al., 2014; Zhang & Liu, 2015) and facilitate corporate financing (Li, 2009). Moreover, real economic operating efficiency is correlated with capital market resource allocation, and skewed allocation caused by the capital market stock price will lead to inefficiency in the real economy. Moreover, earnings management distorts short-term earnings at the cost of firm sustainability; and the adoption of IoT through deterring earnings management

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2See the ‘Outline of the 13th Five-Year Plan for Economic and Social Development of the People’s Republic of China’ (as approved by the fourth session of the 12th National People’s Congress on 16 March 2016): http://www.npc.gov.cn/wxlz/gongbao/2016-07/08/content_1993756.htm; and ‘Made in China 2025’ (State Council document No. 2015 (28)): http://www.gov.cn/zhengce/content/2015-05/19/content_9784.htm.

3The first listed company announcement related to IoT appeared in 2009.
improves long-term operational efficiency. The empirical evidence presented below suggests that IoT adoption reduces real earnings management, thereby lowering the risk of stock price crashes, mitigating firms’ financing constraints, increasing investment efficiency, and improving long-term cost efficiency. In other words, the IoT-reduced real earnings management improved real economic operating efficiency and capital market resource allocation efficiency. However, while IoT adoption reduces accrual earnings management, it has no significant effects on resource allocation efficiency, consistent with the notion that the market can identify and constrain accrual earnings management, but real earnings management is harder to detect.

This study contributes in the following three ways. First, in the earnings management literature, studies focused on traditional manufacturing where the adoption of information technology is lacking. If any, only a single or specific information technology system was examined. As part of the next-generation information technology, IoT is often associated with smart manufacturing. In other words, IoT adoption completely changes earnings management’s basic conditions. It also depresses the space and motivation of earnings management, leading to its systematic reduction. This paper is the first to document that IoT adoption could systematically change earnings management behaviours and expand the earnings management literature. Second, in the literature on economic outcomes of information technology, with the focus on macro issues, empirical evidence at the micro-level is insufficient, particularly regarding the adoption of next-generation information technology (Appelbaum et al., 2017; Gepp et al., 2018; Vasarhelyi et al., 2015). Furthermore, the results are mixed, and no study has examined how information technology could affect firm-level accounting behaviours. This paper presents direct evidence about IoT’s impact on firm-level earnings management behaviours. It fills a gap in the literature by documenting the economic outcomes of information technology adoption at the firm level. Third, for China’s ambition to develop IoT and other cutting-edge information technologies to compete with other countries in technology, this paper indirectly offers some assurance about the effectiveness of China’s IoT implementation strategy. This study’s empirical evidence from the perspective of earnings management suggests that IoT adoption in China has positively affected firm behaviours.

2. Literature review

2.1. Technical background and prospects for IoT adoption

The concept of IoT can be traced back to 1991. Weiser (1991), in the article ‘The Computer for the 21st Century’, proposed that we need an indistinguishable computer network in our daily life. Such ubiquitous network comprises a variety of software and hardware devices connected through wired and wireless networks or infrared technology. The Massachusetts Institute of Technology’s Auto-ID Centre proposed a formal concept of IoT in 1999. This is a technology for automation control by connecting computers to identifiable objects through radio frequency technology. In addition, radio frequency identification and wireless sensor networks are considered the key basic technologies to realise IoT (Riahi Sfar et al., 2018). However, IoT for production and operation, and daily life did not gain traction until recent years due to constraints in telecommunication and integrated circuit manufacturing technologies as well as industrial production
capabilities. From the production and operation perspective, IoT helps firms better design, monitor and improve existing products, thus enhancing product performance and user experience. G.E. Aviation, for example, has installed hundreds of sensors on aircraft engines. Based on the collected data, the company can analyse the difference between actual performance and expectations to further optimise engine performance. An example more relevant to everyday life is the smart home. In China, large real estate companies like Vanke are testing the water in this area, expanding their business scope while improving user experience.

More relevant here is that the IoT adoption offers sufficient direct evidence for related internal decisions and external audits through tracking firm assets and transactions (Brown-Liburd et al., 2015). For example, in agricultural firms, IoT adoption improves data accuracy and frequency for measuring related biological assets; by continuously monitoring the environment and such assets through sensors, agricultural firms that adopt IoT have a more accurate picture of their assets, thus reducing the scope for earnings manipulation in biological asset pricing. It is evident that compared with traditional accounting information systems, IoT emphasises the concept of ‘Internet of Everything’ and expands the scope of information systems from the control process related to financial reporting to all firm assets. From the perspective of technical concepts, it is a breakthrough in technological innovation.

Meanwhile, with the gradual deployment of fifth-generation (5 G) communication technology, IoT will become an important link in the Industry 4.0 process and other similar initiatives characterised by intelligent manufacturing and customised production (Schwab, 2017). International Data Corporation predicted in 2021 that China’s IoT spending would reach 306.98 billion U.S. dollars in 2025, ranking first in the world. In addition, market segments for use cases such as industrial Internet, Internet of vehicles, and the smart city will be the critical growth areas, with a compound growth rate of about 13.4% in the next five years.

2.2. Literature review on economic outcomes of information technology

With increasing information technology adoption by firms (Dorantes et al., 2013; J.-B. Kim et al., 2017), its economic outcomes have become an important research topic (Dedrick et al., 2003; Dehning & Richardson, 2002; Masli et al., 2011). Many studies have shown that information technology adoption can promote macroeconomic growth (Wu & Xie, 1999; Xu & Mao, 2004), reshape market organisation, improve pricing efficiency (Fu & Cai, 2004; Zeng & Lin, 2006), deepen the division of labour, improve productivity and financial performance (Dedrick et al., 2003; Kobelsky et al., 2008), and enhance competitiveness and risk control (Bharadwaj, 2000; Bharadwaj et al., 1999; Dedrick et al., 2003; Dehning & Richardson, 2002). Some studies showed a ‘productivity paradox’ related to information technology adoption (Carr, 2003; Dehning & Richardson, 2002); there is no apparent connection between information technology adoption and the macroeconomy (Lim

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4Evergrande, Country Garden, Vanke Have Officially Entered into the Smart Home Industry: http://news.dichan.sina.com.cn/2021/02/01/1275647.html
5Alibaba Cloud: Intelligent Agricultural Solutions: https://iot.aliyun.com/solution/agriculture.
6International Data Corporation Release 2021 Worldwide Internet of Things Spending Guide: https://www.idc.com/getdoc.jsp?containerId=prCHC47846421
et al., 2011). For this discrepancy, Triplett (1999) considered the computer industry’s limited scale, measurement error in relevant indicators, and the unobservability of the effects of technological progress in the short term as possible reasons to explain the ‘productivity paradox’ of information technology adoption. In addition, with more frequent information technology upgrades, the risk of insufficient adoption capacity and control risks related to information technology themselves increase the negative impact on firms of the failure to adopt information technology (Brown-Liburd et al., 2015; Han et al., 2016; H. W. Kim & Kankanhalli, 2009).

Information technology adoption has direct and indirect effects on firms (Dehning & Richardson, 2002). Direct effects are related to operations, while indirect effects refer to the spillover effects of information technology adoption on management, organisation, control, and other links (Chan, 2000; Y. Chen et al., 2014; Masli et al., 2010). The direct effects of information technology adoption can be observed in the following areas: (1) improved resource allocation in production and operation processes; (2) reduced dependence on human resources for business operation; and (3) enhanced monitoring of the material flow process and key assets (Zhong et al., 2016). The indirect effects can be summarised as: (1) strengthened information integration; (2) reduced private information within organisations (Dikolli & Vaysman, 2006; Jensen & Meckling, 1992); (3) improved efficiency of information transfer (Chan, 2000; Hendricks et al., 2007; Melville et al., 2004); and (4) a better information environment within enterprises (Bendoly et al., 2009; Dorantes et al., 2013). These changes help improve internal control quality (Y. Chen et al., 2014; Morris, 2011) and optimise contractual arrangements (Laux & Laux, 2009; Rajgopal et al., 2008), thus alleviating agency problems.

However, a considerable portion of the above literature deals with enterprise resource planning and other individual use cases. The immaturity of the technology itself and the limited integration with other systems lead to notable uncertainty in economic outcomes. IoT enables unprecedented transformations in production, operation, and management processes (Addo-Tenkorang & Helo, 2016; G. Wang et al., 2016) beyond the capability of any single information technology systems. Therefore, even with the literature on the adoption of single information technology systems, research on IoT adoption could still generate some unique insights. IoT has the potential to remake the enterprise supply chain management model, strengthen monitoring of material flow and key assets, and have broader ‘value-adding’ effects (Addo-Tenkorang & Helo, 2016). Therefore, research on the economic outcomes of IoT adoption is more likely to reach a consistent conclusion with the effects of information technology development. However, the literature on IoT adoption is limited (Appelbaum et al., 2017; Gepp et al., 2018; Vasarhelyi et al., 2015). Theoretically, IoT adoption could have a profound impact on accounting behaviour (Appelbaum et al., 2017; Gepp et al., 2018; Vasarhelyi et al., 2015; Warren et al., 2015), and could affect financial reporting process and earnings quality (Cohen et al., 2008; P. Dechow et al., 2010; Jensen & Meckling, 1976; Jones, 1991; Roychowdhury, 2006). However, these theories have not been supported by any empirical evidence.
2.3. Literature review on earnings management

Due to information asymmetry in principal-agent relationship, management is motivated to manage earnings for specific interests. The motivations could be initial public offerings, executive compensation contracts, loan contracts, or avoiding reporting losses (Chen & Yuan, 2004; Jensen & Meckling, 1976; Teoh et al., 1998). The requirement of professional judgment in accounting estimation and accounting policy selection creates the earnings management opportunities within firms (Balsam et al., 1995; P. Dechow et al., 2010; Jones, 1991; Zmijewski et al., 1981). Management also can manipulate accruals or earnings by constructing real production and transactions, such as overproduction to reduce unit costs, altering credit terms to boost current revenue, and selling productive assets (Cohen et al., 2008; P. Dechow et al., 2010; Roychowdhury, 2006). However, earnings management is not costless. Firms will weigh the pros and cons and choose different levels of earnings management and the combination of different approaches (Zang, 2012).

Earnings management also has adverse effects. The higher the level of earnings management, the lower the firm’s market return (Chen & Yuan, 2004), and real earnings management leads to declining corporate performance after private placement, which is more severe than accrual earnings management (Cohen & Zarowin, 2010). Earnings management may also lead to low stock price information content (Hutton et al., 2009; Jin & Myers, 2006), and distort resource allocation in capital markets due to the stock price will lead to low investment and financing efficiency in the real economy (Li, 2009; H. Liu et al., 2014). Therefore, it is necessary to appropriately restrict earnings management behaviour. The above literatures imply, IoT for intelligent manufacturing reduces human participation, strengthen the human-free management, and control of the production and operation processes and key assets (Zhong et al., 2016); improves the information environment (Jensen & Meckling, 1992); and optimises contracts and improves internal control quality (Rajgopal et al., 2008), which thereby may depress earnings management motivation and space. IoT adoption fundamentally changes earnings management incentives and opportunities. To illustrate the difference, consider what types of buildings we could build on a given foundation, then consider what will happen to the buildings that could have been built when the foundation is changed. This study aims at documenting for the first time the systematic changes in earnings management behaviours when the foundation of earnings management changes, filling the above gaps in the earnings management literature.

2.4. Research hypothesis

According to literature of direct effects of information technology and recent application cases of IoT, the information and analysis methods and tools provided by automated processes reduce the possibility of abnormal business decisions, narrow the scope of accounting professional judgment, and alleviate the ‘distortion’ of real economic business in accounting information, thus limiting the space for earnings manipulation. As the financial reporting system can automatically obtain faithful information from IoT systems, and automatically produce the required information in the reporting system, the degree of human involvement in the financial reporting process can be reduced significantly. Because the requirements of accounting standards and accounting choices have been
internalised in the financial reporting process, it is impossible for human intervention to change the results of earnings reporting unless a procedure setting is changed. In addition, the deep integration of financial reporting and business systems enhances cost and expense traceability. Many indirect costs that need to be allocated in the traditional environment can be directly traced with IoT adoption, greatly reducing the possibility of earnings manipulation through expense allocation. Also, deep integration of financial reporting and business systems can provide more relevant evidence for accounting professional judgment. When evidence is not sufficient, more professional judgment is involved in accounting recognition and measurement. Accounting estimation itself can create a large earnings manipulation space for management. For example, when the asset information is less relevant, management can manipulate earnings by changing depreciation and asset impairment provision (P. Dechow et al., 2010; Houston et al., 1999). By strengthening key asset control and providing more direct evidence for professional judgment, IoT restrains manipulative behaviours related to these assets, making it less likely for firms to conduct real earnings management by constructing real transactions.

Meanwhile, spillover effects from IoT adoption help firms alleviate agency problems by optimising contract arrangement, curb management self-serving behaviours originated from internal information asymmetry, and improve the efficiency of internal controls, especially those related to financial reporting, thereby inhibiting motivation of earnings manipulation. Information asymmetry is the premise earnings management motivation. Inadequate information leads to sub-optimal contracts, which allow management to engage in ‘empire building’. At the same time, without sufficient information verification from information technology, financial information may be the main source for contracting, and self-interested executives may seek to control or manipulate such information. With IoT adoption, the interconnection of things and improve traceability of fundamental information allow firms to include more non-financial and objective information in the contracts. Moreover, the deep integration between business and financial reporting systems enhances matching financial and non-financial information, improving transparency within the organisation and relationships between stakeholders. Thus, the space for seeking personal gains by using information asymmetry is greatly reduced. In other words, IoT adoption can curb firms’ motivation for earnings management, thereby reducing earnings management behaviours. We, therefore, based on the direct and indirect effects of IoT adoption propose the main hypothesis as follows:

Hypothesis: compared with firms that have not adopted IoT, those adopting IoT will experience a significant reduction in earnings management.

3. Research design

3.1. Data sources and sample selection

First of all, this study drew from the techniques used by Morris (2011) and Dorantes et al. (2013). The announcements of listed companies were downloaded by Python from http://www.cninfo.com.cn/, the Shenzhen Stock Exchange’s official platform for information disclosure. Then, crawler technology was employed to screen the announcements for
those containing the keyword ‘IoT’. We also manually sorted the announcements by type, including those related to seasoned equity offerings, private placement, mergers and acquisitions, assets acquisition, research and development, the establishment of buyout funds or industry funds, government subsidies, strategic cooperation agreement, and changes in business scope. To avoid possible measurement errors, because vendors of IoT equipment, technologies, and software are not necessarily IoT adopters or profoundly impacted by IoT, we excluded firms that include ‘IoT’ in their business scope. After that, we obtained a sample containing 360 A-share listed companies, covering 678 IoT-related announcements from 2009 to 2016.

The annual distribution of IoT announcements shows that these announcements emerged in 2009. The number has increased year by year since, indicating that IoT has been increasingly popular for listed companies. In terms of industrial distribution, 62.54% of IoT adopters are from the manufacturing sector, 24.93% from the information technology sector, and 4.13% from the retail sector. The distribution is in line with government policies, which focus on key areas such as ‘smart manufacturing’ and ‘new retail’. Regarding the announcement types, those related to government subsidies account for about 52.95% of the total. According to the ‘Interim Measures for Managing Special Funds for the Development of the Internet of Things’ formulated by the Ministry of Industry and Information Technology in 2011, the release of the announcements regarding government subsidies implies that these listed companies have adopted IoT. About 19.62% relate to IoT strategic agreements signed with government agencies, public institutions, or Internet firms, indicating that some listed companies promote their IoT plans through joint building and sharing. The remaining firms acquired key assets and technologies of IoT through self-financing (18.58%) and investment (8.85%).

Secondly, we combined the above data with the entire dataset for A-share listed companies from 2009 to 2016 in the China Stock Market & Accounting Research Database and obtained a sample containing 20,600 year-firm observations. Among them, 376 observations are from the financial industry, 808 from ST firms, 934 from firms with a debt-asset ratio greater than 1 or less than 0, 3,806 from firms whose industry has less than 20 observations within a year and therefore whose earnings management value cannot be estimated, and 2,140 from firms whose control variables are missing. Removal of the above observations results in a final sample of 12,536 firm-year observations, of which 1,650 have released IoT-related announcements. Finally, 1% Winsorising was performed for all continuous variables to eliminate the influence of outliers.

3.2. Model specification and variable definition

This study drew from Cohen et al. (2008) and constructed the multi-periods difference-in-differences Model (1) to examine how IoT adoption affects earnings management behaviours.

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7According to the 2012 Industrial Classification Code of China Securities Regulatory Commission, they refer to firms with the initial letter J. This type of firms was excluded because the report forms are different.

8If the debt-asset ratio is not in the range of (0, 1), we may infer that the firms are under a major asset reorganisation or other abnormal state. Given the impact on audit behaviours and related measurement errors, these firms were excluded.

9The lack of control variables mainly relates to accounting firms and Tobin’s Q. The missing of the latter is primarily the result of the lack of market value data.
where the explained variable \(Earnings_{management}\) reflects the level of earnings management, comprising accrual earnings management \(|Discretionary_{accruals}|\), real earnings management \(Real_{earnings_{management}}\), and total earnings management \(Total_{earnings_{management}}\). For the measurement of the variables, we calculate \(|Discretionary_{accruals}|\) following P. M. Dechow et al. (1995) and Kothari et al. (2005), on the basis of the Modified Jones Model and with adjustment of the previous return on total assets, to estimate the absolute value of residuals from regressions by industry and year; we calculate \(Real_{earnings_{management}}\) following Roychowdhury (2006) and Cohen et al. (2008), to estimate the abnormal cash flow, abnormal production costs, and abnormal expenses by industry and year, and take the summation; and we calculate \(Total_{earnings_{management}}\) following Chan et al. (2015), by adding up \(|Discretionary_{accruals}|\) and \(Real_{earnings_{management}}\).

The explanatory variable \(IoT\) reflects whether the firm is an IoT adopter. For observations belong to the firm that has released the IoT announcement, \(IoT\) was assigned as 1 for the announcement year and subsequent years; otherwise, \(IoT\) is 0. Since the firm fixed effects \(\delta_i\) and year fixed effects \(\theta_t\) have been controlled for, or the effects of the experimental and control groups before and after treatment are controlled, the regression coefficient of IoT should reflect the changes in earnings management for the experimental group relative to the control group after IoT adoption. Based on the above hypothesis, the regression coefficient for \(IoT \beta_1\) should be significantly negative.

\(X\) are the control variables, specifically including natural logarithm of total assets at the end of the year \(Size\); years after the establishment of the firm \(Firm\_age\); \(Return\_on\_assets\); debt-assets ratio \(Leverage\); the growth rate of sales \(Sale\_growth\); Tobin’s Q \(Tobin\_Q\); whether the firm report at a net loss in the current year \(Loss\); whether the audit is performed by the international Big Four accounting firms in the current year \(Big4\); whether it is a state-owned enterprise \(State\_owned\_enterprise\); the number of board members \(Board\_size\); whether the chairman and CEO are held by the same person \(CEO\_duality\); and the proportion of independent directors \(Board\_independence\). In addition, to eliminate heteroscedasticity caused by firm heterogeneity as much as possible, all the standard errors of regression estimation coefficients were cluster-adjusted at the firm level.

### 3.3. Descriptive statistics

Table 1 presents descriptive statistics for the main variables. The results show that: (1) The mean of IoT adoption is 0.06, indicating that only 6% of the sample firms are IoT adopters. Given the small proportion of the experimental group, to avoid potential sample selection bias, PSM was performed to remove possible measurement bias in robustness tests. (2) The mean and median of the absolute value of \(|Discretionary_{accruals}|\) are 0.076 and 0.048, those of \(Real_{earnings_{management}}\) are −0.035 and 0.036, and of \(Total_{earnings_{management}}\) are 0.045 and 0.078, respectively. The overall distribution is biased but basically consistent with existing literature.
4.2.1. Mechanism analysis: direct and indirect effects of IoT adoption on earnings quality

4.2.1. Earnings management and direct effects of IoT adoption

IoT adoption could reduce firms’ dependence on human operations resources. Particularly, in smart manufacturing, the proportion of production staff can be remarkably reduced. Although IoT adoption requires considerable investments in related equipment and software, supported by IoT, firms could use their assets for more efficient operations, thereby reducing the overall level of asset impairment. Therefore, here, we will discuss IoT’s direct effects from the perspective of the change in the proportion of production staff and assets impairment. In Table 3, Panel A presents the subsample regression results
Table 2. Baseline analysis.

|                      | Discretionary_accruals | Real_earnings_management | Total_earnings_management |
|----------------------|------------------------|--------------------------|---------------------------|
|                      | (1)                    | (2)                      | (3)                       | (4)                       | (5)                       | (6)                       |
| **IoT**              | -0.019***              | -0.031***                | -0.216***                 | -0.121**                 | -0.233***                 | -0.146***                 |
|                      | (-2.312)               | (-3.778)                 | (-4.026)                  | (-2.307)                 | (-4.383)                  | (-2.807)                  |
| **Size**             | 0.054***               |                          | -0.510***                 | -0.464***                |                          |                          |
|                      | (13.169)               |                          | (-19.436)                | (-17.723)                |                          |                          |
| **Firm_age**         | -0.008***              |                          | 0.104***                  | 0.098***                 |                          |                          |
|                      | (-8.514)               |                          | (17.063)                 | (16.215)                 |                          |                          |
| **Sale_growth**      | 0.008***               |                          | -0.060***                 | -0.051***                |                          |                          |
|                      | (7.304)                |                          | (-8.967)                 | (-7.728)                 |                          |                          |
| **Tobin_Q**          | 0.004***               |                          | -0.101***                 | -0.095***                |                          |                          |
|                      | (3.323)                |                          | (-12.651)                | (-11.891)                |                          |                          |
| **Return_on_assets** | 0.332***               |                          | -0.820***                 | -0.072                   |                          |                          |
|                      | (6.726)                |                          | (-2.617)                 | (-2.232)                 |                          |                          |
| **Leverage**         | 0.062***               |                          | -0.417***                 | -0.343***                |                          |                          |
|                      | (4.046)                |                          | (-4.301)                 | (-3.550)                 |                          |                          |
| **Loss**             | 0.032***               |                          | 0.048                     | 0.089***                 |                          |                          |
|                      | (5.254)                |                          | (1.249)                  | (2.329)                  |                          |                          |
| **Big4**             | 0.11                   |                          | 0.121                     | 0.136                    |                          |                          |
|                      | (0.745)                |                          | (1.263)                  | (1.425)                  |                          |                          |
| **State_owned_enterprise** | -0.019*               |                          | 0.066                     | 0.056                    |                          |                          |
|                      | (-1.660)               |                          | (0.911)                  | (0.780)                  |                          |                          |
| **Board_size**       | 0.000                  |                          | 0.029***                  | 0.027***                 |                          |                          |
|                      | (0.065)                |                          | (2.731)                  | (2.472)                  |                          |                          |
| **Board_independence** | -0.040                |                          | -0.143                    | -0.224                   |                          |                          |
|                      | (-0.974)               |                          | (-0.550)                 | (-0.866)                 |                          |                          |
| **CEO_duality**      | 0.011**                |                          | 0.022                     | 0.031                    |                          |                          |
|                      | (2.181)                |                          | (0.701)                  | (0.990)                  |                          |                          |
| **Constant**         | 0.084***               | -1.034***                | -0.183***                 | 9.890***                 | -0.096***                 | 9.001***                 |
|                      | (19.906)               | (-12.120)                | (-6.737)                 | (18.230)                 | (-3.567)                 | (16.655)                 |
| **Firm FE**          | YES                    | YES                      | YES                      | YES                      | YES                      | YES                      |
| **Year FE**          | YES                    | YES                      | YES                      | YES                      | YES                      | YES                      |
| **Observations**     | 12,536                 | 12,536                   | 12,536                   | 12,536                   | 12,536                   | 12,536                   |
| **R-squared**        | 0.022                  | 0.059                    | 0.039                    | 0.101                    | 0.042                    | 0.092                    |
| **F**                | 28.76                  | 33.37                    | 51.93                    | 60.34                    | 56.23                    | 54.06                    |

\[ t\text{-statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels (two-tailed), respectively.} \]

According to whether the proportion of production staff decreases, when the proportion of production staff falls, or with a higher level of operational automation, IoT is significantly and negatively correlated with all earnings management variables at least at the 10% level. These results reveal a possible channel: IoT adoption may improve operational automation, reduce human resources dependence, and thus depress the earnings management space. In Table 3, Panel B presents the subsample regression results according to the industry-year median of the assets impairment to operating revenue ratio. In the group with lower assets impairment, the coefficient of IoT is significantly negative at least at the level of 5%. We can infer that IoT adoption increases firms’ ability to manage and control assets, thereby reducing the earnings management space. In summary, IoT reduces the space of earnings management through its direct effects on firms, thereby supporting this paper’s arguments.

\[ ^{10}\text{Although the China Securities Regulatory Commission requires firms to disclose the information of employee categories, the specific items vary according to firms’ business types. Therefore, the results of this group are estimated based on available data for proportion of production staff (business staff). In line with extant literature, the sample accounts for about 80% of the total sample.} \]
Table 3. Earnings management and direct effects of IoT adoption.

Panel A: Human resources

|               | Discretionary accruals | Real_earnings_management | Total_earnings_management |
|---------------|------------------------|--------------------------|---------------------------|
|               | High (1)               | Low (2)                  | High (3)                  | Low (4)                  | High (5)               | Low (6)                  |
| IoT           | 0.001 (0.099)          | -0.033**                 | -0.123                    | -0.133*                  | -0.121                 | -0.155*                  |
| Controls      | YES                    | YES                      | YES                       | YES                      | YES                    | YES                      |
| Firm FE       | YES                    | YES                      | YES                       | YES                      | YES                    | YES                      |
| Year FE       | YES                    | YES                      | YES                       | YES                      | YES                    | YES                      |
| Observations  | 4,425                  | 5,469                    | 4,425                     | 5,469                    | 4,425                  | 5,469                    |
| R-squared     | 0.099                  | 0.051                    | 0.128                     | 0.139                    | 0.123                  | 0.127                    |
| F             | 14.61                  | 9.687                    | 19.50                     | 29.26                    | 18.49                  | 26.48                    |

Panel B: Impairment

|               | Discretionary accruals | Real_earnings_management | Total_earnings_management |
|---------------|------------------------|--------------------------|---------------------------|
|               | Low (1)                | High (2)                 | Low (3)                   | High (4)                 | High (5)               | Low (6)                  |
| IoT           | -0.012 (−1.245)        | -0.056***                | -0.066                    | -0.224**                 | -0.072                 | -0.278***                |
| Controls      | YES                    | YES                      | YES                       | YES                      | YES                    | YES                      |
| Firm FE       | YES                    | YES                      | YES                       | YES                      | YES                    | YES                      |
| Year FE       | YES                    | YES                      | YES                       | YES                      | YES                    | YES                      |
| Observations  | 6,379                  | 6,157                    | 6,379                     | 6,157                    | 6,379                  | 6,157                    |
| R-squared     | 0.071                  | 0.062                    | 0.112                     | 0.099                    | 0.107                  | 0.087                    |
| F             | 17.98                  | 14.68                    | 29.81                     | 24.38                    | 28.29                  | 21.25                    |

_t-statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

4.2.2. Earnings management and indirect effects of IoT adoption

The indirect effects of IoT adoption are primarily reduced agency problems and increased internal control quality. Therefore, if IoT adoption is effective, the management expenses ratio as the metrics for the first type of agency problems as well as the probability of internal control deficiencies will decrease. In Panel A of Table 4, the agency costs are measured by the management expenditures growth rate. The subsample regression results according to the metrics’ industry-year mean indicate that with lower management expenditures growth, or fewer agency problems, the coefficient of IoT is significantly negative at least at the 10% level. This suggests that IoT adoption can alleviate agency problems and thus inhibit firms’ earnings management motivation. In Table 4, Panel B presents the subsample regression results according to whether internal control deficiencies are disclosed in DIB Database. For those without disclosure of internal control deficiencies, or firms with good internal control quality, IoT is significantly and negatively correlated with earnings management at the level of 5%. This indicates that IoT adoption inhibits firms’ earnings management motivation through improving the quality of internal control. In short, IoT limits earnings management motivation through its indirect effects on the firms, thereby lending more support to this paper’s arguments that lead to the hypothesis.
Table 4. Earnings management and indirect effects of IoT adoption.

Panel A: Agency costs

|                      | Discretionary_accruals | Real_earnings_management | Total_earnings_management |
|----------------------|------------------------|--------------------------|---------------------------|
|                      | High       | Low       | High       | Low       | High       | Low       |
| IoT                  |            |            |            |            |            |            |
|                      | (1)        | (2)       | (3)        | (4)       | (5)        | (6)       |
| Controls             | YES        | YES       | YES        | YES       | YES        | YES       |
| Firm FE              | YES        | YES       | YES        | YES       | YES        | YES       |
| Year FE              | YES        | YES       | YES        | YES       | YES        | YES       |
| Observations         | 3,294      | 9,242     | 3,294      | 9,242     | 3,294      | 9,242     |
| R-squared            | 0.094      | 0.039     | 0.143      | 0.084     | 0.126      | 0.085     |
| F                    | 8.749      | 14.79     | 14.06      | 34.02     | 12.10      | 34.09     |

Panel B: Internal control deficiency

|                      | Discretionary_accruals | Real_earnings_management | Total_earnings_management |
|----------------------|------------------------|--------------------------|---------------------------|
|                      | ICD                    | No ICD                   | ICD                       | No ICD                   | ICD                       | No ICD                   |
|                      | (1)                    | (2)                      | (3)                       | (4)                      | (5)                       | (6)                      |
| IoT                  |                        |                          | -0.020**                  |                          | -0.035                   | -0.129**                 |
|                      | (-1.195)               | (-2.411)                 | (-0.040)                 | (-1.994)                | (-0.166)                 | (-2.285)                |
| Controls             | YES                    | YES                     | YES                      | YES                     | YES                      | YES                     |
| Firm FE              | YES                    | YES                     | YES                      | YES                     | YES                      | YES                     |
| Year FE              | YES                    | YES                     | YES                      | YES                     | YES                      | YES                     |
| Observations         | 1,970                  | 10,566                  | 1,970                    | 10,566                  | 1,970                    | 10,566                  |
| R-squared            | 0.066                  | 0.070                   | 0.113                    | 0.105                   | 0.102                    | 0.095                   |
| F                    | 3.605                  | 32.94                   | 6.454                    | 51.27                   | 5.802                    | 46.02                   |

t-statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

4.3. Robustness tests

4.3.1. Dynamic analysis

Following Bertrand and Mullainathan (2003), we constructed a multi-period dynamic difference-in-differences model to investigate dynamic changes of earnings management in the years before and after IoT adoption. Also, tests were performed to validate the ‘parallel trend assumption’. In the model, $\text{IoT}_{-\text{Before}}$, $\text{IoT}_{-\text{Before}}^1$, $\text{IoT}_{-\text{Current}}$, $\text{IoT}_{-\text{Post}}$, and $\text{IoT}_{-\text{Post}}^2$ denote the first two years, the previous year, the current year, the next year, and the next two years in relation to IoT adoption. The value assigned is 1 for the specific year; otherwise, it is 0. The Table 5 regression results show that: (1) For accrual earnings management, the coefficient of $\text{IoT}_{-\text{Before}}$ is significantly negative, indicating that it does not fully conform to the parallel trend assumption. Also, firms’ accrual earnings management has decreased before IoT adoption, and this effect gradually increases over time. It should be noted that the case of accrual-based earnings management may relate to some managerial actions of IoT adoption before the announcement. In addition, while accrual earnings management occurs at year end, the previous annual report is generally disclosed before April. With a possible overlap between annual report preparation and the IoT adoption, management may adjust last year’s earnings management according to IoT events. (2) For real earnings management and total earnings management, the coefficients for IoT adoption year $\text{IoT}_{-\text{Current}}$ and the subsequent two years are significantly negative. In contrast, those for the previous two years $\text{IoT}_{-\text{Before}}^2$ and previous year $\text{IoT}_{-\text{Before}}^1$ are insignificant, fully conforming to the parallel trend
assumption and indicating that IoT adoption limits firms’ real earnings management. It is understandable as real earnings management is harder to detect and the management will not regulate such earnings management behaviour in advance. Moreover, IoT adoption is closely related to enterprise production and operation; its inhibiting effects on real earnings management are more likely to emerge after IoT adoption. Overall, the results are generally consistent with the regression results, indicating that IoT adoption effectively inhibited earnings management.¹¹

4.3.2. PSM analysis

We also construct a PSM sample to correct for the potential functional form misspecification problem caused by unbalanced sample distribution. In the matching process, the covariates comprise all one-period lagged control variables. The nearest neighbour 1:1 method was used to identify the firm to be paired from the observations in the year during which an experimental group firm adopted IoT. The P-Score was calculated year by year to obtain a control group for each year. Specifically, for a firm that adopted IoT (in the experimental group), we first determined the adoption year. Then, we calculated P-Score by using the above variables for all the observations in the year to identify the nearest neighbour as the control group firm. After that, we matched all the year observations (both before and after adoption) of the experimental group firms with those of control group. After excluding observations without a matched year, we obtained 1,312 pairs of observations for 290 pairs of firms or a total of 2,624 observations. The difference test results of matched variables are shown in Panel A of Table 6. They suggest that the differences between the experimental group and the control group in various covariates are effectively removed. The regression results in Panel B of Table 6 show that a relatively robust conclusion can still be obtained after PSM matching. They suggest that after

¹¹Because we employ the staggered difference-in-differences research design, we do not draw the parallel trend tables or figures for the ex-ante means of earnings management measurements. However, the dynamic analysis in this section is mostly equivalent to the separated parallel trend table or figures.

Table 5. Dynamic analysis.

|                  | Discretionary_accruals | Real_earnings_management | Total_earnings_management |
|------------------|------------------------|--------------------------|---------------------------|
|                  | (1)                    | (2)                      | (3)                       |
| IoT_Before²      | −0.000                 | 0.051                    | 0.053                     |
|                  | (−0.000)               | (0.681)                  | (0.711)                   |
| IoT_Before¹      | −0.028**               | −0.053                   | −0.076                    |
|                  | (−2.398)               | (−0.708)                 | (−1.020)                  |
| IoT_Current      | −0.024**               | −0.179**                 | −0.196**                  |
|                  | (−2.082)               | (−2.397)                 | (−2.655)                  |
| IoT_Post¹        | −0.031**               | −0.249***                | −0.280***                 |
|                  | (−2.246)               | (−2.842)                 | (−3.222)                  |
| IoT_Post²        | −0.042***              | −0.292***                | −0.327***                 |
|                  | (−3.000)               | (−3.227)                 | (−3.659)                  |
| Firm FE          | YES                    | YES                      | YES                       |
| Year FE          | YES                    | YES                      | YES                       |
| Observations     | 12,536                 | 12,536                   | 12,536                    |
| R-squared        | 0.023                  | 0.039                    | 0.043                     |
| F                | 19.88                  | 34.90                    | 37.91                     |

*t-statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels (two-tailed), respectively.
### Table 6. PSM analysis.

**Panel A: Balance tests**

|                | Treated | Control – Before | Control – Post | Diff. |
|----------------|---------|------------------|----------------|-------|
|                | N       | Mean             | N              | Mean  | Before | Post  |
| **Size**       | 1312    | 21.75            | 10,886         | 22.037| 1312   | 21.724| 0.288***| −0.026|
| **Firm_age**   | 1312    | 13.804           | 10,886         | 14.743| 1312   | 13.165| 0.939***| −0.639***|
| **Sale_growth**| 1312    | 0.537            | 10,886         | 0.493 | 1312   | 0.459 | −0.044| −0.078|
| **Tobin_Q**    | 1312    | 2.76             | 10,886         | 2.109 | 1312   | 2.603 | −0.651***| −0.157*|
| **Return_on_assets** | 1312 | 0.049            | 10,886         | 0.038 | 1312   | 0.047 | −0.011***| −0.003|
| **Leverage**   | 1312    | 0.395            | 10,886         | 0.462 | 1312   | 0.392 | 0.067***| 0.003|
| **Loss**       | 1312    | 0.051            | 10,886         | 0.088 | 1312   | 0.059 | 0.037***| 0.008|
| **Big4**       | 1312    | 0.025            | 10,886         | 0.06  | 1312   | 0.018 | 0.035***| −0.007|
| **State_owned_enterprise** | 1312 | 0.355            | 10,886         | 0.47  | 1312   | 0.371 | 0.115***| 0.016|
| **Board_size** | 1312    | 8.555            | 10,886         | 8.904 | 1312   | 8.584 | 0.349***| 0.029|
| **Board_independence** | 1312 | 0.373            | 10,886         | 0.371 | 1312   | 0.37  | −0.002| −0.003|
| **CEO_duality**| 1312    | 0.274            | 10,886         | 0.219 | 1312   | 0.26  | −0.055***| −0.014|

**Panel B: Regression using PSM sample**

|                | [Discretionary_accruals] | Real_earnings_management | Total_earnings_management |
|----------------|--------------------------|--------------------------|---------------------------|
|                | (1)                      | (2)                      | (3)                       | (4)                       | (5)                          | (6)                          |
| **IoT**        | −0.022*                  | −0.024*                  | −0.241***                 | −0.155**                  | −0.259***                    | −0.167***                    |
|                | (−1.691)                 | (−1.900)                 | (−3.579)                  | (−2.389)                  | (−3.810)                     | (−2.621)                     |
| Controls       | NO                       | YES                      | NO                        | YES                       | NO                           | YES                          |
| Firm FE        | YES                      | YES                      | YES                       | YES                       | YES                          | YES                          |
| Year FE        | YES                      | YES                      | YES                       | YES                       | YES                          | YES                          |
| Observations   | 2.624                    | 2.624                    | 2.624                     | 2.624                     | 2.624                        | 2.624                        |
| R-squared      | 0.016                    | 0.029                    | 0.023                     | 0.113                     | 0.026                        | 0.107                        |
| F              | 4.224                    | 3.254                    | 6.149                     | 13.79                     | 6.939                        | 12.96                        |

*t*-statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels (two-tailed), respectively.
conclusions

further controlling the heterogeneity factors at the firm level, IoT adoption still shows an inhibitory effect on earnings management behaviours. The robustness of this paper’s conclusions is thus proved.

4.3.3. Instrumental variable method

Table 7 presents the regression results using the two-stage least-square method, which further dismisses the possible influence of endogeneity on our conclusions. For columns (1) and (2), two instrumental variables were constructed: \( \text{IoT}_\text{Ind}\_\text{Avg}_{t-1} \) and \( \text{IoT}_\text{Ind}\_\text{Sum}_{t-1} \), respectively, represent the proportion of listed companies of the same industry that adopted IoT in the previous year and the natural logarithm of the number of those firms. Linear probability model\(^{12}\) was used to predict whether the target firm will adopt IoT in the first-stage regressions. Generally, IoT adoption is affected by factors such as a firm’s industrial policies, product competition, and market demand. As these factors are similar in the same industry, and a listed company tends to follow the business strategies of their competitors and adopt the strategies as appropriate, the IoT adoption by other firms in the industry may affect the target firm’s technological strategies. Meanwhile, the other firms’ behaviours in adopting technologies generally have no direct effect on the target firm’s disclosure quality. Therefore, the instrumental variables used in this study adequately meet the restrictions of exclusion. The first-stage regression also shows that the \( F \) values are 8.380 and 8.021, respectively, which reject the hypothesis of weak instrumental variables to some extent. The second stage regression results presented in columns (3)–(8) reveal that the fitted values for IoT adoption are significantly and negatively correlated to \( |\text{Discretionary}\_\text{accruals}| \) at the 10% level, and to \( \text{Real}\_\text{earnings}\_\text{management} \) and \( \text{Total}\_\text{earnings}\_\text{management} \) at the 1% level. The results prove that our conclusions are still robust after further considering endogeneity.

\(^{12}\)The benchmark regression model in this paper includes firm fixed effects. To maintain the consistency of the measurement method, the effects were also incorporated in the first stage. However, some observations were lost due to multicollinearity in Logistic or Probit model estimation. Therefore, the ordinary least square model, or the linear probability model was used for estimation. The results estimated by Logistic or Probit models with fixed effects are basically consistent with the listed results except for the reduction of sample size.

### Table 7. Instrumental variable method.

|                  | (1)       | (2)       | (3)       | (4)       | (5)       | (6)       | (7)       | (8)       |
|------------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| \( \text{IoT}_\text{Ind}\_\text{Avg}_{t-1} \) | 1.026***  | (7.738)   |           |           |           |           |           |           |
| \( \text{IoT}_\text{Ind}\_\text{Sum}_{t-1} \) | 0.048***  | (7.620)   |           |           |           |           |           |           |
| \( \text{IoT}\_\text{Predicted}^1 \)       | –0.007*   | (−1.649)  | –1.301*** | (−6.703)  | –1.091*** | (−5.806)  |           |           |
| \( \text{IoT}\_\text{Predicted}^2 \)       | –0.007*   | (−1.835)  | –2.730*** | (−8.915)  | –2.459*** | (−8.194)  |           |           |
| Controls         | YES       | YES       | YES       | YES       | YES       | YES       | YES       | YES       |
| Firm FE          | YES       | YES       | YES       | YES       | YES       | YES       | YES       | YES       |
| Year FE          | YES       | YES       | YES       | YES       | YES       | YES       | YES       | YES       |
| Observations     | 10,785    | 10,785    | 10,785    | 10,785    | 10,785    | 10,785    | 10,785    | 10,785    |
| R-squared        | 0.110     | 0.093     | 0.696     | 0.059     | 0.048     | 0.095     | 0.065     | 0.053     |
| \( F \)          | 8.380     | 8.021     | 28.99     | 19.41     | 17.23     | 30.39     | 20.00     | 17.78     |

In column (1) and (2), the dependent variables are \( \text{IoT} \); in column (3) and (6), the dependent variable is \( |\text{Discretionary}\_\text{accruals}| \); in column (4) and (7), the dependent variable is \( \text{Real}\_\text{earnings}\_\text{management} \); in column (5) and (8), the dependent variable is \( \text{Total}\_\text{earnings}\_\text{management} \). \( t \)-statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels (two-tailed), respectively.
In addition, we performed other robustness tests. First, we excluded ‘cheap talk’ firms that did not follow through with their announcements. In the IoT-related announcements investigated here, details of government subsidies and information related to strategic agreements are not definitely associated with following investments. Therefore, they were excluded from the robustness test. Second, by only shortening research sample period from 2011 to 2015 or deleting the observations for the adoption year, our main conclusions still hold. Finally, by falsifying the listed companies and the date of IoT announcements, we constructed a placebo sample for testing. The results show that none of the IoT adoption regression coefficients is significant, confirming that the changes in firms’ earnings management are indeed caused by IoT adoption.

5. Effects of IoT adoption on resource allocation efficiency through reduced earnings management

5.1. Effects of IoT adoption on resource allocation efficiency in the capital market through reduced earnings management

Accounting information influences the flow of capital through market price and effective accounting information contributes to efficient capital flow. Poor quality financial reports and a high degree of information asymmetry provide management with space to hide bad news, thus distorting the available information in the capital market and misleading capital flow, ultimately leading to stock price crashes (J. B. Kim & Zhang, 2016; J. Chen et al., 2001; Hutton et al., 2009; Jin & Myers, 2006). Therefore, here, we used the risk of stock price crashes to measure resource allocation efficiency in the capital market. Following J. B. Kim et al. (2011), we constructed Model (2) to investigate whether IoT adoption has improved resource allocation efficiency in the capital market through reduced earnings management.

\[ MktEff_{it,t+1} = \beta_0 + \beta_1 \text{IoT}_{it} + \beta_2 \text{EM}_{it} + \beta_3 \text{IoT}_{it} \times \text{EM}_{it} + \beta \sum X_i + \delta_i + \theta_t + \epsilon \] (2)

The explained variable \( MktEff \) reflects the resource allocation efficiency in the capital market. We followed Hutton et al. (2009) by measuring the risk of stock price crashes by calculating \( \text{Negative\_cond\_return\_skewness} \) and \( \text{Down\_to\_up\_volatility} \). Considering the time-lagged effects of IoT adoption and the possibility of reverse causality, we used the one-period lagged indicators for resource allocation efficiency. It was expected that the regression coefficient of the interaction term between IoT and \( \text{Earnings\_management} \) \( \beta_3 \) would be significantly negative.

Table 8 presents the regression results for the effects of IoT adoption on the risk of stock price crashes through reduced earnings management. The results reveal that the coefficients for the interaction terms between IoT and \( \text{Real\_earnings\_management} \) and between IoT and \( \text{Total\_earnings\_management} \) are significantly negative at the level of 5%. However, the coefficient for the interaction term between IoT and \( \text{Discretionary\_accruals} \) is insignificant. Basically, the results suggest that IoT adoption mitigates the risk of stock price crashes and improves resource allocation efficiency in the capital market by reducing real earnings management.
Table 8. Capital market efficiency.

| Negative_cond_return_skewness_{t+1} | Down_to_up_volatility_{t+1} |
|-------------------------------------|-----------------------------|
| (1) | (2) | (3) | (4) | (5) | (6) |
| IoT | 0.13 | 0.06 | 0.069 | 0.12 | 0.051 | 0.059 |
| | (0.167) | (0.911) | (1.055) | (0.187) | (0.957) | (1.110) |
| Earnings_management | 0.236*** | 0.011 | 0.015 | 0.241*** | 0.007 | 0.012 |
| | (2.951) | (0.925) | (1.233) | (3.697) | (0.723) | (1.142) |
| IoT* Earnings_management | 0.914 | −0.122*** | −0.130** | 0.786 | −0.105** | −0.116** |
| | (1.452) | (−2.078) | (−2.185) | (1.535) | (−2.201) | (−2.385) |
| Negative_cond_return_skewness | −0.132*** | −0.131*** | −0.131*** | (−11.378) | (−11.299) | (−11.295) |
| Down_to_up_volatility | −0.154*** | −0.153*** | −0.153*** | (−11.948) | (−11.865) | (−11.860) |
| Sigma | 1.884*** | 1.912*** | 1.912*** | 2.008*** | 2.034*** | 2.035*** |
| | (2.730) | (2.771) | (2.771) | (3.376) | (3.620) | (3.621) |
| Return | 1.031 | 1.029 | 1.038 | −2.487* | −2.486* | −2.477* |
| | (0.640) | (0.639) | (0.645) | (−1.785) | (−1.783) | (−1.777) |
| Detrended_avg_monthly_stock_turnover | −0.001*** | −0.001*** | −0.001*** | −0.001*** | −0.001*** | −0.001*** |
| | (−4.274) | (−4.295) | (−4.302) | (−5.025) | (−5.035) | (−5.043) |
| Controls | YES | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES |
| Observations | 12,536 | 12,536 | 12,536 | 12,536 | 12,536 | 12,536 |
| R-squared | 0.071 | 0.071 | 0.071 | 0.075 | 0.074 | 0.074 |
| F | 31.25 | 30.94 | 30.97 | 33.13 | 32.60 | 32.65 |

In column (1) and (4), Earnings_management is |Discretionary_accruals|; in column (2) and (5), Earnings_management is Real_earnings_management; in column (3) and (6), Earnings_management is Total_earnings_management. t-statistics in parentheses. *** denotes significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

5.2. Effects of IoT adoption on investment and financing efficiency in the real economy through reduced earnings management

A quality financial report significantly reduces underinvestment in firms facing financing constraints and significantly reduces overinvestment when cash flow is abundant (Biddle et al., 2009). That is, higher earnings quality can help improve investment efficiency (Li, 2009; H. Liu et al., 2014; Zhang & Liu, 2015). High-quality financial reports are also conducive for financing through the capital market (Li, 2009), reducing adverse selection in resource allocation and improving financing efficiency(Cheng et al., 2012; Qu et al., 2011). It follows that as long as IoT adoption could reduce earnings management, it should have the potential to further improve investment and financing efficiency in the real economy. Similarly, by establishing Model (3), we investigated whether IoT adoption has improved investment and financing efficiency in the real economy by reducing earnings management.

$$\text{RealEff}_{i,t+1} = \beta_0 + \beta_1 \text{IoT}_{i,t} + \beta_2 \text{EM}_{i,t} + \beta_3 \text{IoT}_{i,t} \cdot \text{EM}_{i,t} + \beta \sum \chi_i \cdot \delta_i + \theta_i + \epsilon$$

The explained variable RealEff denotes the real economy’s resource allocation efficiency, including financing efficiency and investment efficiency. Specifically, we used Financial_constraints developed by Hadlock and Pierce (2010) to measure financing constraints and converted the index into a decile ordinal variable. The larger the measurement, the more the financing constraints. We also followed Richardson (2006) to construct the regression equation for investment spending and estimated the residual
by year and industry. Then, the absolute values were used to measure Inefficient_investment. Considering the time-lagged effects of IoT adoption and the possibility of reverse causality, we used the one-period lagged indicators for resource allocation efficiency. It was expected that the regression coefficient of the interaction term between IoT and Earnings_management \( \beta_3 \) would be significantly negative.

Columns (1)–(3) of Table 9 present the regression results for the effects of IoT adoption on the financing efficiency through reduced earnings management. The results reveal that the coefficients for the interaction terms between IoT and Real_earnings_management and between IoT and Total_earnings_management are significantly negative at the level of 1%. However, the coefficient for the interaction term between IoT and |Discretionary_accruals| is insignificant. Essentially, the results suggest that IoT adoption improves firms’ financing efficiency by limiting real earnings management behaviours. Columns (4)–(6) of Table 9 present the regression results for the effects of IoT adoption on investment efficiency through reduced earnings management. The results indicate that the coefficients for the interaction terms between IoT and Real_earnings_management and between IoT and Total_earnings_management are significantly negative at the level of 1%. However, the coefficient for the interaction term between IoT and |Discretionary_accruals| is insignificant.

To sum up, the reduction of accrual earnings management by IoT has no impact on resource allocation efficiency; through reducing real earnings management, IoT could further improve resource allocation efficiency. This is fully consistent with the mechanisms identified in extant literature. Accrual earnings management is often related to future expected earnings and its damage to firms’ long-term value is less severe than that of real earnings management (Gong et al., 2015; B. Liu et al., 2016). Furthermore, the market can identify accrual earnings management behaviours more readily, and regulators would constrain such firm behaviours (Lu et al., 2008). Real earnings management is more difficult to detect (Zang, 2012). The market has limited ability to identify real earnings

| Table 9. Real financing and investment efficiency. |
|---------------------------------------------------|
|                                                 |
| **Financial_constrains\(_{t+1}\)**                |
|                                                  |
|       | (1)  | (2)  | (3)  |
| IoT   | −0.237** | −0.195*** | −0.184*** |
|       | (−4.503) | (−4.379) | (−4.144) |
| Earnings_management | −0.122** | 0.086*** | 0.081*** |
|       | (−2.256) | (10.016) | (9.467) |
| IoT * Earnings_management | 0.634 | −0.133*** | −0.125*** |
|       | (1.479) | (−3.339) | (−3.095) |
| Controls | YES | YES | YES |
| Firm FE | YES | YES | YES |
| Year FE | YES | YES | YES |
| Observations | 12,536 | 12,536 | 12,536 |
| R-squared | 0.715 | 0.717 | 0.717 |
| F | 1216 | 1232 | 1230 |
| **Inefficient_investment\(_{t+1}\)**              |
|                                                  |
|       | (4)  | (5)  | (6)  |
| IoT   | 0.004 | 0.003 | 0.004 |
|       | (1.215) | (1.389) | (1.585) |
| Earnings_management | 0.005 | 0.000 | 0.001 |
|       | (1.578) | (0.865) | (1.169) |
| IoT * Earnings_management | 0.010 | −0.006*** | −0.007*** |
|       | (0.410) | (−2.910) | (−2.967) |
| Controls | YES | YES | YES |
| Firm FE | YES | YES | YES |
| Year FE | YES | YES | YES |
| Observations | 12,536 | 12,536 | 12,536 |
| R-squared | 0.201 | 0.201 | 0.201 |
| F | 122.4 | 122.4 | 122.4 |

In column (1) and (4), Earnings_management is |Discretionary_accruals|; in column (2) and (5), Earnings_management is Real_earnings_management; in column (3) and (6), Earnings_management is Total_earnings_management. t-statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels (two-tailed), respectively.
management, and the management is more likely to seek personal interests through real earnings management. Therefore, IoT adoption is more effective in improving resource allocation efficiency through reducing real earnings management.

5.3. Effects of IoT adoption on long-term operating efficiency through reduced earnings management

Table 10 presents the analysis on how IoT adoption could affect firms’ long-term operating efficiency by limiting earnings management. For the analysis, the ratio of management expenses to costs from Periods 1 to 3 was used as the explained variable. Model (4) below was used to investigate the changes in long-term operating efficiency by incorporating the interaction term between IoT and earnings quality indicator Earnings_management.

\[
LTCEff_{t+3} = \beta_0 + \beta_1 IoT_{t,t} + \beta_2 EM_{t,t} + \beta_3 IoT_{t,t} * EM_{t,t} + \beta \sum X_{it} + \delta_i + \theta_t + \epsilon
\]  

(4)

Earnings management behaviours, especially the real earnings management realised through over-production, will spread costs and improve short-term turnover. Meanwhile, IoT could inhibit the behaviours, but the changes in the ratio of expenses to costs may not be observable in the short term. Nevertheless, given that real earnings management is harmful to firms’ long-term operation, by curbing the behaviours, IoT could substantially improve firms’ operation efficiency over a longer horizon. In conclusion, this paper predicts that the interaction between IoT and earnings quality may be insignificant during the short term, and it will be significantly and negatively correlated with the ratio of management expenses to costs in the long term. The regression results in Table 10 confirm the speculation about the changes in the ratio of management expenses to costs. Also, the significant and negative relationship is only reflected by real earnings management and total earnings management in \( t + 3 \) period.

6. Conclusions and implications

In this study, we constructed the indicator for IoT adoption based on ‘IoT’ announcements issued by listed companies from 2009 to 2016. Then, the difference-in-differences approach was employed to examine how IoT adoption has affected earnings management behaviours and relevant economic outcomes. The empirical results reveal that: (1) IoT adoption reduces firms’ earnings management. The relationship is significant in the group with a lower proportion of production staff, lower assets impairment, lower agency costs, and higher quality of internal control. The results suggest that by reducing human involvement in production and operation processes, IoT can strengthen key asset monitoring, thereby narrowing firms’ scope for earnings management. Meanwhile, with a better information environment, reduced agency costs, and improved internal control, IoT adoption can also restrain firms’ motivation for earnings management. Through

\[\text{We also tested against the ratio of management expenses to costs and working capital turnover rate for the current period of IoT adoption. The insignificant results confirm our speculation. With the working capital turnover rate as the proxy variable, the results are generally consistent with those obtained by the regression against the ratio of management expenses to costs. Due to lack of space, the results are not presented here.}\]
|                     | Costs_{t+1}          | Costs_{t+2}          | Costs_{t+3}          |
|---------------------|----------------------|----------------------|----------------------|
|                     | (1)                  | (2)                  | (3)                  | (4)                  | (5)                  | (6)                  | (7)                  | (8)                  | (9)                  |
| **IoT**             | -0.014               | -0.012               | -0.012               | -0.025***            | -0.022***            | -0.023***            | -0.012               | -0.006               | -0.004               |
|                     | (-1.608)             | (-1.431)             | (-1.406)             | (-2.869)             | (-3.198)             | (-2.958)             | (-1.137)             | (-0.978)             | (-0.654)             |
| **Earnings_Management** | 0.004               | 0.002               | 0.002               | -0.003               | -0.013               | -0.014               | 0.002               | 0.001               | 0.001               |
|                     | (0.342)              | (0.753)              | (0.810)              | (-0.154)             | (-0.870)             | (-0.876)             | (0.317)              | (0.450)              | (0.432)              |
| **IoT * Earnings_Management** | 0.029               | 0.001               | 0.002               | 0.176                | -0.017               | -0.014               | 0.279               | -0.029***            | -0.026***            |
|                     | (0.751)              | (0.102)              | (0.272)              | (1.139)              | (-0.903)             | (-0.743)             | (1.376)              | (-2.748)             | (-2.707)             |
| **Controls**        | YES                  | YES                  | YES                  | YES                  | YES                  | YES                  | YES                  | YES                  | YES                  |
| **Firm FE**         | YES                  | YES                  | YES                  | YES                  | YES                  | YES                  | YES                  | YES                  | YES                  |
| **Year FE**         | YES                  | YES                  | YES                  | YES                  | YES                  | YES                  | YES                  | YES                  | YES                  |
| **Observations**    | 11,782               | 11,782               | 11,782               | 11,614               | 11,614               | 11,614               | 9,595               | 9,595               | 9,595               |
| **R-squared**       | 0.013                | 0.013                | 0.013                | 0.011                | 0.013                | 0.013                | 0.003               | 0.003               | 0.003               |
| **F**               | 8.281                | 9.057                | 8.804                | 5.902                | 6.328                | 6.266                | 3.858               | 4.140               | 4.118               |

In column (1), (4), and (7), Earnings_management is |Discretionary_accruals|; in column (2), (5), and (8), Earnings_management is Real_earnings_management; in column (3), (6), and (9), Earnings_management is Total_earnings_management. t-statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels (two-tailed), respectively.
reduced earnings management at the firm level, IoT can improve the financing and investment efficiency of the real economy, mitigate the risk of stock price crashes, and improve capital market resource allocation efficiency. This study contributes to the literature on the economic outcomes of information technology adoption and the effects of earnings management.

Due to a limited number of observations, insufficient information for IoT disclosed in the announcements (for example, number of mergers and acquisitions, amount of assets, amount of financing, and other quantitative information), and the lack of detailed individual cases of IoT adoption, we acknowledge that the mechanism is not fully understood. However, some novel ideas proposed here deserve further development in future research. We performed a PSM robustness test by removing the biases caused by sample distribution as much as possible. The results accompanied with other robustness tests indicate that the conclusions are rather reliable. Finally, in this study, earnings quality was only defined from the perspective of current earnings management, which may not fully reflect firms’ real quality of reported earnings. Other factors may include accounting robustness and long-term business performance. Generally, considering its novelties, we believe that the study presented in this paper could partially fill the gap in relevant research areas.

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