Digital Washing under Conflicting Institutional Logics: Evidence from China

Abstract: This study examines how employee pressure influences digital washing—when firms exaggerate their digital transformation in public disclosures without matching substantive, actual actions. Using data on Chinese listed firms from 2008 to 2021, we measure digital washing as the gap between digital-related keywords in annual reports and digital-related intangible assets. Results show that firms facing higher employee pressure are more likely to engage in digital washing. This effect is more pronounced in state-owned firms, labor-intensive firms, and firms in less market-oriented regions. A Difference-in-Differences analysis using the 2017 U.S.-China trade war supports our findings. Moreover, the consequences test shows that digital washing is associated with increased stock liquidity, indicating a favorable market response to digital washing. Overall, the findings highlight how firms facing conflicting institutional logics—pressures to modernize through digital transformation while maintaining employment—may engage in digital washing as a response.

JEL Codes: D22, D23, L20, M14

Keywords: Digital Washing; Institutional Logics; Digital Transformation; Employee pressure

1. Introduction

The rapid advancement and widespread adoption of digital technologies, such as cloud computing, big data, artificial intelligence (AI), the Internet of Things (IoT), and blockchain, have significantly driven firms' digital transformation.[1] Digital transformation is now widely regarded as a critical enabler of innovation, competitiveness, and long-term organizational growth. In response, firms across industries have increasingly integrated digital strategies into their corporate narratives, frequently emphasizing their commitment to and efforts toward digitalization to signal future-readiness to stakeholders such as investors, consumers, and regulators.

However, growing anecdotal evidence suggests that such disclosure regarding digitalization are not always accompanied by corresponding substantive technological change. Many firms engage in what we term as digital washing—the strategic exaggeration or misrepresentation of digital transformation efforts aimed at creating a more favorable image, without matching those efforts with substantive, actual implementation.[2] This practice often involves symbolic actions, such as the use of digital buzzwords, selective disclosure of marginal technological upgrades, and narrative framing that conceals a lack of meaningful digital integration in operations or strategy. A prominent example is Long Island Iced Tea Corp, which rebranded as Long Blockchain Corp in 2017 despite no substantive operational shift. The firm's stock price surged nearly 300% following the announcement, before being delisted by the U.S. Securities and Exchange Commission for misleading investors (Hankin, 2018).

[1] Global spending on digital transformation is set to hit \$3.9 trillion by 2027, reflecting rapid growth and investment worldwide (IDC, 2023).

[2] The term "digital washing" is inspired by the concept of "greenwashing" in the sustainability literature, where firms exaggerate or misrepresent their environmental practices to gain legitimacy or appeal to environmentally conscious stakeholders (Delmas and Burbano, 2011; Pope and Wæraas, 2016). Similarly, digital washing refers postivie discrepancy between communicated and actual digital efforts. Seele and Schultz (2022) use the term "machine washing" to describe misleading claims around AI ethics and responsible AI usage. Our focus on digital washing centers on the overstatement of overall digital transformation efforts, rather than ethical concerns or issues specific to AI technologies.

Digital washing presents significant challenges by distorting market perceptions and obscuring the line between genuine digital transformation and superficial signaling, making it difficult for stakeholders—such as investors, consumers, and regulators—to assess the true extent of a firm's digital transformation efforts based on its disclosures. These misleading practices can undermine the broader goals of digital transformation by allowing companies to avoid the substantial organizational changes required for real progress. Therefore, recognizing and scrutinizing digital washing is essential. As Pope and Wæraas (2016) argue, such vigilance promotes transparency and accountability, compelling firms to shift from symbolic gestures toward substantive digital efforts.

Despite its prevalence and potential impact, digital washing remains a largely underexplored topic in academic research. This study seeks to address the research gap in the literature by examining the phenomenon of digital washing—strategic practice involving the overstatement or misrepresentation of digital transformation efforts to portray a more advanced digital posture than has been substantively implemented, thereby misleading stakeholders. In particular, this research examines how conflicting institutional logics shape firms' propensity to engage in such behavior. Specifically, it focuses on the tension between two competing expectations: the push for digital transformation, which often involves automation and labor reduction (Bertani et al., 2020), and the simultaneous societal and governmental demands to preserve or even increase employment. This institutional conflict may incentivize firms to highlight digital efforts in their communications while avoiding the disruptive organizational changes associated with genuine implementation.

To examine this dynamic, we draw on a unique dataset of Chinese publicly listed firms from 2008 to 2021. China presents an ideal context for this study, as the conflicting institutional pressures central to our analysis are particularly pronounced. On the one hand, the imperative for industrial upgrading— especially for low- and mid-end segments of China's manufacturingdominated economy—makes digital transformation a national priority. On the other hand, the country's large population and low per capita gross domestic product (GDP) intensify employee pressure, generating strong societal and governmental expectations for firms to undertake a greater share of employment responsibility. These opposing demands are further complicated by challenges such as capital constraints, workforce adaptation issues, and the inherent tension between automation and job preservation. Together, these factors make China an ideal setting to explore the strategic responses firms employ under conflicting pressures, particularly the practice of digital washing.

We operationalize digital washing as the discrepancy between a firm's digital rhetoric ("talking") and its actual digital actions ("walking"). First, to measure digital rhetoric, we conduct a textual analysis of the Management Discussion and Analysis (MD&A) sections in firms' annual report employing a comprehensive, policy-related keyword dictionary to identify and count references to digital transformation. This approach captures both the frequency and intensity of a firm's emphasis on digitalization in its narrative disclosures. Second, actual digital actions are quantified by calculating the proportion of intangible assets related to digital technologies in standarzied and audited year-end financial statements. As these assets must meet accounting recognition standards and are often linked to government incentives in China, they serve as a reliable indicator of real technological investment and capability. Third, the degree of digital washing is then derived as the standardized difference between these two measures, reflecting the extent to which a firm's narrative diverges from its real digital engagement.

Given the institutional tension between digital transformation demands and employment responsibility, we hypothesize that higher employee pressure is positively associated with the extent of digital washing. We measure employee pressure by the excess employee ratio (the firm's employment relative to industry norms, scaled by total assets or sales revenue), which directly quantifies labor hoarding and captures how many jobs exist mainly reasons other than economic reasons. Our findings support this hypothesis, revealing a statistically significant positive relationship between employee pressure and digital washing. Further cross-sectional analysis shows that this effect is particularly pronounced in (1) state-owned enterprises (SOEs), (2) labor-intensive firms, and (3) firms operating in regions with lower levels of marketization.

To address potential endogeneity concerns, we conduct a Difference-in-Differences (DID) analysis exploiting the 2017 U.S.-China trade war as an exogenous shock. The trade war imposed tariffs on specific Chinese export industries, resulting in a decline in exports and increased unemployment in affected industries—effectively serving as a shock to employment pressure. Firms in impacted industries (such as automobiles, hardware and aircraft components, steel products, electrical machinery, railway products, instruments and equipment) are classified as the treatment group, while unaffected firms serve as the control group. The results show that employee pressure significantly increases the degree of digital washing.

Furthermore, we examine the economic consequences of digital washing by analyzing its impact on stock liquidity, using the Amihud Illiquidity Index as the measurement. The results show that digital washing is associated with increased stock liquidity, indicating a favorable market response to firms' digital washing. Together, these findings suggest that employee pressure plays a significant role in driving digital washing, as firms strategically exaggerate their digital transformation efforts to navigate conflicting institutional demands.

We contribute to the literature in the following ways. First, we contribute to the literature on the role of digital transformation in corporate behavior by exploring how firms navigate the pressures of digital transformation while facing conflicting institutional logics. Prior studies have found that digital transformation impacts corporate behavior, including productivity (Zhang and Dong, 2023), innovation (Wang et al., 2023), financialization (Wu and

Lu, 2023), risk-taking (Tian et al., 2022), and labor structure (Dou et al., 2023). Less is known about how firms respond when dital transformation is constrained by other institutional pressures. Our study highlight how firms may use digital washing as a strategic response to reconcile the tension between digital transformation and other institutional responsibilities such as employment preservation.

Second, we contribute to the literature on conflicting institutional logics by demonstrating the consequences of these competing demands. Reay and Hinings (2007) identified that conflicting logics can coexist when managed through collaborative mechanisms, allowing organizations to navigate conflict and maintain stability. Pache and Santos (2013) explored how hybrid organizations respond to institutional pressures by selectively coupling elements of competing logics, strategically combining practices to meet the demands of different stakeholders. Bekki and Turker (2022) emphasized that suppliers adopt varying strategies, including symbolic actions, to balance competing institutional pressures related to sustainability and performance. We build on this research and demonstrate how the tension between the push for digital transformation and expectations surrounding social responsibility, particularly in employment, can lead to behaviors such as digital washing, where firms symbolically signal a commitment to transformation without fully engaging in substantial changes.

Our research offers practical implications for external stakeholders. Other stakeholders such as investors are encouraged to critically assess firms' digital transformation claims, recognizing potential discrepancies between rhetoric and actions. Policymakers could consider to develop more stringent reporting standards to curb corporate digital washing.

2. Conceptual Background

2.1 Digital Transformation

In recent years, firms have faced growing expectations to embrace digital transformation, not only as a means of improving operational efficiency but also as a signal of innovation and future-readiness to investors, regulators, and other stakeholders. Digital transformation in firms is influenced by a combination of internal and external factors (Feliciano-Cestero et al., 2023). Externally, the regulatory landscape, market competition, customer expectations, technological advancements, economic conditions, and stakeholder interests all play critical roles. Internally, key influences include leadership, organizational culture, employee skills, IT infrastructure, and the allocation of resources.

Digital transformation is a complex and multifaceted process that necessitates substantial investments in new technologies, training, and organizational restructuring, affecting every aspect of a business (Mishra et al., 2022; Vial, 2019). Yoo et al. (2010) note that these costs extend beyond technology to include product innovation and IT infrastructure upgrades, making it essential for firms to manage both technical and strategic changes. Correani et al. (2020) further argue that, in the digital age, companies must rethink how they create and capture value, which may involve developing new products, optimizing processes, or entering new markets. Successfully navigating these changes is crucial for firms to remain competitive and protect their intellectual property while striking a balance between openness and security on their digital platforms.

Digital transformation offers significant benefits. Digital transformation enhances efficiency by automating processes, improving resource allocation, and promoting agility, ultimately leading to improved productivity and performance (Leão and da Silva, 2021). This efficiency gain often translates into reduced costs, allowing for more competitive pricing and higher profit margins (Goldfarb and Tucker, 2019). Moreover, digital transformation fosters innovation by enabling the creation of new business models and improving customer experiences, both of which contribute to long-term growth and value creation. Additionally, it helps companies navigate and integrate into global value chains, expanding their geographic reach and facilitating international growth (Leão and da Silva, 2021). These combined benefits make digital transformation a critical driver of competitive advantage.

However, digital transformation also presents challenges, including concerns related to privacy, market power, and inequality (Goldfarb and Tucker, 2019). Digital transformation, such as the use of AI tools, can result in unintended consequences such as diminished employee competence, job satisfaction, and critical thinking within organizations. Over-reliance on digital tools may also exclude certain customer groups and weaken unique selling points by reducing human intervention (Mishra et al., 2022). Many companies mistakenly focus too much on technological aspects without adequately addressing the broader transformation needed in strategy, culture, and organizational structure. This can result in misallocated resources and wasted costs, particularly when firms adopt a “me-too” strategy, following trends without clear direction (Leão and da Silva, 2021). Feliciano-Cestero et al. (2023) further note that digital transformation faces challenges like cybersecurity risks, regulatory complexities across countries, and employee skill gaps. These issues increase costs, requiring ongoing investment in compliance and training, which can slow implementation and hinder success.

Empirical evidence on digital transformation reveals mixed effects on firms, influencing performance, productivity, risk-taking, and organizational structures in various ways. While Usai et al. (2021) noted that digital technologies improve efficiency but have minimal impact on long-term innovation, Guo et al. (2023) highlighted a “digitalization paradox”, where increased productivity comes with short-term performance declines due to higher costs. Digital transformation has been shown to boost total factor productivity (TFP), particularly in state-owned enterprises, as evidenced by Zhang and Dong (2023) and Lei and Wang (2023), with gains in TFP linked to improved internal control quality and technological advancements. Moreover, Zhang and Liu (2023) found that digitalization enhances firm centralization by lowering communication costs, while Dou et al. (2023) reported that it drives labor structure upgrading by increasing the share of skilled workers such as those working in R&D. On the financial side, Wu and Lu (2023) revealed that digital transformation promotes corporate financialization, especially in firms with high agency costs, motivated by profit-seeking behaviors. In terms of risk-taking, Tian et al. (2022) found that digital transformation increases firms' willingness to take risks by improving operational flexibility and access to financing, with a more pronounced effect in non-state-owned firms and developed regions. Gal et al. (2019) and Oduro et al. (2023) further emphasized the uneven gains from digitalization across sectors and regions, particularly in manufacturing, where larger firms benefit more, but skill shortages and implementation complexities in emerging economies delay returns.

Digital transformation in China is crucial as it drives the country's evolution from a manufacturing hub to a leader in technology and innovation, with significant advancements in e-commerce, digital payments, and consumer-facing services.[3] Moreover, China's focus on digital inclusiveness has integrated marginalized communities into the broader economy, fostering greater social and economic equality. This digital transformation is also critical in positioning China in strategic competition with the U.S., as it quickly closes the gap in telecommunications technology, while also achieving substantial progress in mobile payments and e-commerce. Despite facing challenges in semiconductors and core software technologies, where the U.S. remains dominant, China's advancements are reshaping its economic landscape and establishing the country as a major force in the global digital economy (Jiang and Murmann, 2022).

[3] China's approach, centered around building a mobile-first, fiber-intensive, and inclusive digital infrastructure, has facilitated the rapid adoption of online platforms, even in rural areas, resulting in significant internet penetration across the country. Local innovations tailored for its vast population, like Alipay and WeChat Pay, have transformed consumer habits, surpassing comparable Western alternatives in both adoption and integration into daily life.

2.2 Employee Pressure

In recent years, firms have faced growing expectations not only to deliver financial performance but also to demonstrate social responsibility, particularly in how they manage and support their workforce. This evolving landscape has heightened the relevance of environmental, social, and governance (ESG) standards as a benchmark for corporate accountability and stakeholder engagement. ithin this framework, sharing responsibility for employee welfare with the government is now widely regarded as a core component of a firm's ESG commitments. The "Social" dimension of ESG, in particular, underscores the role of companies in promoting fair labor practices, ensuring job security, and contributing to societal well-being. For example, companies with highly capable managers who allocate resources towards employee welfare as part of their ESG initiatives see enhanced shareholder value, indicating that effective employee support can lead to long-term financial benefits for firms (Welch and Yoon, 2023). Moreover, ESG-focused initiatives positively influence employee morale and retention, further emphasizing the importance of integrating these practices to manage workforce transformations effectively (Lee et al., 2023).

In China, employment stability plays a crucial role in maintaining social stability, especially during periods of economic or technological disruption. Firms, especially state-owned enterprises (SOEs), play a pivotal role in shaping employment patterns under the government's emphasis on job security. SOEs are often tasked with absorbing surplus labor and providing social services as part of government directives (Yang and Zhao, 2016) This approach frequently involves excess employment—maintaining a workforce larger than what is operationally necessary—to address unemployment and uphold societal stability. However, such practices have also resulted in inefficiencies, including higher agency costs and weakened managerial incentive (Bai et al., 2010; Li, 2008). By distributing the burden of employment across firms, this model reduces individual hardship, helps prevent social unrest, and reinforces the central government's priority of societal stability (Li, 2008; Yang and Zhao, 2016).

Other non-state-owned firms, while theoretically free of some state obligations, still encounter employment burdens due to local government pressures. These enterprises may maintain surplus workers as part of implicit agreements to secure financial or regulatory support, illustrating the lingering impact of China's pre-reform social policies (Fang et al., 2023; Li, 2008).

Government policies and interventions further amplify firms' influence on employment. For example, firms with excess employment are often preferred for initial public offerings (IPOs), signaling their alignment with government priorities of promoting labor stability over efficiency. This politically driven capital allocation sometimes results in underperforming firms post-IPO such as prioritizing firms with high levels of excess employment for initial public offerings (IPOs), particularly in the private sector (Johansson et al., 2017).

2.3 Conflicting institutional logics

Organizations frequently operate in environments shaped by multiple institutional logics, which are distinct sets of values, beliefs, and practices that influence decision-making and behavior. These logics often create tensions within organizations, especially when they conflict with one another. When firms face these competing logics, they must navigate tensions that arise from trying to meet the demands of diverse institutional actors. For example, balancing profitability with environmental sustainability or social responsibility often requires firms to adopt strategies that reconcile or manage these conflicts (Bekki and Turker, 2022; Testa et al., 2018).

Reay and Hinings (2007) argue that organizations develop mechanisms to balance these demands by selectively adopting practices from both logics. Some organizations respond by engaging in selective coupling, combining elements of conflicting logics to satisfy both internal and external stakeholders (Pache and Santos, 2013). Others may marginalize one logic to the periphery of their operations or adopt innovative practices to harmonize the contradictions. The degree of conflict, as well as the firm's ability to manage it, depends on the *compatibility* of the logics (whether they align or contradict) and their *centrality* (how integral each logic is to the firm's core functions) (Besharov and Smith, 2014). Successfully managing these tensions can drive innovation and adaptability, while failure to address them can lead to instability or even organizational failure.

An example of such tension lies in the relationship between digital transformation and employment responsibility. While both are essential to a firm's development, they are rooted in different institutional logics. Digital transformation reflects the logic of technological innovation, efficiency, and market competitiveness. It often entails automation, restructuring, and a reduction in labor dependence. In contrast, labor responsibility aligns with the logic of social stability, requiring firms to maintain employment, provide worker protections, and uphold their societal role. These competing demands are especially salient in countries like China, where firms are expected to simultaneously modernize and safeguard employment. Understanding how firms manage these opposing demands offers critical insight into the strategic behaviors shaped by institutional complexity.

2.4 Hypothesis Development

Digital transformation and employment often embody conflicting dynamics, as digitalization often leads to a reduction in the reliance on human labor. Globally, Digital transformation places significant pressure on employees to quickly adapt to new technologies while fearing job displacement. According to the Future of Jobs Report 2023, up to 44% of workers' skills will be disrupted by 2027, with businesses prioritizing AI and big data training (World Economic Forum, 2023). Although new roles are emerging, many jobs face displacement, causing anxiety and uncertainty. This shift increases stress, as employees must keep pace with rapid technological change (World Economic Forum, 2023). These disruptions create opportunities for new roles but also amplify stress and uncertainty for workers.

On the one hand, firms are under growing pressure from various stakeholders, including the government, to undergo digital transformation. On the other hand, these companies also bear societal and governmental responsibilities regarding employment. These two objectives may come into conflict. In this context, firms are increasingly pressured by various stakeholders, including government bodies (Wang et al., 2023), to pursue digital transformation. Digital transformation is viewed as a form of creative destruction (Schumpeter, 1942), where digital innovations disrupt traditional business models and processes, pushing firms to adopt more agile and technology-driven solutions. Companies are compelled to adapt in order to maintain their competitive edge, while governments and regulatory bodies emphasize transparency, efficiency, and digital integration, further accelerating the pace of transformation (Leão and da Silva, 2021).

On the other, companies further face responsibilities related to employment, often driven by societal and governmental demands, particularly in regions with high unemployment rates (Bai et al., 2010; Yang and Zhao, 2016). Employment is often considered a key aspect of a firm's social responsibility. Beyond generating profits and driving innovation, firms are expected to contribute positively to society, and one of the most direct ways to do this is by creating and maintaining jobs. Employment supports economic stability, reduces poverty, and enhances the well-being of individuals and communities. In many regions, governments and societies expect companies to act as responsible employers, especially in times of economic downturn or high unemployment rates.

Firms undergoing digital transformation face a fundamental tension between the imperative to restructure operations through automation and the responsibility to maintain employment. On one hand, digital transformation initiatives frequently involve automating processes and reorganizing the workforce, which can reduce overall staff levels. On the other hand, firms face strong stakeholder pressures—particularly from government and civil society—to sustain or even increase employment levels. This conflict is further compounded by labor protection regulations and high dismissal costs, which make workforce reductions economically burdensome and politically sensitive. Moreover, because digital transformation is a relatively new phenomenon, its costs and benefits are often unclear, and it requires substantial organizational change.

This tension is further amplified in the context of corporate disclosures and stakeholder evaluation processes. Employment outcomes—such as workforce size and layoffs—are tracked using transparent, standardized, and frequently audited metrics. As a result, workforce reductions carry significant legal and reputational risks. In contrast, the outcomes of digital transformation initiatives tend to be inherently uncertain and are typically assessed using loosely defined, long-term metrics. Consequently, achievements in digital transformation may appear ambiguous or be difficult for external stakeholders to verify.

Given this combination of pressures and evaluation asymmetries, firms may strategically engage in digital washing, a practice involving exaggerated disclosures of digital transformation activities without corresponding substantive actions. By overstating their digital initiatives, firms project an impression of innovation and forward-looking change, thereby satisfying stakeholder expectations for digital modernization without incurring the significant social and economic costs associated with genuine workforce reductions.

In other words, firms may navigate conflicting logics by resorting to digital washing to align their image with stakeholder expectations while continuing business as usual, which allows firms to gain reputational benefits without incurring the costs of genuine efforts (Pope and Wæraas, 2016).

Hypothesis: Firms facing conflicting institutional logics regarding digital transformation and employment are more likely have digital washing behaviour.

3. Research Design

3.1 Measuring Digital Washing

Digital washing denotes the strategic overstatement of a firm's reported digital transformation efforts in comparison to its underlying substantive implementation. Accordingly, we operationalize digital washing as the gap between a company's 'talk' and 'action' on digital transformation, using the following three-step approach.

In the first step, we measure firms' digital "talking" by analyzing the textual content of the Management Discussion and Analysis (MD&A) sections in their annual reports, following the approach of Zhu and Yu (2024). Their method relies on a dictionary of 87 digital transformation-related keywords (see Appendix B for the full list), developed based on prior academic research and relevant Chinese government documents on digital policy. These keywords are grouped into five thematic categories across two levels: the technical level includes artificial intelligence, big data, cloud computing, and blockchain technologies, while the application level focuses on areas such as e-commerce, the Internet of Things, and smart manufacturing. To quantify each firm's yearly emphasis on digital transformation, we extracted the MD&A section from its annual report and identified the frequency of the selected keywords. The total count of keyword occurrences for each firm-year was then log-transformed to construct a continuous index that captures the extent of a firm's digital transformation discourse. This textual analysis serves as a proxy for the firm's digital rhetoric—its "talking"—about transformation efforts (see details in Appendix C).

In the second step, we measure digital "actions". A firm's actual digital transformation efforts are measured by calculating the proportion of intangible assets directly related to digital technologies. This is based on the detailed disclosures in the year-end intangible asset notes of the financial reports. Items classified as "digital technology intangible assets" include those with keywords such as "software," "network," "client," "management system," "intelligent platform," and relevant patents. The aggregated value of these digital technology assets for each firm is then divided by the total intangible assets to represent the firm's actual investment in digital technology. One notable advantage of the Chinese setting is that the tax authorities rely directly on financial statements to assess eligibility for certain tax credits or benefits. As a result, firms have limited incentive to underreport intangible assets, particularly those related to digital technologies.

In the third step, we quantify digital washing using the difference between "talking" and "actions. Both the "talking"(*DIGITALTALKING*) and "actions" (*DIGITALACTION*) scores are standardized using the z-score method. The degree of digital washing is computed by subtracting the standardized "actions" score from the standardized "talking" score. A higher result indicates a greater discrepancy between a firm's rhetoric and its actual efforts, reflecting a higher level of digital washing. More specifically, digital washing is calculated as follows: *DIGITALWASHING=DIGITALTALKING-DIGITALACTION.*

3.2 Measuring Employee Pressure

To measure the employee pressure faced by firms, the excess employee ratio is utilized as a proxy. This ratio is designed to capture the extent to which a firm employs more personnel than is typical for its industry, given its size. given its size. Based on prior literature (Bai et al., 2005; Dong and Putterman, 2003; Liao et al., 2009), the excess employee ratio is calculated as follows:

$$EMPLOYEEPRESSURE_{i,t} = (EMP\_FIRM_{i,t} - ASSET\_FIRM_{i,t} \times \frac{EMP\_IND_t}{ASSET\_IND_t})/EMP\_FIRM_{i,t}$$

Where *EMPLOYEEPRESSURE* represents the firm's excess employee ratio, *EMP_FIRM* is the number of employees in the firm, *ASSET_FIRM* is the firm's total assets, *EMP_IND* is the average number of employees in the industry, and *ASSET_IND* is the average asset size of the industry.[4]

This measure reflects deviations from the industry norm, with positive values indicating excessive employment relative to industry standards. The methodology is particularly suited for capturing employee pressures in transition economies, where firms often bear social burdens like maintaining high levels of employment to satisfy government objectives (Dong and Putterman, 2003).

Additionally, for robustness checks, we replace asset size with sales revenue and use the following equation to recalculate the excess employee ratio:

$$EMPLOYEEPRESSURE2_{i,t} = (EMP\_FIRM_{i,t} - SALES\_FIRM_{i,t} \times \frac{EMP\_IND_t}{SALES\_IND_t})/EMP\_FIRM_{i,t}$$

This adjustment accounts for potential variability in the relationship between firm size and employment based on operational output rather than asset holdings.

3.3 Empirical Model

To empirically test our hypothesis—that firms facing greater employee pressure are more likely to engage in digital washing, we examine the association between excess employees and digital washing as follows:

$$DIGITALWASHING = \alpha + \beta_1 EMPLOYEEPRESSURE_{i,t} + \beta_2 SIZE_{i,t} + \beta_3 LEV_{i,t} + \beta_4 ROA_{i,t} + \beta_5 BM_{i,t} + \beta_6 GROWTH_{i,t} + \beta_7 BOARD_{i,t} + \beta_8 INDEP_{i,t} + \beta_9 INSTR_{i,t} + \beta_{10} TOP1_{i,t} + \beta_{11} SOE_{i,t} + \beta_{12} GDP_{i,t} + \beta_{13} POPU_{GROW_{i,t}} + \mu_i + \lambda_t + \delta_r + \varepsilon_{i,t} \quad (1)$$

where the dependent variable, *DIGITALWASHING*, and our variable of interest, *EMPLOYEEPRESSURE*, are defined previously. In line with H1, we expect a positive coefficient, β_1, on *EMPLOYEEPRESSURE*, indicating that excess employees will significantly improve digital washing.

[4] We classify firms into industries based on the China Securities Regulatory Commission (CSRC) industry codes, which are commonly used in studies on Chinese listed firms (e.g., Fan et al., 2007).

We also capture the financial and corporate governance characteristics at the firm level. Drawing on prior literature (e.g., Liao et al., 2009; Zhu and Yu, 2024), we include controls for financial characteristics such as asset size (*SIZE)*, the leverage ratio (*LEV*), profitability (*ROA*), the book-to-market ratio (*BM*), and the annual growth rate of operating income (*GROWTH).* Additional control variables are incorporated to control corporate governance characteristics, including the natural logarithm of the number of board members (*BOARD*), the percentage of independent directors (*INDEP),* institutional investor shareholding ratio (*INSTR*), and the shareholding ratio of the largest shareholder (*TOP1*). To account for ownership structure differences between state-owned enterprises and private firms in China, we include a dummy variable (*SOE*), which takes the value of 1 for state-owned enterprises and 0 otherwise.

At the city level, we include the GDP (*GDP*) and population growth rate (*POPU_GROW*) of the city where the listed company is headquartered. GDP reflects economic development and market size, influencing a firm's environment and strategies. Population growth rate indicates demographic changes and market dynamics, which can encourage digitalization to meet growing demands. These controls account for potential external factors affecting a firm's digital transformation and performance.

In addition to the firm and regional characteristics discussed above, our regression models also include indicator variables to capture industry-fixed effects (μ_i) to absorb unobservable time-invariant industry characteristics, year fixed effects (λ_t) to control for common time effects, δ_r to control for city level fixed effects.

3.4 Sample Selection

The empirical analysis is conducted on firms listed on the Shanghai and Shenzhen stock exchanges in China between 2008 and 2021. The choice of 2008 as the starting point for the sample is based on two primary considerations. First, China implemented its green credit policy and issued guidelines for environmental information disclosure in 2007. Second, the newly established Accounting Standards for Business Enterprises, aligned with International Financial Reporting Standards, also began implementation in 2007. To mitigate the impact of these policies, we select 2008 as the starting point of the sample.

The analysis excludes financial firms, firms under special treatment (i.e., ST and *ST stocks), and particular transferred (i.e., PT) stocks. Corporate governance data, firm-level financial statement data, and trading data are collected and merged from the China Stock Market and Accounting Research database (CSMAR) and the Wind Economic Database (WIND). Observations lacking sufficient data for the variables are excluded from the sample. Additionally, all continuous variables are winsorized at the 1% level to address outliers. The final sample comprises 25,809 firm-year observations (3,497 unique firms) over the sample period. The sample selection process is detailed in Table 1.

[Insert Table 1 here]

3.5 Descriptive statistics

Table 2 presents descriptive statistics for all variables. The mean value of *DIGITALWASHING* is 0.059, with a standard deviation of 1.342, indicating significant variation across firms. The values range from -4.793 to 2.936, where larger positive values suggest a higher likelihood of digital washing. It is important to note that *DIGITALWASHING* is a relative measure; negative values do not indicate the absence of digital washing but rather reflect lower levels relative to other firms. Similarly, *EMPLOYEEPRESSURE* is also a relative measure, with a mean of -0.258 and a standard deviation of 1.219. The values range from -6.773 to 0.857, where positive values suggest firms are employing more workers than the industry norm, while negative values indicate relatively lower employment levels. Additionally, the values of other control variables are generally consistent with those found in previous studies using similar samples.

[Insert Table 2 here]

4. Empirical Results

4.1 Primary Analysis: The relationship between Excess employees and Digital washing

We first investigate the effect of excess employee pressure (*EMPLOYEEPRESSURE*) on corporate digital washing (*DIGITALWASHING*). Column (1) of Table 3 presents the regression results, incorporating industry and year fixed effects, while Column (2) further includes city fixed effects. The estimated coefficients for *EMPLOYEEPRESSURE* in both specifications are 0.043 and 0.046, respectively, and are statistically significant at the 1% level. The results indicate that there is a positive relationship between the extent of digital washing and the employee pressure faced by firms. These findings provide support for Hypothesis H1, demonstrating that employee pressure's effect on the extent of digital washing is both statistically and economically significant. The economic effect is sizeable as a standard deviation increase in *EMPYLOYEEPRESSURE* yields an effect of 4.2% (=0.046 * 1.219 / 1.342) increase in *DIGITALWASHING*, measured in terms of its standard deviation.

[Insert Table 3 here]

4.2 Difference-in-Difference Test

To address potential endogeneity concerns and enhance the robustness of our findings, we employ a Difference-in-Differences (DID) model based on an exogenous event. In 2017, the U.S. initiated a trade war, imposing tariffs on specific Chinese export industries. This event resulted in a decline in exports and increased unemployment in certain Chinese industries. We use this trade war as an exogenous shock, categorizing affected firms as the treatment group and unaffected firms as the control group based on whether the firm' industry is affected or not.

The coefficient on *TREAT*POST* is positive and significant at the 5% level.[5] This indicates that increased employee pressure significantly amplifies corporate digital washing, further reinforcing the robustness of the study's conclusions.

[Insert Table 4 here]

4.3 Robustness Tests

We further perform robustness tests. In Table 5, Column (1) examines the robustness of the results by employing an alternative proxy for employee pressure. We replace asset size with sales revenue as an alternative scaling factor and recalculate the excess employee ratio *EMPLOYEEPRESSURE2*. We observe a consistent positive association between the extent of digital washing and the employee pressure experienced by firms. This ensures that the observed relationship between employee pressure and digital washing is not an artifact of the specific operationalization of employee pressure.

In Column (2), the analysis addresses the potential issue arising from the discretionary nature of intangible asset disclosures. Since the classification and reporting of intangible assets are not mandatory, some firms may have undertaken genuine digital transformation efforts but failed to disclose the relevant details in their financial statement notes. This omission could lead to an overestimation of digital washing. To mitigate this concern, the analysis excludes firms that did not provide detailed intangible asset disclosures and re-runs the regression model. Again, we find a positive association between the extent of digital washing and the employee pressure experienced by firms. This approach enhances the reliability of the findings by reducing the risk of measurement bias.

Column (3) considers the possibility that different firms adopt varying disclosure strategies. Firms that disclosed detailed intangible assets related to digital transformation are

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[5] The variable *TREAT* is subsumed in firm fixed effects, and *POST* is subsumed in year fixed effects.

classified as the treatment group, while the control group comprises firms that did not provide such disclosures. Using the propensity score matching (PSM) method, the control group is constructed based on covariates from the main regression model, following the methodology of DeFond et al. (2016). We apply nearest-neighbor matching and the re-examine the regression in equation (1). Again, we find that the result is robust to our main specification in Table 3.

[Insert Table 5 here]

4.4 Additional Analysis

Ownership Structure

State-owned enterprises (SOEs) often bear greater social responsibilities, such as maintaining employment stability, due to their close ties with government policy objectives (Leutert, 2024). To examine the heterogeneous effects of employee pressure on digital washing across firms with different ownership structures, the sample is divided into two groups: state-owned enterprises (SOEs) and non-state-owned enterprises (non-SOEs). Separate regression analyses are conducted for each group to assess the impact of employee pressure on digital washing.

The results, presented in Table 6 Columns (1) and (2), indicate that the relationship between employee pressure and digital washing is statistically significant for SOEs but not for non-SOEs. These findings suggest that SOEs are more susceptible to the effects of employee pressure in terms of digital washing.

Labor-Intensity

Labor-intensive industries often employ a large number of low-skilled workers, making them particularly sensitive to employee pressures. Layoffs in these sectors can lead to significant social consequences, including increased labor disputes and social unrest (Bao, 2025). To investigate whether labor intensity influences the relationship between employee pressure and digital washing, firms are categorized into labor-intensive and non-labor-intensive groups, following established methodologies in the literature (Yin and Sheng, 2019). Separate regression analyses are performed for each group.

The results, reported in Columns (3) and (4) of Table 6, reveal that employee pressure significantly increases digital washing in labor-intensive firms, whereas no significant effect is observed in non-labor-intensive firms. These results highlight the amplifying role of labor intensity in the relationship between employee pressure and digital washing.

Degree of Marketization

In less marketized regions, governments tend to exert stronger administrative influence over firms, often imposing implicit social responsibilities such as maintaining local employment stability (Allen et al., 2005; Fan et al., 2010). Firms operating in such environments may face heightened political and reputational pressure to preserve jobs, even in the absence of formal mandates. Moreover, layoffs and other market-oriented employment adjustments can result in more severe social consequences in these areas—such as government intervention, media scrutiny, or public unrest (Fan et al., 2010)—making firms more inclined to use symbolic strategies like digital washing to signal social compliance and deflect criticism. To explore the influence of regional marketization on the relationship between employee pressure and digital washing, the marketization index developed by Fan et al. (2010) is utilized. Firms are divided into two groups based on the median marketization level of the regions in which they operate: high-marketization and low-marketization. Separate regression analyses are conducted for these two groups.

The results, shown in Columns (5) and (6) of Table 6, show that the effect of employee pressure on digital washing is more pronounced in regions with lower levels of marketization. These findings suggest that firms in less marketized regions are more likely to engage in digital washing under employee pressure.

[Insert Table 6 here]

4.5 Economic consequences

As previously discussed, firms facing dual pressures from employment responsibilities and the demands of digital transformation may adopt a digital washing strategy as a coping mechanism. While this strategy helps firms navigate these conflicting institutional demands, the potential economic consequences of digital washing warrant further exploration. Building on our institutional logic framework, we investigate whether digital washing—despite its symbolic nature—can yield tangible market benefits. Specifically, we examine how digital washing, particularly under conditions of heightened employee pressure, influences stock liquidity, a key indicator reflecting market perceptions of a firm's performance.

To measure stock liquidity, we apply the Amihud Illiquidity Index, following the methodology proposed by Amihud (2002). This index reflects the daily price impact of trading volume: a higher value indicates lower liquidity, while a lower value suggests higher liquidity.

The results, presented in Table 7, suggest that digital washing leads to improved stock liquidity, indicating that the market responds favorably to firms' rhetorical emphasis on digital transformation, even when it does not fully align with substantive actions. Furthermore, the interaction term *DIGITALWASHING*EMPLOYEEPRESSURE* is significantly negative at 1% level. This suggests that the association between digital washing and stock liquidity is stronger for firms facing higher employee pressure.

Overall, the results indicate that the market responds favorably to firms' digital washing. This positive association is more pronounced among firms facing higher employee-related institutional pressures. These findings suggest that digital washing may serve as a short-term, market-oriented strategy, particularly for firms under employee pressure, allowing them to navigate institutional tensions while maintaining favorable perceptions in capital markets.

[Insert Table 7 here]

5. Conclusion

This study investigates the phenomenon of digital washing, where firms strategically exaggerate their digital transformation efforts to manage conflicting institutional pressures. We expect and find a positive and significant relationship between employee pressure and the extent of digital washing. We validate our results through multiple robustness tests, including a Difference-in-Differences approach leveraging the 2017 U.S.-China trade war as an exogenous shock. We also explore the heterogeneous effects of digital washing across different firm characteristics, indicating that state-owned enterprises, labor-intensive firms, and firms in less marketized regions are particularly prone to this practice. Furthermore, we demonstrate the economic consequence of digital washing, showing its positive impact on stock liquidity, which suggests that firms can benefit from improved investor perceptions despite the symbolic nature of their actions.

By shedding light on the drivers and consequences of digital washing, this study contributes to the broader understanding of how firms navigate the pressures of digital transformation and employment responsibilities. Future research could further explore the long-term impacts of digital washing on firm performance, stakeholder response and organizational legitimacy. Our findings also have significant implications for policymakers, underscoring the need for greater transparency and accountability in corporate digital initiatives.

Appendix A Variable Definition

Variable	Definition	Data Source
DIGITALWASHING	The discrepancy between a firm's stated digital transformation efforts ("talking") and its actual implementation ("actions"). Digital washing is calculated as the difference between standardized scores for "talking" and "actions" (z-scores). "Talking" is measured through textual analysis of the Management Discussion and Analysis (MD&A) sections in annual reports. "Actions" are measured by the proportion of intangible assets related to digital technologies, identified through financial report disclosures, using keywords such as "software," "network," "client," and "intelligent platform."	Firms's annual resports
EMPLOYEEPRESSURE	$EMPLOYEEPRESSURE = (EMP\_FIRM - ASSET\_FIRM \times \frac{EMP\_IND}{ASSET\_IND})/EMP\_FIRM$ Where *EMPLOYEEPRESSURE* represents the firm's excess employee ratio, *EMP_FIRM* is the number of employees in the firm, *ASSET_FIRM* is the firm's total assets, *EMP_IND* is the average number of employees in the industry, and *ASSET_IND* is the average asset size of the industry.	CSMAR, Wind
EMPLOYEEPRESSURE2	$EMPLOYEEPRESSURE2 = (\mathrm{EMP\_FIRM} - \mathrm{SALES\_FIRM} \times \frac{EMP\_IND}{SALES\_IND})/EMP\_FIRM$ Where *EMPLOYEEPRESSURE2* represents the firm's excess employee ratio, *EMP_FIRM* is the number of employees in the firm, *SALES_FIRM* is the firm's sales revenue, *EMP_IND* is the average number of employees in the industry, and *SALES_IND* is the average sales revenue of the industry.	CSMAR, Wind
SIZE	The natural logarithm of the book value of total assets.	CSMAR
LEV	Total debts scaled by total assets.	CSMAR
ROA	Net income scaled by total assets.	CSMAR
BM	Book-to-market ratio, the ratio of a firm's book value of equity to its market value of equity.	CSMAR
GROWTH	The annual growth rate of operating income.	CSMAR
BOARD	The natural logarithm of the number of board members.	CSMAR

INDEP	The proportion of independent directors: number of independent directors/number of board members.	CSMAR
INSTR	The percentage of a firm's outstanding shares held by institutional investors.	CSMAR
TOP1	The shareholding ratio of the largest shareholder.	CSMAR
SOE	An indicator variable equal to 1 if the firm is state-owned, and 0 otherwise.	CSMAR
GDP	The natural logarithm of total gross domestic product (GDP) of the city where the firm is headquartered.	CSMAR
POPU_GROW	Annual percentage change in the city's population where the firm is headquartered.	CSMAR
LABOR	An indicator variable equal to 1 if the firm operates in a labor-intensive industry, and 0 otherwise.	CSMAR
AMIHUD	Amihud Illiquidity Index.	CSMAR

Appendix B Digital Transformation Disclosure Words List

Indicator	Keywords
Technical level	
Artificial intelligence technology	Artificial intelligence, Business intelligence, High-end intelligence, Image understanding, Intelligent terminal, Intelligent manufacturing, Investment decision support system, Intelligent equipment, Intelligent production, Intelligent data analysis, Intelligent robot, Machine learning, Deep learning, Semantic search, Biological recognition technology, Face recognition, Voice recognition, Identity verification, Automatic driving, Natural language processing
Big data technology	Big data, Data mining, Text data mining, Data visualization, Heterogeneous data, Credit investigation, Augmented reality, Mixed reality, Virtual reality
Cloud computing technology	Cloud computing, Stream computing, Graph computing, Memory computing, Cloud IT, Multi-party security computing, Brain like computing, Green computing, Cognitive computing, Fusion architecture, Billion-level concurrency, EB level storage, Internet of Things, Information physical systems
Blockchain technology	Blockchain, Cryptocurrency, Digital currency, Distributed computing, Differential privacy technology, Smart financial contract
Application level	
Digital technology application	Mobile Internet, Industrial Internet, Internet marketing, Internet strategy, Mobile Internet, Industrial Internet, Internet medical care, E-commerce, Mobile payment, Third-party payment, NFC payment, Smart energy, Internet Ecology, B2B, B2C, C2C, O2O, Internet connection, ‘Internet+’ smart wear, Smart agriculture, Intelligent transportation, Smart medical care, Smart customer

	service, Smart home, Intelligent investment consultants, Intelligent cultural tourism, Intelligent environmental protection, Smart grid, Intelligent marketing, Digital marketing, Unmanned retail, Internet finance, Digital finance, Fintech, Financial technology, Quantitative finance, Open bank

Source: Zhu and Yu (2024).

Appendix C Illustration of Digital Rhetoric

To illustrate our measurement of "digital talking", we present four representative types of firms based on their textual emphasis and actual investment in digital transformation.

Type 1: Talking more, doing less – In its 2021 annual report, Foshan Shunde FSL Co., Ltd. (stock code: 605318) mentioned digital transformation-related keywords 164 times in the MD&A section, including frequent terms such as big data (24 times), mobile internet (40 times), and artificial intelligence (16 times). However, the firm's software-related intangible assets were valued at only RMB 401,600, accounting for merely 0.008% of its total intangible assets. This discrepancy suggests strong rhetorical commitment but limited actual investment.

Type 2: Talking less, doing more – By contrast, Shunfa Hengye Co., Ltd. (stock code: 000631) made no mention of digital transformation keywords in its MD&A section. Yet, it reported digital software-related intangible assets of RMB 578,000, representing 100% of its total intangible assets. This case highlights substantive digital investment despite the absence of public discourse.

Type 3: Talking more, doing more – Jiadu Technology Co., Ltd. (stock code: 600728) demonstrated both high levels of digital rhetoric and significant investment. Its MD&A section included 140 mentions of digital keywords (e.g., big data: 49; Internet of Things: 52), and its software-related intangible assets reached RMB 490 million, accounting for 95.15% of total intangible assets. This indicates strong alignment between discourse and action.

Type 4: Talking less, doing less – Finally, Guoji Shiye Co., Ltd. (stock code: 000159) neither mentioned any digital keywords nor reported software-related intangible assets in 2021, reflecting minimal engagement both rhetorically and financially in digital transformation.

Table 1 Sample Selection

Unique firm-year observations of A-share listed companies on the Shanghai and Shenzhen stock exchanges in China from 2008 to 2021.	44,253
Drop firms under special treatment (i.e. ST and *ST stocks) or particular transferred (i.e. PT stocks).	-228
Drop financial firms (CSRC industry code classification code 2012: J)	-999
Exclude firms that were newly listed during the fiscal year	-3,303
Remove observations lacking disclosed digital information.	-7,915
Remove observations lacking employee pressure.	-10,017
Remove observations with missing financial data	-512
Final sample	**25,809**

Table 2 Descriptive statistics

Variable	N	Mean	SD	Min	P25	P50	P75	Max
DIGITALWASHING	25,809	0.059	1.342	-4.793	-0.505	-0.057	2.245	2.935
EMPLOYEEPRESSURE	25,809	-0.258	1.219	-6.773	-0.459	0.121	0.725	0.857
EMPLOYEEPRESSURE2	25,809	-0.033	1.105	-6.089	-0.174	0.317	0.781	0.882
UNEM RATE	25,809	90.93	55.47	17.28	53.50	77.81	194.9	344.1
SIZE	25,809	22.24	1.288	20.00	21.31	22.06	24.67	26.27
LEV	25,809	0.424	0.200	0.054	0.264	0.420	0.762	0.864
ROA	25,809	0.051	0.041	0.002	0.020	0.041	0.132	0.206
BM	25,809	0.617	0.250	0.123	0.423	0.611	1.029	1.168
GROWTH	25,809	0.002	0.004	-0.005	0.000	0.001	0.008	0.028
BOARD	25,809	2.250	0.177	1.792	2.079	2.303	2.485	2.773
INDEP	25,809	0.374	0.053	0.333	0.333	0.333	0.50	0.571
INSTR	25,809	0.704	0.630	0.007	0.349	0.569	1.998	3.726
TOP1	25,809	0.348	0.149	0.087	0.231	0.328	0.620	0.746
SOE	25,809	0.404	0.491	0.000	0.000	0.000	1.000	1.000
GDP	25,809	11.36	0.556	9.766	11.04	11.44	12.10	12.22
POPU_GROW	25,809	0.006	0.005	0.000	0.002	0.005	0.018	0.0220
IV	25,809	0.002	0.001	0.000	0.001	0.002	0.003	0.007
LABOR	25,809	0.272	0.445	0.000	0.000	0.000	1.000	1.000
AMIHUD	25,809	0.005	0.007	-0.001	0.001	0.003	0.014	0.338

Table 3 The relationship between Excess employees and Digital washing

	(1) *DIGITALWASHING*	(2) *DIGITALWASHING*
EMPLOYEPRESSURE	0.043***	0.046***
	(2.723)	(2.876)
SIZE	0.116***	0.125***
	(6.079)	(6.449)
LEV	-0.360***	-0.365***
	(-3.645)	(-3.569)
ROA	-0.011	0.176
	(-0.029)	(0.475)
BM	0.107	0.102
	(1.296)	(1.242)
GROWTH	-1.074	-1.761
	(-0.478)	(-0.788)
BOARD	-0.092	-0.089
	(-0.849)	(-0.804)
INDEP	0.114	0.221
	(0.362)	(0.703)
INSTR	-0.032	-0.034
	(-1.505)	(-1.578)
TOP1	-0.319**	-0.343***
	(-2.516)	(-2.600)
SOE	-0.097**	-0.026
	(-2.336)	(-0.573)
GDP	-0.031	-0.056
	(-0.975)	(-0.763)
POPU_GROW	-1.593	-2.804
	(-0.494)	(-0.887)
Constant	-2.072***	-1.678**
	(-3.676)	(-1.972)
Industry FE	Yes	Yes
Year FE	Yes	Yes
City FE	No	Yes
Adj_R^2	0.183	0.201
N	25,809	25,809

*, **, and *** denote significance at the 10%, 5% and 1% levels, respectively. Standard errors are corrected for heteroskedasticity (t-statistics are in parentheses).

Table 4 Difference-in-Difference Test: Exploiting US Tariffs

VARIABLES	(1) *DIGITALWASHING*
*TREAT*POST*	0.083**
	(2.014)
SIZE	0.112***
	(3.726)
LEV	0.014
	(0.127)
ROA	-0.275
	(-0.881)
BM	-0.055
	(-0.758)
GROWTH	-2.538
	(-1.364)
BOARD	0.035
	(0.315)
INDEP	-0.068
	(-0.259)
INSTR	-0.017
	(-0.854)
TOP1	-0.124
	(-0.698)
SOE	0.031
	(0.420)
GDP	-0.008
	(-0.118)
POPU_GROW	-3.088
	(-1.038)
Constant	-2.293**
	(-2.206)
Firm FE	Yes
Year FE	Yes
City FE	Yes
Adj_R^2	0.611
N	25,809

*, **, and *** denote significance at the 10%, 5% and 1% levels, respectively. Standard errors are corrected for heteroskedasticity (t-statistics are in parentheses).

Table 5 Robustness Tests

	(1) Alternative measure of Employee Pressure *DIGITALWASHING*	(2) Excluding observations without digital intangible asset *DIGITALWASHING*	(3) PSM *DIGITALWASHING*
EMPLOYEEPRESSURE		0.067***	0.030*
		(3.579)	(1.683)
EMPLOYEEPRESSURE2	0.053***		
	(3.060)		
SIZE	0.113***	0.147***	0.089***
	(5.987)	(6.46)	(3.993)
LEV	-0.306***	-0.388***	-0.325***
	(-3.110)	(-3.178)	(-2.877)
ROA	0.198	0.322	0.053
	(0.534)	(0.741)	(0.115)
BM	0.116	0.122	0.052
	(1.395)	(1.270)	(0.530)
GROWTH	-0.579	-4.171	3.656
	(-0.256)	(-1.556)	(1.098)
BOARD	-0.091	-0.203	0.101
	(-0.840)	(-1.625)	(0.827)
INDEP	0.099	0.1841	0.291
	(0.315)	(0.503)	(0.834)
INSTR	-0.034	-0.043*	0.025
	(-1.621)	(-1.732)	(0.887)
TOP1	-0.300**	-0.269*	-0.470***
	(-2.370)	(-1.794)	(-3.241)
SOE	-0.091**	0.0074	-0.137***
	(-2.193)	(0.143)	(-2.969)
GDP	-0.028	-0.075	-0.019
	(-0.867)	(-0.880)	(-0.184)
POPU_GROW	-1.609	-0.712	-7.279
	(-0.498)	(-0.190)	(-1.536)
Constant	-2.080***	-1.450	-2.301*
	(-3.992)	(-1.437)	(-1.917)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Adj_R^2	0.184	0.238	0.206
N	25,809	19,309	8,332

*, **, and *** denote significance at the 10%, 5% and 1% levels, respectively. Standard errors are corrected for heteroskedasticity (t-statistics are in parentheses).

Table 6 Additional Analysis

	(1)	(2)	(3)	(4)	(5)	(6)
	SOE	NON-SOE	Labor-intensive firms	Non-Labor-intensive firms	Low marketization	High marketization
VARIABLES	*DIGITAL WASHING*	*DIGITAL WASHING*	*DIGITAL WASHING*	*DIGITAL WASHING*	*DIGITAL WASHING*	*DIGITAL WASHING*
EMPLOYEEPRESSURE	0.072***	0.019	0.072***	0.028	0.073***	0.020
	(3.211)	(0.840)	(3.175)	(1.271)	(2.987)	(1.005)
SIZE	0.151***	0.115***	0.144***	0.115***	0.162***	0.097***
	(4.833)	(4.352)	(4.006)	(4.878)	(6.195)	(3.419)
LEV	-0.503***	-0.232*	-0.209	-0.413***	-0.462***	-0.252*
	(-3.154)	(-1.734)	(-1.121)	(-3.393)	(-3.463)	(-1.680)
ROA	0.399	0.064	0.044	0.233	-0.459	0.850
	(0.633)	(0.142)	(0.068)	(0.535)	(-0.949)	(1.544)
BM	0.060	0.101	0.099	0.127	0.038	0.155
	(0.441)	(0.960)	(0.669)	(1.291)	(0.331)	(1.348)
GROWTH	-3.484	-0.778	-0.472	-2.015	-1.826	-0.623
	(-1.051)	(-0.262)	(-0.123)	(-0.714)	(-0.641)	(-0.173)
BOARD	-0.208	0.034	-0.171	-0.039	-0.156	-0.052
	(-1.354)	(0.205)	(-0.881)	(-0.286)	(-1.067)	(-0.324)
INDEP	-0.040	0.471	-0.201	0.389	-0.299	0.528
	(-0.095)	(0.978)	(-0.377)	(1.003)	(-0.723)	(1.133)
INSTR	-0.075**	0.004	-0.090**	-0.012	-0.024	-0.038
	(-2.061)	(0.154)	(-2.345)	(-0.462)	(-0.821)	(-1.233)
TOP1	-0.159	-0.518***	-0.279	-0.420***	-0.414**	-0.313
	(-0.812)	(-2.853)	(-1.224)	(-2.636)	(-2.384)	(-1.586)
SOE			0.190**	-0.093*	-0.122**	0.076
			(2.195)	(-1.729)	(-2.149)	(1.069)
GDP	-0.113	-0.010	-0.246*	0.021	-0.139	0.017
	(-1.032)	(-0.103)	(-1.737)	(0.254)	(-1.435)	(0.151)
POPU_GROW	-5.576	-0.978	-4.380	-1.916	-2.271	-0.981
	(-1.152)	(-0.234)	(-0.748)	(-0.515)	(-0.613)	(-0.152)

Constant	-0.745	-2.751**	-0.555	-1.689*	-1.155	-2.646*
	(-0.573)	(-2.332)	(-0.378)	(-1.649)	(-1.021)	(-1.955)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj_R^2	0.244	0.206	0.167	0.227	0.228	0.188
N	10,414	15,395	7,026	18,783	13,276	12,265
Test of coefficient differences	chi2(1)=9.94***		chi2(1)=6.83***		chi2(1)=9.56***	

*, **, and *** denote significance at the 10%, 5% and 1% levels, respectively. Standard errors are corrected for heteroskedasticity (t-statistics are in parentheses). 268 observations are dropped due to the missing data of *AMIHUD*.

Table 7 Economic consequence

VARIABLES	(1) AMIHUD
*DIGITALWASHING*EMPLOYEEPRESSURE*	-0.014***
	(-3.429)
DIGITALWASHING	-0.017**
	(-1.970)
EMPLOYEEPRESSURE	-0.009
	(-0.938)
SIZE	-0.371***
	(-19.738)
LEV	0.599***
	(6.539)
ROA	0.560
	(0.871)
BM	0.758***
	(9.491)
GROWTH	8.184**
	(2.390)
BOARD	-0.024
	(-0.347)
INDEP	0.062
	(0.272)
INSTR	0.103***
	(4.155)
TOP1	0.304***
	(3.767)
SOE	-0.049*
	(-1.950)
GDP	-0.086
	(-1.067)
POPU_GROW	2.642
	(0.813)
Constant	10.263***
	(10.921)
Industry FE	Yes
Year FE	Yes
City FE	Yes
Adj_R^2	0.119
N	25,809

*, **, and *** denote significance at the 10%, 5% and 1% levels, respectively. Standard errors are corrected for heteroskedasticity (t-statistics are in parentheses). To facilitate interpretation of the coefficients, we multiply the *AMIHUD* illiquidity measure by 1,000 before running the regressions.

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