Making better workplaces? The impact of digital finance on corporate employee treatment

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Abstract

This study investigates the impact of digital finance, the integration of traditional financial services with modern information technology, on corporate employee treatment. While prior research has highlighted the influence of digital finance on firm operations and external financing, its effects on internal stakeholder outcomes remain underexplored. Using firm level data from China, our study presents robust evidence that digital finance significantly improves employee treatment. Specifically, digital finance can effectively reduce firms' financial constraint and improve information transparency, thereby enabling firms to offer better treatment to their employees. Further heterogeneity analysis reveals that the positive relationship is more prominent in firms located in the regions with lower marketization levels and severe air pollution, indicating that disadvantaged firms are taking advantage of digital inclusive finance to attract employees in a competitive market. Last, we find digital finance promotes corporate digital transformation and increases the proportion of high-skilled workers within firms, underscoring the importance for employees to invest in skills that are increasingly valued in a digitally enabled economy. Overall, this study deepens our understanding of the role of financial technology in corporate employee treatment strategy and is a timely addition to the current literature.

Keywords: Digital finance, employee treatment, financial constraint, information transparency

JEL classification: G30, J30, O33, I31

1. Introduction

Technology and humanity are timeless topics in today's world (Leonhard, 2016). Digital finance (DF), as an emerging integration of various digital technologies, has experienced rapid development in recent years. Given the development of digital technology is an inevitable trend and has strong externalities, how DF influence human capital in firms via, in particular, employee treatment, warrants further investigation. We believe the study of DF and its relationship with employee treatment enriches the literature relating to employee wellbeing and is of particular interest to economists and managers who are concerned with how new finance technology affects human capital and reshapes the labour market.

Finance researchers have found that DF influences corporate decisions and performance in multiple ways, including improving financial performance (Wu & Huang, 2022), reducing carbon emission intensity (Lu et al., 2023), reducing bankruptcy risk (Ji et al., 2022), and encouraging risk-taking behaviours such as green innovation (Tian et al., 2022). Since DF operates as a macro-level indicator, its impact on firm behaviour can be studied while minimizing endogeneity concerns, making it a widely adopted variable in corporate finance research (e.g., Mu et al., 2023; Ji et al., 2022). However, whether and how DF affects firm strategy with respect to employee treatment is unclear.

The relationship between DF and employee treatment can be theoretically explained through both positive and negative mechanisms. On the positive side, drawing on the resource-based view (Barney, 1991), DF can enhance employee treatment by easing firms' financing constraints and improving information transparency (e.g. Ji et al., 2022; Sun et al., 2023). Reduced financing constraints allow firms to allocate more resources toward employee welfare programmes, while improved transparency fosters stronger trust and engagement between management and employees. From the perspective of technological enablement and organisational change theory (Cascio & Montealegre, 2016), DF also acts as a catalyst for broader digital adoption (Wu & Huang, 2022), enabling process optimisation, better decision-making, and more inclusive management practices that strengthen employee treatment as part of a strategic approach to sustaining human capital advantages.

Conversely, a negative pathway is also plausible. The efficiency gains enabled by DF adoption may lead to technology-driven substitution of labour (Carpenter et al., 2019), reducing the need for certain roles and thus weakening employees' bargaining power. Additionally, as firms reallocate resources to prioritise technological investment and competitive positioning, employee welfare initiatives may receive lower priority (Schein, 2010). Organisational culture and strategic focus may also shift toward performance metrics and shareholder returns, potentially crowding out employee-oriented considerations (Li et al., 2024). These dynamics suggest that while DF has the potential to foster better employee treatment under resource-rich and inclusive strategies, it could also weaken employee treatment when the dominant logic emphasises cost efficiency and rapid technological scaling.

To investigate the relationship between DF and employee treatment, we conduct empirical analysis based on the Chinese market. China is an ideal setting for this study for the following reasons. First, China is a world-leading country in its telecom and internet construction. The new DF technology is gradually becoming an integral part of China's financial system (Mu et al., 2023), and significant heterogeneity exits in DF across space and time. Taking advantage of the DF ranking framework published by Peking University, we can easily measure the development level of DF in Chinese cities. Second, China has the world's second largest population and a huge labour market. In recent years, the former "factory of the world" has been actively optimising and upgrading its industrial structure for sustainable development. The Fifth Plenary Session of the 19th Central Committee of the Communist Party of China in 2020 emphasized that common prosperity is an important feature of Chinese-style modernization. Instruments to implement this policy, such as income and employee treatment, and its determinants need further investigation.

To construct corporate employee treatment measures, we employ three proxies, which are Huazheng employee safety index, average employee compensation and Hexun employee scores[1]. The employee health and safety score from Huazheng is an indicator from the social category in the ESG raking system. The score is based on the company's plans to reduce employee safety accidents, accident and health trends and related factors, reflecting the company's effort in relation to employee wellbeing in terms of employment safety and health. Following previous research (Dai et al., 2017), we calculate average employee compensation as the total salary expenses for all employees minus the total salary paid to management, divided by the total number of ordinary employees[2]. The employee index from Hexun.com offers comprehensive rating of all listed Chinese firms in terms of employee treatment performance (Wang et al., 2021). We capture city level development of DF using the DF index published by the Peking University which has been widely used in many empirical studies (e.g. Dou et al., 2023).

We use panel data of 12,421 observations from 2011 to 2020 to examine the relationship between DF and employee treatment in China. Our main results indicate a significant and positive relationship between DF and employee treatment. The result is robust to adding forward values of employee treatment measures and to adapting sub-categories of the DF index in the ranking system. Following previous studies (Kong et al., 2020; Ouyang et al., 2024), we also employ the propensity score matching approach and entropy balancing approach in the robustness tests and the baseline findings still hold.

[1] The last two measures are for robustness checks, given space limitation.
[2] Ordinary employee means total number of employments minus management people.

To address potential endogeneity concerns from reverse causality, where firms with more employee-friendly practices may contribute to local DF facilities and infrastructure and thereby bias upward the estimated effect of digital finance on employee treatment, we adopt a two-stage least squares (2SLS) approach with two instrumental variables (IVs). The first IV follows Zhu et al. (2023) and uses the geographical distance from a firm's city to Hangzhou, the birthplace of Alipay and a central hub for DF development in China. Because geographical distance is time-invariant, we follow Zhang et al. (2020) and construct a time-varying IV by interacting the distance with the national average DF index (excluding the specific city), capturing exogenous variation in DF exposure across cities and over time. The second IV builds on Chen and Zhang (2021) and reflects the role of communication infrastructure in DF development. It is defined as the number of fixed-line telephones per 100 people in 1984 multiplied by the number of Internet users in each city in the previous year. This interaction combines a historical proxy for infrastructure readiness with a time-varying measure of digital adoption, providing a credible source of exogenous variation in DF. In the first-stage regressions, both instruments are significantly related to the DF index: cities further from Hangzhou tend to have lower DF development, and DF growth is positively associated with stronger historical communication infrastructure and greater Internet use. The second-stage results remain consistent with the baseline findings, confirming the robustness of the positive relationship between DF and employee treatment after addressing endogeneity.

Furthermore, to shed light on the mechanisms underlying the relationship between DF and employee treatment, we examine two potential ones emphasised in prior literature (Ji et al., 2022; Mu et al., 2023), which are alleviating financial constraints and improving information transparency. Our analysis reveals that the positive impact of DF on employee treatment is concentrated in financially constrained firms and in those with lower transparency, suggesting that DF promotes more employee-oriented practices by easing resource limitations and reducing information asymmetry.

We also conduct a series of heterogeneity tests. Results indicate the positive impact of DF on employee treatment differs depending on a number of factors. We find the positive effect is prominent in firms located in regions with lower marketization levels and regions with server air pollution. These firms can be viewed as disadvantaged firms in a competitive market and DF increases the ability for such firms to provide better treatment for employees, to compensate for working in them. Also the effect is more pronounced in state-owned-enterprises (SOEs), firms with more board independence, firms with higher managerial ability and firms with lower CEO power, indicating that government support and good corporate governance are indispensable factors in promoting DF's positive impact on employee treatment policies. Last, we examine how DF development affects firms' employment structures and find that DF leads to a trend of corporate digital transformation and increases demand for high skilled labour. This shift reflects a growing demand for skilled labour as financial technology develops, underscoring the importance of investing in human capital for both individual career advancement and organizational competitiveness.

The novelty of this paper is as follows. Whereas the existing economics and finance literature has primarily focused on the effects of DF on labour-related outcomes such as the labour income share (e.g., Chen et al., 2023; Yang et al., 2023), labour structure (e.g., Dou et al., 2023; Li et al., 2024), and labour investment efficiency (Wang et al., 2024), much less attention has been paid to how DF affects employee treatment, which constitutes a fundamental aspect of firms' internal stakeholder relations. Employee treatment reflects not only compensation and welfare but also broader considerations of fairness, working conditions, and long-term commitment, all of which are essential for sustaining firm competitiveness and social responsibility. By shifting the focus from macro-level labour market indicators to micro-level employee well-being, our study aims to filling an important gap in the literature.

This paper makes three main contributions. First, it advances the understanding of how DF benefits firms through the dual mechanisms of alleviating financing constraints and enhancing information transparency. By easing access to external capital while subjecting firms to greater scrutiny from investors and regulators, DF simultaneously shapes both the capacity and the motivation for firms to adopt more responsible labour practices. This highlights the dual role of financial technology in strengthening socially responsible corporate behaviour and extends the scope of financial research to incorporate employees as critical internal stakeholders.

Second, we provide new evidence on the inclusive role of DF in supporting disadvantaged firms. By mitigating institutional and environmental disadvantages faced by firms in highly polluted or less market-oriented regions, DF reduces systemic barriers and promotes more equitable participation in economic development. This contribution underscores the developmental significance of DF as an instrument of inclusive finance, highlighting its potential to narrow inequalities in corporate opportunities and strengthen the sustainability of economic growth. Moreover, we emphasize that under an advanced DF environment, sound corporate governance practices remain essential in translating these advantages into improved employee-related policies.

Third, we document the impact of DF development on corporate digital adoption and employment structure. Our results show that greater DF adoption is associated with deeper corporate digital transformation and a rising share of high-skilled workers, reflecting a complementary relationship between technological advancement and employee upskilling. This finding aligns with the view expressed by Simon Johnson and Daron Acemoglu, recipients of the 2024 Nobel Prize in Economic Sciences, in their book *Power and progress: Our* *thousand-year struggle over technology and prosperity (2023)* that technological forces are inexorable and the appropriate response is to invest in future-relevant skills. In this way, our study demonstrates that DF is not only a driver of reduced financing frictions and improved transparency but also a transformative force reshaping labour structures and human capital development in the digital economy.

The remainder of paper is as follows. Section 2 reviews relevant literature and develops our hypotheses for the study. In section 3, we discuss our research design. We present the main empirical results and several robustness checks in Section 4. Further analyses and findings are discussed in section 5. Section 6 concludes the paper.

2. Literature review and hypothesis development

Recent literature has linked the development of DF to a wide range of economic consequences, such as stimulating household consumption (Li et al., 2020), increasing women's entrepreneurship and bargaining power (Han et al., 2023), industrial structure upgrading (Ren et al., 2023) and strengthening regional economic resilience (Yu et al., 2023; Yang et al., 2024). With respect to firms, DF provides more digital resources and sustainable services for firms (Li et al., 2023), enabling firms to easily achieve more sustainable financial services, to increase information transparency with suppliers and reduce operational risk (Guo et al., 2023). In addition, DF has broadened the boundaries of financial services through modern information technology, thereby reducing transaction costs of financial institutions, and improving the overall efficiency of the financial system (Wu et al., 2022). These factors benefit firms a great deal by easing financial constraints (Li et al., 2023). However, how DF development affects employee treatment has been less well investigated.

On the one hand, DF may have a positive impact on employee treatment. Drawing on the resource-based view (Barney, 1991), DF constitutes a strategic resource that is inclusive, inimitable and non-substitutable, enabling firms to overcome capital market frictions. By facilitating more efficient access to external financing, diversifying funding sources, and lowering transaction costs (Mu et al., 2023), DF can effectively ease financial constraints, thereby allowing firms to allocate greater resources toward employee welfare, skills development, and workplace enhancements. Furthermore, in line with the technological enablement and organizational change perspective (Cascio & Montealegre, 2016), the development of DF enhances information transparency by digitizing financial transactions and expanding data availability. Improved information transparency reduces asymmetries between management and employees (Akerlof, 1982). Under increased external monitoring, firms face stronger incentives to maintain a positive reputation and demonstrate compliance with social responsibility standards. As a result, they are more likely to improve employee treatment. Hence, DF functions not only as a financial enabler but also as an informational and organizational catalyst that supports a shift toward more employee-oriented management practices.

On the other hand, there may exist a negative relationship between DF and employee treatment. First, although DF may ease financial constraints (Li et al, 2023), the additional financial slack is not necessarily channelled towards employee-related investments. Consistent with resource-based view, firms often redirect such resources to activities with more immediate and measurable returns, including technological upgrading, market expansion, and shareholder remuneration (e.g. Ji et al., 2023; Carpenter et al., 2019), thereby diminishing the allocation available for long-term commitments to employee welfare. Second, the large-scale adoption of DF may signal a broader strategic reorientation towards efficiency maximization and return optimization. Such a shift can reshape organizational norms and values, embedding a performance-centric culture that reduces the salience of employee treatment and wellbeing as strategic objectives (Schein, 2010). Third, the integration of DF into core operations is frequently accompanied by automation and process digitization, which substitute for routine labour, compress staffing levels, and intensify work demands on remaining employees (Li et al., 2024).

Based on the discussion and analysis above, we propose two competing research hypotheses:

H1a: DF enhances corporate employee treatment.

H1b: DF reduces corporate employee treatment.

3. Research design

3.1 Sample

This paper employs a sample of A-share listed firms in China's Shanghai and Shenzhen markets from 2011 to 2020. We exclude firms from financial industries, and special treatment firms to mitigate survivorship bias. After removing observations with missing data, the final sample consists of 12,421 firm-year observations for 2,680 unique firms. All the continuous variables are winsorzied at the 1st and 99th percentiles to mitigate outlier effects on our results. Detailed definitions of all relevant variables in the study are reported in Appendix A1.

3.2 Variable selections

3.2.1 Measure of employee treatment

The main explanatory variable is employee treatment (*ET*), and we employ the employee safety scores from the Huazheng ESG database. The health and safety score from Huazheng is an indicator from the social category, which is based on the company's disclosure on reducing employee safety accidents and reflects the firm's approach in terms of employee safety and health. The reason we choose Huazheng ESG ranking is because it performs well in terms of updating frequency and calculation accuracy and has been widely used in existing corporate ESG performance studies (e.g. Zhang et al., 2023; Fang et al., 2023). In terms of updating frequency, Huazheng updates quarterly, while other ESG ratings are typically updated semi-annually or annually. Also Huazheng adopts integrated semantic analysis and natural language process intelligent algorithms, which make scores more accurate (Zhang et al., 2023).

Second, we use average employee compensation (*Compensation*) and Hexun employee treatment score (*ES*) as alternative measures of employee treatment. Following previous studies (e.g. Chang et al., 2015; Dai et al., 2017; Dong et al., 2020), we use the total labour wage of a firm minus the total wage of all its top executives, directors, and supervisors to calculate the total wage of ordinary employees. We then calculate the average employee compensation by using the total wage divided by the total number of ordinary employees. The ES index is sourced from Hexun.com, a leading financial information platform in China that has published CSR scores and rankings for all listed Chinese firms since 2010. A key advantage of Hexun's data is its comprehensive coverage, avoiding the sample selection bias seen in other CSR ratings like RKS, which only include firms that voluntarily disclose CSR reports (Wang et al., 2021).

3.2.2 Measure of digital finance development

Based on previous studies (Dou et al., 2023; Guo et al., 2023), we capture city level development of DF using the DF index published by the Digital Finance Research Centre of Peking University. DF is a comprehensive measure that captures the development of digital finance in China across dimensions such as coverage, depth of use, and degree of digitalization (Mu et al., 2023).

3.2.3 Control variables

Following previous literature on DF and employee treatment (Edmans, 2011; Zhang et al., 2020b; Chen & Zhang, 2021), we control firm-level variables including company size (*Firm Size*), firm age (*Firm Age*), debt ratio (*Leverage*), and the largest shareholding (*Concentration*).

We also include the ratio of market value to book value of total assets (Tobin's Q) (*Q*), return on assets (*ROA*) and sales growth rate (*Growth*). We include a dummy variable indicating whether a firm is controlled by the government (*SOE*). As for corporate governance, following Wang et al. (2021) we control the number of independent directors to the total number of directors on the board (*Independence*), the number of directors (*Board Size*), power of CEO (*Duality*), as well as the changing rate of employee numbers in a firm (*EmChange*). Finally, considering macroeconomic factors may have an influence on a firm's employment policy, we include the development of marketization (*Marketization*), the regional unemployment rate (*Unemployment*) and the provincial annual GDP growth rate (*GDP Growth*). The firm-level financial and corporate governance data and industry information is obtained from the Chinese Stock Market and Accounting Research Database (CSMAR). Other macroeconomics data is retrieved from National Bureau of Statistics of China (NBSC).

3.3 Model specification

To test our main hypothesis, the OLS regression model is designed as follows:

$$Employee\ Treatment_{i,t} = \alpha + \beta_1 DF_{i,t} + \beta_2 Firm\ Size_{i,t} + \beta_3 Firm\ Age_{i,t} + \beta_4 Leverage_{i,t} + \beta_5 Concentration_{i,t} + \beta_6 Q_{i,t} + \beta_7 ROA_{i,t} + \beta_8 Growth_{i,t} + \beta_9 SOE_{i,t} + \beta_{10} Independence_{i,t} + \beta_{11} Board\ Size_{i,t} + \beta_{12} Duality_{i,t} + \beta_{13} EmChange_{i,t} + \beta_{14} Marketization_{i,t} + \beta_{15} Unemployment_{i,t} + \beta_{16} GDP\ Growth_{i,t} + \sum \text{Industry FE} + \sum \text{Province FE} + \sum \text{Year FE} + \varepsilon_{i,t} \quad (1)$$

4. Empirical results

4.1 Sample distribution

This section discusses the sample distribution of our main dependent variables, employee treatment (*ET*). Table 1 shows the sample distribution of employee treatment across provinces and industries.

Insert Table 1 here

In panel A, we see that there are some differences in employee treatment between regions. To illustrate this further, we draw a heat map for each province using their average numbers during the sample period. Figure 1 shows the average employee safety index in each province. The darker the colour, the better the safety treatment of firms. Overall, Panel A and Figure 1 imply large variations in the key dependent variable across different regions.

Insert Figure 1 here

Panel B of Table 1 reports the treatment distribution at the industry level using the one-digit CSRC industry code. The panel reflects significant differences between industries. The better employee treatment is mainly concentrated in the energy and high-tech industries. In explanation of this, first, industries like electricity, gas and water are mostly SOEs, which have higher employee welfare standards compared with non-SOEs (Zhou, 2004). Second, scientific research and services industries employ many highly educated and highly skilled people. Companies often raise their treatment standards to attract employees to work for them, which is consistent with the efficiency wage theory (Wang et al., 2021).

4.2 Summary statistics

Table 2 reports the sample descriptive statistics. Consistent with previous literature (e.g. Mu et al., 2023; Ren et al., 2023). we divide the original DF index by 100 to make data comparable. The average DF index is 2.414 with a standard deviation of 0.534, indicating the development of DF still varies greatly from city to city. For the employee treatment index, the minimum and maximum value are 0.352 and 1. The average annual employee compensation ranges from RMB43,059 to RMB394,736. In terms of control variables, the average leverage ratio is 40.9%, and the average ROA is 5.2%. The average board size is 9 members and nearly 38% of board members act as independent directors. This composition structure complies with the China

Securities Regulatory Commission (CSRC) standards. The average increase in employee numbers in our sample is 11%. Overall, the distribution of the control variable statistics in our sample is consistent with previous Chinese studies (e.g. Wang et al., 2021).

Insert Table 2 here

4.3 Correlation analysis

Table 3 shows the correlation matrix and VIF test for independent variables. Most of the correlations reported are between -0.30 and 0.30. Both the correlations and VIFs show there is no significant evidence of multicollinearity.

Insert Table 3 here

4.4 Baseline results

Table 4 reports the baseline results of Eq. (1), which utilize regression models to explore the relationship between DF and employee treatment. We display all the control variables and include industry, province and year-fixed effects. In all model specifications, the coefficients of digital finance (*DF*) are positive and statistically significant at the 5% level; this supports our hypothesis H1a, namely, that DF is positively associated with employee treatment. Regarding the control variables, our findings demonstrate that large firms and SOEs have better employee-friendly treatment. Overall, the regression results for the control variables are consistent with prior studies (e.g. Ji et al., 2022).

Considering there is likely to be a lag between the DF's impact and the implementation of the firm policy and the firm's performance, we follow Wang et al. (2021) and take the one-year forward value of our treatment measurement. We present the results in the column (3) of Table 4. Consistent with our baseline findings, the coefficients of *DF* are still positive and statistically significant at the 5% level, which indicates our baseline results are robust.

Insert Table 4 here

4.5 Mechanism tests

While the baseline regressions establish a positive association between DF and employee treatment (ET), understanding the underlying mechanism is critical. Prior studies suggest that DF may influence firm behaviour through multiple pathways, including alleviating financial constraints and improving information transparency (e.g. Ji et al., 2022; Mu et al., 2023). However, the relative importance of these mechanisms remains unclear, particularly in the context of employee treatment. Therefore, we conduct mechanism tests by stratifying firms based on financial constraint and information transparency levels to empirically examine how these factors moderate the impact of DF on employee treatment.

Tables 5 and 6 present the results of the mechanism tests. Table 5 divides firms into high and low financial constraint subsamples based on the Kaplan-Zingales (KZ) index and Whited-Wu (WW) index. The results indicate that DF significantly enhances employee treatment in firms facing high financial constraints, whereas the effect is insignificant for firms with low constraints. These findings suggest that DF primarily benefits employee treatment when firms are financially constrained, consistent with the view that DF alleviates resources limitations and enables greater investment in employee welfare.

Insert Table 5 here

Table 6 examines the information transparency mechanism, using firm-level transparency rating from CSMAR and disclosure quality index from Huazheng. We find that the effect of DF on employee treatment is significantly positive in firms with lower transparency while the impact is insignificant for firms with higher transparency. This indicates that DF contributes more to employee investment in contexts where information asymmetry is greater, supporting the mechanism that DF enhances internal and external information flows, reduces asymmetry, and fosters better and more timely employee treatment.

Insert Table 6 here

Overall, these results provide robust empirical evidence that the positive influence of DF on employee treatment operates through easing financial constraints and improving information transparency, highlighting the dual financial and informational pathways through which DF promotes more employee-oriented practices.

4.6 Robustness tests

We next conduct a series of tests to ensure our results are robust.

4.6.1 Sub-categories of DF

In the baseline regression, we proxy digital finance by using the total DF index of city-level data. According to previous literature (e.g. Li et al., 2020), DF is a multi-dimensional concept, and therefore our paper not only examines the impact of the total index of DF on employee treatment but also uses the sub-category indices in the regression analysis. The ranking system of the DF index consists of three second-level indices, which are the index of coverage breadth (*Coverage*), the index of usage depth (*Depth*) and the index of degree of digitization (*Digit*). The breadth of coverage is reflected in the number of Alipay accounts owned and the number of bank cards per capita on the mobile phone applications. Coverage measures how widely DF is used. Depth of use measures the actual usage of online financial services such as online payment, insurance, investment, credit loans and investigation services. Degree of digitization focuses on the higher mobility, affordability and convenience of digital financial services.

Panel A of Table 7 presents the results for the impact of DF on employee treatment using the different dimensions of the DF index. We find both depth and usage contribute to better employee safety.

Insert Table 7 here

4.6.2 Propensity score matching

Next, we apply a propensity score matching (PSM) approach after converting the contiuno8ir DF variable into a binary indicator based on city-year median split (Rosenbaum & Rubin, 1983). Our matching procedure relies on a one-to-one neighbor matching of propensity scores without replacement, which is estimated by a probit regression of the binary dummy variable on a set of control variables. The balanced test results are consistent with pairwise comparisons of the covariates on which the matching is performed before and after the matching process (Kong et al., 2020). Specifically, the results show no statistical differences across any of the firm characteristics after the PSM, suggesting that firms in the matched sample are comparable. The balanced test results after PSM are reported in Appendix A2. The post-matching results shown in panel B of Table 7 indicate that DF positively affects employee treatment, which is consistent with baseline results

4.6.3 Entropy balancing

Next, we conduct the entropy balancing (EB) approach (Hainmueller, 2012). This approach aims to reweight a dataset such that the covariate distributions in the reweighted data satisfy a set of conditions; this is useful for creating balanced samples with a binary treatment where the control group data can be reweighted to match the covariate moments in the treatment group (Hainmueller & Xu, 2013). We divide the sample into treatment and control firms based on median value of city level DF index in a year. We present the results after matching consistent with the approach in Ouyang et al. (2024). Appendix A3 shows the balance tests. Before EB, the treatment firms are significantly different from the control firms along all dimensions, excluding leverage. After EB, the control and treatment groups become similar with differences equal to zero, suggesting that the matching is effective. The second column of Panel B in Table 7 reports the regression results obtained using the stacked matched sample, which are consistent with the baseline findings that DF promotes better employee treatment.

4.7 Endogeneity – 2SLS

Our baseline results may be affected by endogeneity issues. First, potential omitted variables may affect firm policies on employee treatment. Second, even though we adapt the city level data as an independent variable, causality problems may also exist. To address these issues, we use an instrumental variable (IV) and a two-stage least square (2SLS) regression to reproduce the baseline estimation. Previous literature has shown that geographical distance of the company from Hangzhou is a good IV for DF (e.g. Mu et al., 2023; Yu et al., 2023). Hangzhou, the capital of the economically developed province of Zhejiang, is located in the eastern region of China. Hangzhou is the birthplace and headquarters of Alipay, which is a typical DF company and a leader in DF development. Thus, Hangzhou is recognized as the centre of DF technology in mainland China and has many IT and DF talents. However, distance does not change over time, which invalidates the second-stage estimation as an instrumental variable. Therefore, following Zhang et al. (2020b), we interact the instrumental variable with the mean of the DF index at the national level (except for the specific city of the observation) as a new instrumental variable (*IV-Distance*) with time-varying effects.

In addition, given the well-documented link between communication infrastructure and the development of digital finance, we follow the approach of prior studies, such as Chen and Zhang (2021), and introduce a second instrumental variable (*IV-Intel*), to further address potential endogeneity concerns. *IV-Intel* is constructed as the product of the number of Internet users in a given city in year *t–1* and the number of fixed-line telephones per 100 people in that city in 1984. By interacting a time-varying component (Internet users) with a time-invariant historical infrastructure proxy, *IV-Intel* captures exogenous variation in digital finance development that is plausibly uncorrelated with unobserved determinants of firm-level employee treatment, satisfying the relevance and exclusion restrictions required for a valid instrument.

We first regress index of city level digital finance (*DF*) on our *IV-Distance*. As expected, IV-*Distance* is negatively related to *DF* index, and the coefficients are statistically significant at the 1% level, implying that the further away from the centre of DF, the lower the level of DF development. Results are presented in Panel A of Table 8. The first stage F statistic is 1503.658, which is significantly larger than the critical value of 10 suggested by Staiger and Stock (1994), indicating that *Distance* is a not weak IV. The second stage results are shown in the column (2) of Panel A. The coefficient of *DF* remains significantly positive, which is consistent with the baseline results.

Panel B of Table 8 reports an F-value of 2718.507 for *IV-Intel*, indicating that the instrumental variable is sufficiently strong. Column (1) presents the results of the first-stage regression, showing a significantly positive relationship between the *IV-Intel* and *DF*. This suggests that the development of DF is closely affected by the widespread adoption of fixed-line telephone and internet technology, as expected. The second-stage results, displayed in Column (2), indicate that the coefficient of DF remains significantly positive at the 1% level, consistent with the baseline findings. Overall, our 2SLS IV analysis results support our baseline finding that DF improves employee treatment within firms.

Insert Table 8 here

4.8 Alternative measure of employee treatment

In this section, we further confirm the validity of our measure of employee treatment by introducing two alternative measures to replace primary *ET* index – average employee compensation (*Compensation*) and employee treatment score (*ES*) retrieved from Hexun CSR ranking database.

We first rerun the baseline regression using compensation and ES scores and report the results in Table 9 Panel A. It is clear to see that DF contributes to higher employee compensation and ES scores. Then, we follow previous robustness check by taking forward value of compensation and ES, and we can see the results from the Panel B that the positive relations between DF and compensation still hold. Panel C presents the results for the impact of DF on employee treatment using the different dimensions of the index. We find all the sub-indices including coverage breath, depth of usage and level of digitization have positive impacts on employee compensation. Last, the PSM method, the Entropy Balancing match and the IV-2SLS test are all conducted, and Panel D and Panel E show the baseline regression is robust.

Insert Table 9 here

5. Further analysis

5.1.1 Heterogeneity tests across geographic differences

To better understand the effect of DF on employee treatment across regions, we examine how the impacts differ subject to regional marketization levels and air pollution levels. In the competitive labour market, firms located in low marketization regions and heavily polluted regions are more disadvantaged in attracting higher-educated and higher-skilled employees compared with those located in regions with better market development and better air quality, since the worse external environment is considered to be negatively related to employees' commitment to firms (Zhang et al., 2020). Similar evidence is found by Wang et al. (2021), who find air pollution significantly enhances employee treatment, as firms headquartered in polluted cities invest more in human capital to compensate for unmet health and safety needs as a result of working in locations with air pollution.

Compared with other resources and technologies, DF has own virtue of inclusiveness (e.g. Guo et al., 2023) which make it easily achievable by firms. Thus, we predict that DF will help companies located in regions with lower market development and severe air pollution to provide better employee treatment. Therefore, we expect the positive relationship between DF and employee treatment to be stronger for these disadvantaged firms. Using the Fan Gang index, which is publicly available and frequently employed in Chinese studies to proxy regional marketization (Wang et al., 2017), we divide our sample into high marketization regions and low marketization regions based on the sample median of the year. As reported in Table 10 Panel A, we find that the impact of DF on ET is larger in low marketization regions. Then, following previous studies (Dong et al., 2021), we calculate the city level air quality index based on the concentration level of six atmospheric pollutants[3] and separate our sample into high-polluted cities and low-polluted cities. The empirical results are shown in Table 10 Panel B and support the argument that the positive impact of DF on ET is more pronounced in firms located in areas with more severe air pollution.

Insert Table 10 here

5.1.2 Heterogeneity tests across firm level characteristics

In this section, we examine whether firm characteristics influence the positive impact of DF on employee treatment. Specifically, we focus on ownership structure and corporate governance. Table 11 reports the heterogeneity analysis for state ownership, board independence, managerial ability and CEO power.

[3] Detailed composition of pollutants is discussed in the Appendix A1.

SOEs play a significant role in China and are documented as one of the most important institutional features of the Chinese economy (Wang et al., 2021). Compared with non-SOEs, SOEs offer better job benefits and treatment for their employees, as in contrast to a private company's value maximization goals, SOEs have additional social stability and social development goals (Zhou, 2004; Bai et al., 2006). We divide our sample of firms into SOEs and non-SOEs based on the ultimate controller of the firm. We rerun our baseline regressions and the results in Panel A of Table 11 provide evidence that DF only contributes to better ET in SOEs. It indicates that compared with non-SOEs, SOEs have a stronger incentive to improve employee treatment.

Many scholars have previously tested the role of corporate governance in affecting firm-specific investment and its performance (e.g. Hu et al., 2021; Fan et al., 2024). These influences include internal factors such as board characteristics, managerial efficiency as well as CEO characteristics. In contrast to its impact in relation to, for example, replacing a machine or adapting a new technology in the production process, the agency problem has potentially serious repercussions with respect to employee investment. For example, investments such as improving job conditions and the working environment could be easily manipulated by managers so that it appears to investors that they are ethical leaders, in order to cover up their misconduct (Prior et al., 2008; Ben-Nasr & Ghouma, 2018). Employees as beneficiaries, are less likely to become potential whistle blowers, which may damage shareholders' value in the long run. Therefore, we expect that the positive influence of DF on ET is dependent on good corporate governance.

First, we divide our sample into two sub-samples based on the sample median of the number of independent directors at the industry and year level. We rerun the baseline regression and Panel B of Table 11 reports the results. We find a stronger impact of DF on ET in firms with higher board independence. Second, we spilt the sample based on the median of managerial ability at the industry and year level. The managerial ability (MA) is measured by the MA index, first introduced by Demerjian et al. (2012), which is based on the efficiency with which managers generate revenues[4]. The sub-sample results are reported in Panel C of Table 11, and show DF only promotes employee treatment when the MA index is higher. Last, we consider CEO power as an influence on employee-friendly policies. We select the sample based on whether the CEO also serves as the chairman of the board. The regression results shown in Panel D of Table 11 indicate that DF contributes to better employee treatment when CEO power in the firm is lower.

Insert Table 11 here

In all, the heterogeneity analysis reveals that the positive effect of DF on employee treatment is influenced by a number of factors. We find this positive relationship is more pronounced in disadvantaged firms, firms with strong government support and firms with good corporate governance.

5.2 Corporate digital transformation and demand for high skilled labour

According to human capital theory (Sweetland, 1996), human capital plays a crucial role in enabling firms to adapt and thrive amid technological change (Shrader & Siegel, 2007). In modern firms, skilled employees serve as key drivers of innovation and knowledge transfer, forming the backbone of firms' technological performance (Nelson, 2003; Faems & Subramanian, 2013). Their education and capabilities underpin sustained competitive advantage (Barney, 1991; Warhurst et al., 2004). As a form of technological innovation, DF accelerates firms' digital adoption, thereby raising the demand for highly educated and skilled

[4] In the first step, data envelopment analysis (DEA) is used to estimate relative firm efficiency by evaluating their inputs relative to their output. The output is net sales. The inputs include cost of goods sold (*COGS*); selling and administrative expenses (*SG&A*); property, plant and equipment (*PPE*); operating lease (*OpsLease*); goodwill (*Goodwill*); and other intangible assets (*OtherIntan*). DEA forms an efficient frontier, and firm efficiency is estimated then. To mitigate extreme observations, we use the decile ranks of *MA* according to the year and industry, following Dai et al. (2017).

labour (Liu & Hou, 2023; Dou et al., 2023). To compete for such talent, firms increasingly adopt employee-friendly policies to enhance participation and reduce turnover, consistent with efficiency wage theory (Akerlof, 1982). Moreover, by easing financial constraints, DF enhances firms' capacity to invest in human capital and improve employment conditions (Mu et al., 2023).

We therefore adapt three mediation measures to test this argument: corporate digital transformation (*DT*), practise of artificial intelligence inside firms (*AI*) and proportion of high-skilled employees (*Skill*). The index of corporate digital transformation (*DT*) is retrieved from the CSMAR database[5]. This index measures the level of DT in the firms; the higher the index, the higher the level of DT. Then, to better capture the firm digitalization relating to human capital, we develop textual analysis in Python on corporate textual disclosures in annual reports to find key words related to artificial intelligence. Consistent with the literature (e.g. Tang et al., 2023), we exclude the "Management Discussion and Analysis" (MD&A) sections of listed firms' annual corporate reports as they mainly disclose firms' strategies and future prospects, not their daily activities. Finally, the total word frequency is calculated and adapted as our proxy of firm practices with respect to artificial intelligence (*AI*). Last, we collect employee education information and define skilled labour (*Skill*) as the proportion of employees who have a bachelor's degree or higher in a firm, following Dai et al. (2017).

To test our conjectures, we conduct the mediation analysis using the approach followed in the finance literature (e.g. Xiong et al., 2021; Wheeler, 2019), namely the Sobel test (Hayes, 2009). Table 12 presents the results in relation to the predictions. First, we rerun the baseline

[5] The corporate digital transformation index of Chinese listed firms is derived from CSMAR's Digital Transformation Research Database. The database contains systematic measurements of strategic leadership, technology drive, organisational empowerment, environmental support at the macro level, enterprise digitalisation achievements and applications, which ultimately constructs the evaluation system of the digital transformation index. Using textual analysis to calculate the frequency of words related to digital transformation in listed firms' annual reports is a practical and scientific approach to assessing the extent of corporate digital transformation, currently employed in the literature (e.g. Chen et al., 2023; Tang et al., 2023).

regression and results are reported in the first column of each panel. The effect of DF on three mediation factors are presented in the second column of each panel. Results reveal that DF promotes corporate digital transformation, simulates the practice of artificial intelligence and increases the proportion of high-skilled employees within firms. Then the impact of DF on corporate employee treatment (*ET*) after controlling *DT*, *AI* and *Skill* are tested, and the results are presented in columns (3) in each panel. The coefficients of DF after controlling all three channel variables are still significantly positive but all lower than those without the controls in columns 1, as expected. In addition, the Sobel test is conducted to test the indirect effect of DF on employee treatment through the three variables. The Sobel test statistics are significant across all panels. Overall, the results suggest that DF promotes better corporate employee treatment through the adoption of corporate digital transformation and the increasing demand for high-skilled talents.

Insert Table 12 here

6. Conclusion

This paper examines the impact of DF on firm's employee treatment using a panel of Chinese listed firms from 2011 to 2020. Our main results indicate that firms headquartered in a city with better DF development tend to engage in better employee treatment. A series of robustness tests using the PSM and EB approaches, the forward value of employee treatment measurements and the sub-categories of the DF index, show the baseline results remain consistent. To mitigate the endogeneity issue, we use the geographic distance from the firm's headquarters to Hangzhou, a centre of DF in mainland China, and the historical fixed-line phones users in 1984 to construct two DF's IVs and our main results hold.

We further demonstrate that the positive impact of DF on employee treatment operates through two main mechanisms: the alleviation of firms' financial constraints and the enhancement of information transparency. By easing access to capital and improving the flow of information, digital finance enables firms to allocate more resources toward employee welfare and adopt more transparent, trust-enhancing practices, thereby strengthening their ability to attract and retain talent. Moreover, the positive relationship between DF and employee treatment is more prominent in disadvantaged firms located in the regions with lower marketization levels and regions with severe air pollution, where attracting and retaining talent is more challenging. We also find government support and good corporate governance are important factors that strength the positive relationship.

Finally, we examine the impact of DF development on corporate digital adoption and employment structure. The results show that greater DF adoption is associated with enhanced corporate digital transformation and a higher share of high-skilled workers. This evidence underscores the complementary relationship between technological advancement and workforce upgrading, highlighting the importance of human capital investment for sustaining both firm competitiveness and employee development in the digital economy. Overall, our study provides novel evidence that DF plays a pivotal role in shaping firms' human capital strategies and employee treatment policies, offering important implications for both corporate management and labour market policy.

References

Akerlof, G. A. (1982). Labour contracts as a partial gift exchange. *Quarterly Journal of Economics*, *97*(4), 543–569.

Bai, C. E., Lu, J., & Tao, Z. (2006). The multitask theory of state enterprise reform: Empirical evidence from China. *American Economic Review, 96*(2), 353–357.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, *17*(1), 99-120.

Ben-Nasr, H., & Ghouma, H. (2018). Employee welfare and stock price crash risk. *Journal of Corporate Finance*, *48*, 700–725.

Carpenter, D., Young, D. K., Barrett, P., & McLeod, A. J. (2019). Refining technology threat avoidance theory. *Communications of the Association for Information Systems*, *44*.

Cascio, W. F., & Montealegre, R. (2016). How technology is changing work and organizations. *Annual Review of Organizational Psychology and Organizational Behavior*, *3*(1), 349-375.

Chang, X., Fu, K., Low, A., & Zhang, W. (2015). Non-executive employee stock options and corporate innovation. *Journal of Financial Economics*, *115*(1), 168-188.

Chen, C., Wang, S., Yao, S., & Lin, Y. (2023). Does digital transformation increase the labour income share? From a perspective of resources reallocation. *Economic Modelling*, *128*, 106474.

Chen, S. S., & Wang, Y. (2012). Financial constraints and share repurchases. *Journal of Financial Economics*, *105*(2), 311-331.

Chen, S., & Zhang, H. (2021). Does digital finance promote manufacturing servitization: Micro evidence from China. *International Review of Economics & Finance*, *76*, 856-869.

Dai, Y., Kong, D., & Xu, J. (2017). Does fairness breed efficiency? Pay gap and firm productivity in China. *International Review of Economics & Finance*, *48*, 406-422.

Demerjian, P., Lev, B., & McVay, S. (2012). Quantifying managerial ability: A new measure and validity tests. *Management Science*, *58*(7), 1229-1248.

Dong, R., Fisman, R., Wang, Y., & Xu, N. (2021). Air pollution, affect, and forecasting bias: Evidence from Chinese financial analysts. *Journal of Financial Economics*, *139*(3), 971-984.

Dou, B., Guo, S., Chang, X., & Wang, Y. (2023). Corporate digital transformation and labour structure upgrading. *International Review of Financial Analysis*, *90*, 102904.

Edmans, A. (2011). Does the stock market fully value intangibles? Employee satisfaction and equity prices. *Journal of Financial Economics*, *101*(3), 621-640.

Faems, D., & Subramanian, A. M. (2013). R&D manpower and technological performance: The impact of demographic and task-related diversity. *Research Policy*, *42*(9), 1624-1633.

Fang, M., Nie, H., & Shen, X. (2023). Can enterprise digitization improve ESG performance?. *Economic Modelling*, *118*, 106101.

Guo, B., Feng, Y., & Lin, J. (2023). Digital inclusive finance and digital transformation of enterprises. *Finance Research Letters*, *57*, 104270.

Hainmueller, J (2012). Entropy balancing for causal effects: A multivariate reweighting

Han, X., Zhang, H., & Zhu, W. (2023). The impact of digital finance on women's bargaining power: Evidence from China. *China Economic Review*, *80*, 102007.

Hayes, A. F. (2009). Beyond Baron and Kenny: Statistical mediation analysis in the new millennium. *Communication Monographs*, *76*(4), 408-420.

Hemingway, C. A., & Maclagan, P. W. (2004). Managers' personal values as drivers of corporate social responsibility. *Journal of Business Ethics*, *50*(1), 33–44.

Ji, Y., Shi, L., & Zhang, S. (2022). Digital finance and corporate bankruptcy risk: Evidence from China. *Pacific-Basin Finance Journal*, *72*, 101731.

Johnson, S., & Acemoglu, D. (2023). *Power and progress: Our thousand-year struggle over technology and prosperity*. Hachette UK.

Jung, B., Lee, W. J., & Weber, D. P. (2014). Financial reporting quality and labour investment efficiency. *Contemporary Accounting Research*, *31*(4), 1047-1076.

Kim, J., Yang, I., Yang, T., & Koveos, P. (2021). The impact of R&D intensity, financial constraints, and dividend payout policy on firm value. *Finance Research Letters*, *40*, 101802.

Kong, D., Wang, Y., & Zhang, J. (2020). Efficiency wages as gift exchange: Evidence from corporate innovation in China. *Journal of Corporate Finance*, *65*, 101725.

Leonhard, G. (2016). *Technology vs. Humanity: The coming clash between man and machine*. Lodge, UK: FutureScapes.

Li, C., Huo, P., Wang, Z., Zhang, W., Liang, F., & Mardani, A. (2023). Digitalization generates equality? Enterprises' digital transformation, financing constraints, and labour share in China. *Journal of Business Research*, *163*, 113924.

Li, J., Wu, Y., & Xiao, J. J. (2020). The impact of digital finance on household consumption: Evidence from China. *Economic Modelling*, *86*, 317-326.

Li, W., Yang, X., & Yin, X. (2024). Digital transformation and labour upgrading. *Pacific-Basin Finance Journal*, *83*, 102280.

Liu, Z., & Hou, W. (2023). Social and Environmental Impacts of Digital Finance. In *Digital Finance: How Innovation Reshapes the Capital Markets* (pp. 139-155). Singapore: Springer Nature Singapore.

Lu, F., Li, Z., & Zhang, S. (2023). Does digital finance development affect carbon emission intensity: Evidence from China. *International Review of Economics & Finance*, *88*, 1272-1286.

Mu, W., Liu, K., Tao, Y., & Ye, Y. (2023). Digital finance and corporate ESG. *Finance Research Letters*, *51*, 103426.

Nelson, R. R. (2003). On the uneven evolution of human know-how. *Research Policy*, *32*(6), 909-922.

Ouyang, C., Xiong, J., Liu, L., & Yao, J. (2024). Geographic proximity and trade credit: Evidence from a quasi-natural experiment. *Journal of Corporate Finance*, *84*, 102535.

Prior, D., Surroca, J., & Tribo, J. A. (2008). Are socially responsible managers really ethical? Exploring the relationship between earnings management and corporate social responsibility. *Corporate Governance: An International Review, 16*(3), 160–177.

Ren, X., Zeng, G., & Gozgor, G. (2023). How does digital finance affect industrial structure upgrading? Evidence from Chinese prefecture-level cities. *Journal of Environmental Management*, *330*, 117125.

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, *70*(1), 41-55.

Schein, E. H. (2010). *Organizational Culture and Leadership* (Vol. 2). John Wiley & Sons.

Shrader, R., & Siegel, D. S. (2007). Assessing the relationship between human capital and firm performance: Evidence from technology–based new ventures. *Entrepreneurship Theory and Practice*, *31*(6), 893-908.

Staiger, D. O., & Stock, J. H. (1994). Instrumental variables regression with weak instruments. In: National Bureau of Economic Research Cambridge, Mass., USA.

Sun, G., Li, T., Ai, Y., & Li, Q. (2023). Digital finance and corporate financial fraud. *International Review of Financial Analysis*, *87*, 102566.

Sweetland, S. R. (1996). Human capital theory: Foundations of a field of inquiry. *Review of Educational Research*, *66*(3), 341-359.

Tang, M., Liu, Y., Hu, F., & Wu, B. (2023). Effect of digital transformation on enterprises' green innovation: empirical evidence from listed companies in China. *Energy Economics*, *128*, 107135.

Tian, G., Li, B., & Cheng, Y. (2022). Does digital transformation matter for corporate risk-taking?. *Finance Research Letters*, *49*, 103107.

Titman, S. (1984). The effect of capital structure on a firm's liquidation decision. *Journal of Financial Economics*, *13*(1), 137–151.

Wang, L., Dai, Y., & Kong, D. (2021). Air pollution and employee treatment. *Journal of Corporate Finance*, *70*, 102067.

Wang, X., Fan, G., & Yu, J. (2017). Marketization index of China's provinces: NERI report 2016. *Social Sciences Academic Press*.

Warhurst, C., Grugulis, I., & Keep, E. (Eds.). (2004). *The skills that matter*. Basingstoke: Palgrave Macmillan.

Wheeler, P. B. (2019). Loan loss accounting and procyclical bank lending: The role of direct regulatory actions. *Journal of Accounting and Economics*, *67*(2-3), 463-495.

Whited, T. M., & Wu, G. (2006). Financial constraints risk. *The Review of Financial Studies*, *19*(2), 531-559.

Wu, K., Fu, Y., & Kong, D. (2022). Does the digital transformation of enterprises affect stock price crash risk?. *Finance Research Letters, 48*, 102888.

Wu, Y., & Huang, S. (2022). The effects of digital finance and financial constraint on financial performance: Firm-level evidence from China's new energy enterprises. *Energy Economics*, *112*, 106158.

Xiong, J., Ouyang, C., Tong, J. Y., & Zhang, F. F. (2021). Fraud commitment in a smaller world: Evidence from a natural experiment. *Journal of Corporate Finance*, *70*, 102090.

Yang, G. Z., Si, D. K., & Ning, G. J. (2023). Does digital transformation reduce the labour income share in enterprises?. *Economic Analysis and Policy*, *80*, 1526-1538.

Yang, Y., Lin, Z., Xu, Z., & Liu, S. (2024). The impact of digital finance on regional economic resilience. *Pacific-Basin Finance Journal*, *85*, 102353.

Yu, Z., Li, Y., & Dai, L. (2023). Digital finance and regional economic resilience: Theoretical framework and empirical test. *Finance Research Letters*, *55*, 103920.

Zhang, J., Li, Y., Xu, H., & Ding, Y. (2023). Can ESG ratings mitigate managerial myopia? Evidence from Chinese listed companies. *International Review of Financial Analysis*, *90*, 102878.

Zhang, J., Wang, J., & Kong, D. (2020). Employee treatment and corporate fraud. *Economic Modelling*, *85*, 325-334.

Zhang, X., Yang, T., Wang, C., & Wan, G. (2020b). Digital finance and household consumption: theory and evidence from China. *Management World, 11*, 48-63. (in Chinese)

Zhou, G. S., Fan, G., & Shen, G. J. (2014). Income gap, social capital and health level empirical analysis based on China Family Panel Survey. *Management World, 7*. (in Chinese)

Zhou, H. (2004). High benefits and low wages: Employees as monitor of management in SOEs. *China Economic Review*, *15*(4), 407-423.

Zhu, M., Wang, Y., Wei, M., & Cai, Z. (2023). How does digital finance affect consumer online shopping: A comprehensive analysis based on econometric model. *Finance Research Letters, 54*, 103734.

Table 1. Sample distributions

	Employee Treatment
Panel A.	
Employee treatment across provinces	
Provinces	
Hainan	0.872
Xinjiang	0.873
Jilin	0.877
Chongqing	0.880
Tianjin	0.880
Yunnan	0.886
Jiangxi	0.887
Shanghai	0.888
Gansu	0.890
Tibet	0.890
Inner Mongolia	0.891
Anhui	0.893
Guangdong	0.893
Zhejiang	0.895
Hunan	0.896
Guangxi	0.897
Shaanxi	0.898
Sichuan	0.899
Hubei	0.901
Jiangsu	0.903
Henan	0.904
Qinghai	0.908
Shandong	0.908
Guizhou	0.908
Liaoning	0.908
Heilongjiang	0.911
Beijing	0.913
Hebei	0.915
Fujian	0.921
Ningxia	0.925
Shanxi	0.932
Panel B.	
Employee treatment across industries	
Industry	
Transportation	0.712
Agriculture, Forestry, Animal Husbandry, and Fishery	0.780
Public Facilities Management	0.888
Construction	0.893
Manufacturing	0.895
Comprehensive	0.907

Mining	0.915
Information Technology	0.922
Real Estate	0.923
Leasing and Business Services	0.930
Health and Social Service	0.965
Scientific Research and Services	0.969
Electricity, Gas and Water	0.976
Wholesale and Resale Trade	0.977
Culture, Sports and Entertainment	0.997

This table presents the mean of average safety index by province and industry separately.

Figure 1. Employee treatment index prefecture-level map of China

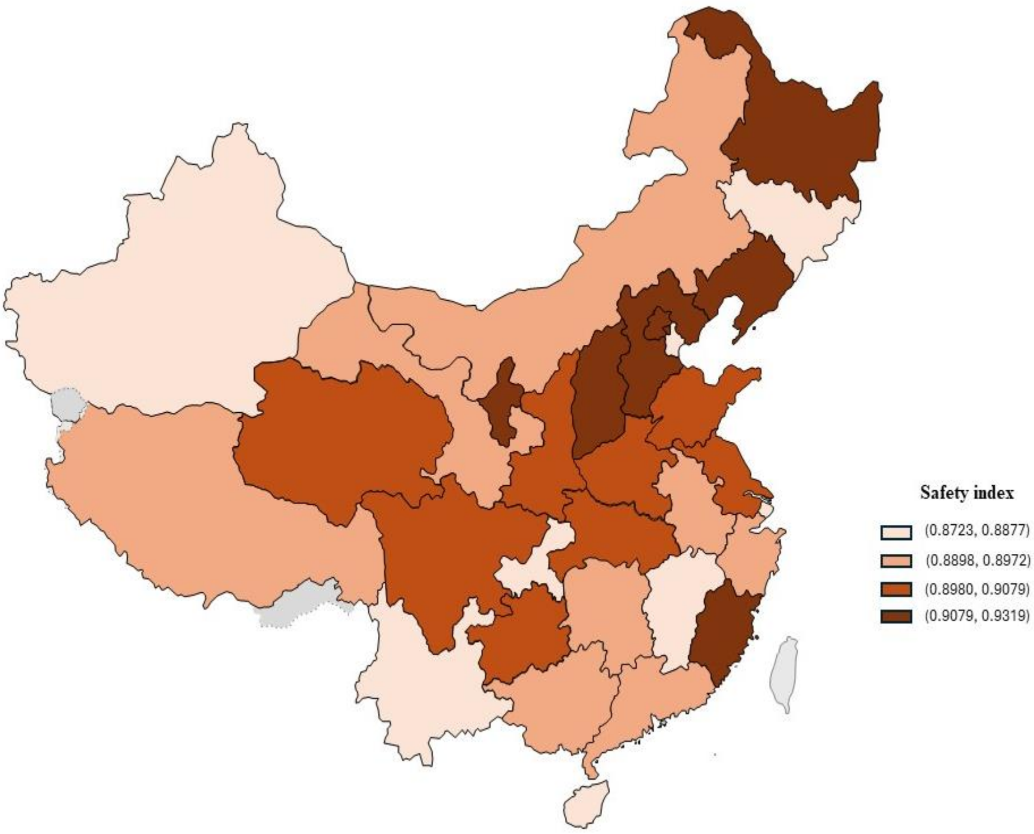

Table 2. Summary statistics

Variables	Obs.	Mean	Std.	Min	50%	Max
DF	12,421	2.414	0.534	0.952	2.476	3.216
ET	12,421	0.901	0.093	0.352	0.901	1.000
Compensation	12,421	126,470	64,095	43,059	109,883	394,736
ES	12,421	2.209	2.545	0.000	1.470	13.430
Firm Size	12,421	22.363	1.260	20.166	22.167	26.305
Firm Age	12,421	2.851	0.316	1.946	2.890	3.466
Leverage	12,421	0.409	0.190	0.062	0.402	0.851
Concentration	12,421	0.335	0.143	0.088	0.315	0.721
Q	12,421	2.112	1.317	0.854	1.698	8.353
ROA	12,421	0.052	0.044	0.001	0.042	0.213
Growth	12,421	0.188	0.385	-0.419	0.226	2.445
SOE	12,421	0.323	0.468	0.000	0.000	1.000
Independence	12,421	0.376	0.054	0.333	0.364	0.571
Board Size	12,421	2.126	0.198	1.609	2.197	2.708
Duality	12,421	0.281	0.449	0.000	0.000	1.000
EmChange	12,421	0.108	0.345	-0.421	0.030	2.280
Marketization	12,421	9.609	1.518	4.862	9.746	11.934
Unemployment	12,421	2.949	0.700	1.300	3.000	4.220
GDP Growth	12,421	0.079	0.045	-0.071	0.082	0.202

This table presents summary statistics for main variables in our samples. All variables are defined in the Appendix A1.

Table 3. Correlation Matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	VIF
1.DF	1.000																1.52
2.Firm Size	0.064	1.000															1.93
3.Firm Age	0.280	0.115	1.000														1.20
4.Leverage	-0.017	0.551	0.119	1.000													1.73
5.Concentration	-0.063	0.222	-0.093	0.096	1.000												1.15
6.Q	-0.062	-0.387	-0.072	-0.336	-0.082	1.000											1.35
7.ROA	0.061	-0.090	-0.042	-0.369	0.058	0.347	1.000										1.42
8.Growth	-0.001	0.017	-0.0570	0.041	-0.032	0.033	0.1879	1.000									1.39
9.SOE	-0.129	0.379	0.156	0.294	0.264	-0.168	-0.1948	-0.093	1.000								1.47
10.Independence	0.070	0.021	-0.020	0.001	0.057	0.028	-0.0057	-0.015	0.031	1.000							1.50
11.Board Size	-0.128	0.265	0.064	0.166	0.034	-0.121	-0.0456	-0.022	0.265	-0.543	1.000						1.69
12.Duality	0.087	-0.171	-0.091	-0.124	-0.047	0.086	0.0810	0.044	0.287	0.119	-0.191	1.000					1.13
13.EmChange	-0.053	0.023	-0.078	0.019	-0.021	0.023	0.1252	0.497	0.0860	0.000	-0.025	0.045	1.000				1.35
14.Marketization	0.449	-0.088	0.045	-0.087	-0.047	0.042	0.1034	-0.0056	0.222	0.041	-0.130	0.141	0.018	1.000			1.32
15.Unemployment	-0.209	-0.042	0.085	0.018	-0.021	0.012	-0.0279	-0.019	0.055	-0.049	0.039	-0.057	-0.016	-0.144	1.000		1.14
16.GDP Growth	-0.128	-0.036	-0.116	0.002	0.013	-0.029	0.0022	0.050	0.004	-0.002	0.011	0.026	0.028	-0.039	-0.211	1.000	1.09

This table displays the correlation statistics of main variables. All variables are defined in the Appendix A1. The VIFs are also calculated, and results show that there is no multicollinearity issue in our model.

Table 4. Baseline results

Variables	(1) ET	(2) ET	(3) ET_{t+1}
DF	0.013**	0.014**	0.018**
	(2.387)	(2.214)	(2.244)
Firm Size		0.002*	0.003**
		(1.924)	(2.123)
Firm Age		0.000	-0.002
		(0.016)	(-0.583)
Leverage		0.001	-0.000
		(0.068)	(-0.027)
Concentration		-0.004	-0.009
		(-0.448)	(-1.062)
Q		0.000	-0.000
		(0.020)	(-0.062)
ROA		-0.038	-0.039
		(-1.546)	(-1.443)
Growth		-0.001	0.000
		(-0.416)	(0.096)
SOE		0.006**	0.009**
		(2.738)	(2.781)
Independence		-0.039***	-0.047**
		(-3.945)	(-2.761)
Board Size		-0.003	-0.005
		(-0.895)	(-0.903)
Duality		-0.003	-0.002
		(-1.651)	(-0.699)
EmChange		-0.000	0.003
		(-0.020)	(1.199)
Marketization		-0.002	-0.003
		(-0.656)	(-1.082)
Unemployment		-0.004*	-0.002
		(-1.749)	(-0.543)
GDP growth		-0.035*	-0.047**
		(-2.046)	(-2.484)
Constant	0.868***	0.883***	0.880***
	(79.703)	(23.250)	(27.424)
Observations	12,421	12,421	8,594
Industry FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adj. R^2	0.178	0.180	0.865

The sample consists of 12,421 firm-year observations between 2011 and 2020. The independent variable is the city level digital finance index. *ET is* firm employee treatment index, which is obtained from Huazheng ESG database. All control variables are defined in the Appendix A1. The *t*-statistics in parentheses are calculated from the robust standard errors clustered at the city level. The symbols ***, **, and * denote significance level at the 1%, 5%, and 10% levels, respectively.

Table 5. Mechanism tests: Easing financial constraints

Panel A. KZ index

	High Constraint	Low Constraint
	(1)	(2)
Variables	ET	ET
DF	0.036***	-0.007
	(3.527)	(-0.491)
Constant	0.900***	0.869***
	(15.822)	(14.108)
Observations	6,252	6,169
Control	Yes	Yes
Industry FE	Yes	Yes
Province FE	Yes	Yes
Year FE	Yes	Yes
Adj. R^2	0.174	0.191

Panel B. WW index

	High Constraint	Low Constraint
	(1)	(2)
Variables	ET	ET
DF	0.013*	0.015
	(1.800)	(1.325)
Constant	0.785***	0.974***
	(15.480)	(15.804)
Observations	6,255	6,166
Control	Yes	Yes
Industry FE	Yes	Yes
Province FE	Yes	Yes
Year FE	Yes	Yes
Adj. R^2	0.208	0.165

Table 5 reports the results of mechanism tests exploring whether the impact of DF on employee treatment operates through the alleviation of financial constraints. Firms are divided into subsamples based on the Kaplan-Zingales (KZ) index and the Whited-Wu (WW) index to capture differences in financial constraint levels. All variables are defined in the Appendix A1. Robust *t*-statistics are reported in parentheses. The symbols ***, **, and * denote significance level at the 1%, 5%, and 10% levels, respectively.

Table 6. Mechanism tests: Addressing information asymmetry

Panel A. Information transparency level

	High	Low
	(1)	(2)
Variables	ET	ET
DF	-0.008	0.019**
	(-0.482)	(2.372)
Constant	0.849***	0.895***
	(9.335)	(19.929)
Observations	2,801	9,620
Control	Yes	Yes
Industry FE	Yes	Yes
Province FE	Yes	Yes
Year FE	Yes	Yes
Adj. R^2	0.185	0.181

Panel B. Information disclosure level

	High	Low
	(1)	(2)
Variables	ET	ET
DF	-0.006	0.019**
	(-0.189)	(2.750)
Constant	0.880*	0.844***
	(2.109)	(20.541)
Observations	1,848	10,573
Control	Yes	Yes
Industry FE	Yes	Yes
Province FE	Yes	Yes
Year FE	Yes	Yes
Adj. R^2	0.205	0.176

This table reports the results of mechanism tests exploring whether the impact of DF on employee treatment operates through the improvement of information transparency. Firms are divided into subsamples based on the information transparency rating from CSMAR database and the information disclosure quality index from Huazheng database to capture differences in information transparency levels. All variables are defined in the Appendix A1. Robust *t*-statistics are reported in parentheses. The symbols ***, **, and * denote significance level at the 1%, 5%, and 10% levels, respectively.

Table 7. Robustness tests

Panel A. Sub-categories of DF

Variables	(1) ET	(2) ET	(3) ET
Coverage	0.010**		
	(2.199)		
Usage		0.018**	
		(2.524)	
Digitalization			-0.001
			(-0.200)
Constant	0.887***	0.880***	0.896***
	(23.498)	(23.248)	(23.014)
Observations	12,421	12,421	12,421
Control	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adj. R^2	0.180	0.181	0.180

Panel B. Matched sample regression

	PSM	EB
Variables	(1) ET	(2) ET
DF	0.018**	0.022**
	(2.237)	(2.190)
Constant	1.035***	0.928***
	(10.745)	(13.720)
Observations	3,910	12,421
Control	Yes	Yes
Industry FE	Yes	Yes
Province FE	Yes	Yes
Year FE	Yes	Yes
Adj. R^2	0.097	0.159

This table shows the robustness results obtained by introducing Sub-categories of DF index in Panel A. Robust *t*-statistics are reported in parentheses. We rerun the baseline regression after PSM using the matched sample, and rerun the baseline regression after EB using the balanced sample and present the results in Panel B. All control variables are defined in the Appendix A1. The symbols ***, **, and * denote significance level at the 1%, 5%, and 10% levels, respectively.

Table 8. Endogeneity check – Instrumental variable approach

Panel A. Distance to Hangzhou as instrumental variable

Variables	(1) DF	(2) ET
IV-Distance	-0.017***	
	(-13.400)	
DF		0.074**
		(2.059)
Constant	0.982***	0.831***
	(8.477)	(14.408)
Observations	12,421	12,421
Control	Yes	Yes
Industry FE	Yes	Yes
Province FE	Yes	Yes
Year FE	Yes	Yes
Adj. R^2	0.939	0.024
Cragg-Donald Wald F statistic	1503.658	

Panel B. Internet users and fixed-line telephones in 1984 as instrumental variable

Variables	(1) DF	(2) ET
IV-Intel	0.126***	
	(6.551)	
DF		0.065***
		(2.894)
Constant	-0.425*	0.838***
	(-1.729)	(15.775)
Observations	12,421	12,421
Control	Yes	Yes
Industry FE	Yes	Yes
Province FE	Yes	Yes
Year FE	Yes	Yes
Adj. R^2	0.944	0.025
Cragg-Donald Wald F statistic	2718.507	

This table reports the results of the 2SLS regression with instrumental variables. The instrumental variable in panel A, *Distance*, is calculated as the interaction term between the mean of the DF index at the national level (except for the specific city) and the distance to Hangzhou city. Panel B uses the interaction term between the number of Internet users in *t-1* and the number of fixed-line telephones per 100 people per city in 1984 as instrumental variable. All variables are defined in Appendix A1. Robust *t*-statistics are reported in parentheses. The symbols ***, **, and * denote significance level at the 1%, 5%, and 10% levels, respectively.

Table 9. Alternative measures of employee treatment

Panel A. DF and employee compensation and ES

Variables	(1) Compensation	(2) Compensation	(3) ES	(4) ES
DF	0.362***	0.360***	0.966***	0.987***
	(7.507)	(7.872)	(4.332)	(4.754)
Firm Size		0.089***		0.464***
		(10.832)		(12.785)
Firm Age		0.010		0.029
		(0.467)		(0.240)
Leverage		-0.143***		-0.091
		(-3.961)		(-0.434)
Concentration		-0.002		-0.399*
		(-0.039)		(-1.735)
Q		0.036***		0.066**
		(8.624)		(2.541)
ROA		0.528***		4.851***
		(4.173)		(6.269)
Growth		0.090***		0.049
		(9.524)		(0.771)
SOE		0.138***		0.529***
		(7.120)		(5.916)
Independence		0.111		0.977
		(0.924)		(1.415)
Board Size		-0.032		0.165
		(-0.817)		(0.744)
Duality		-0.001		-0.017
		(-0.036)		(-0.262)
EmChange		-0.173***		0.040
		(-15.900)		(0.534)
Marketization		-0.007		0.198***
		(-0.853)		(2.768)
Unemployment		0.018		-0.192*
		(0.984)		(-1.795)
GDP growth		0.042		-0.067
		(0.543)		(-0.103)
Constant	10.872***	8.838***	2.668***	-9.827***
	(155.443)	(39.902)	(5.191)	(-8.494)
Observations	12,421	12,421	12,421	12,421
Industry FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.350	0.434	0.157	0.218

Panel B. Forward looking

Variables	(1) $\text{Compensation}_{t+1}$	(2) ES_{t+1}
DF	0.378***	0.937***
	(7.399)	(4.299)
Constant	8.963***	-6.376***

	(35.706)	(-4.932)
Observations	8,594	8,594
Control	Yes	Yes
Industry FE	Yes	Yes
Province FE	Yes	Yes
Year FE	Yes	Yes
Adj. R^2	0.399	0.208

Panel C. Sub-categories of DF

Variables	(1) Compensation	(2) Compensation	(3) Compensation	(4) ES	(5) ES	(6) ES
Coverage	0.262***			0.696***		
	(7.069)			(4.260)		
Usage		0.315***			0.718***	
		(6.662)			(3.529)	
Digitalization			0.134***			0.660***
			(3.741)			(3.639)
Constant	8.942***	8.887***	9.021***	-9.522***	-9.568***	-9.620***
	(41.908)	(38.904)	(40.596)	(-8.290)	(-8.212)	(-8.250)
Observations	12,421	12,421	12,421	12,421	12,421	12,421
Control	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.433	0.429	0.423	0.218	0.217	0.217

Panel D. PSM and Entropy Balancing

	PSM		EB	
Variables	(1) Compensation	(2) ES	(3) Compensation	(4) ES
DF	0.401***	1.420***	0.375***	1.248***
	(6.330)	(4.752)	(5.665)	(3.320)
Constant	8.652***	1.035***	8.861***	-9.068***
	(27.010)	(10.745)	(33.474)	(-4.950)
Observations	3,910	3,910	12,421	12,421
Control	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.383	0.097	0.415	0.219

Panel E. Endogeneity

	IV-Distance		IV-Intel	
Variables	(1) Compensation	(2) ES	(3) Compensation	(4) ES
DF	0.605***	2.140***	0.444***	1.296**
	(9.565)	(3.320)	(3.910)	(2.567)
Constant	8.378***	-10.423***	8.529***	-9.700***
	(36.251)	(-8.044)	(35.707)	(-7.959)
Observations	12,421	12,421	12,421	12,421
Control	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

F-value	1503.658		2718.507	
Adj. R^2	0.428	0.204	0.371	0.204

Table 9 presents coefficients from regressions of the effect of DF on firms' employee treatment by adapting *Compensation* and *ES*, as alternative measures to replace our primary measure *ET*. *Compensation* is average employee compensation, measured as the natural logarithm of the total average employee compensations, which calculated as the total salary expenses for all employees minus that of management, divided by the total number of ordinary employees. *ES* is the employee treatment score obtained from Hexun CSR database. Robust *t*-statistics are reported in parentheses. All control variables are defined in the Appendix A1. The symbols ***, **, and * denote significance level at the 1%, 5%, and 10% levels, respectively.

Table 10. Heterogeneity analysis – Geographic differences

Panel A. Marketization

	High	Low
	(1)	(2)
Variables	ET	ET
DF	0.008	0.022**
	(0.434)	(2.173)
Constant	0.836***	0.859***
	(34.525)	(28.573)
Observations	6,687	5,734
Control	Yes	Yes
Industry FE	Yes	Yes
Province FE	Yes	Yes
Year FE	Yes	Yes
Adj. R^2	0.163	0.201

Panel B. Air pollution (AQI)

	High	Low
	(1)	(2)
Variables	ET	ET
DF	0.016**	0.006
	(2.545)	(0.508)
Constant	0.943***	0.816***
	(21.313)	(12.156)
Observations	6,465	5,956
Control	Yes	Yes
Industry FE	Yes	Yes
Province FE	Yes	Yes
Year FE	Yes	Yes
Adj. R^2	0.193	0.171

This table reports results of subsample tests in terms of geographic differences, which are *marketization* and *air quality index* specifically. All variables are defined in the Appendix A1. Robust *t*-statistics are reported in parentheses. The symbols ***, **, and * denote significance level at the 1%, 5%, and 10% levels, respectively.

Table 11. Heterogeneity analysis – ownership and corporate governance

Panel A. State ownership

	SOE	Non-SOE
	(1)	(2)
Variables	ET	ET
DF	0.035***	0.006
	(3.345)	(0.779)
Constant	0.864***	0.864***
	(14.756)	(13.629)
Observations	4,009	8,412
Control	Yes	Yes
Industry FE	Yes	Yes
Province FE	Yes	Yes
Year FE	Yes	Yes
Adj. R^2	0.429	0.180

Panel B. Board independence

	High	Low
	(1)	(2)
Variables	ET	ET
DF	0.017***	0.008
	(3.953)	(0.493)
Constant	0.870***	0.812***
	(19.705)	(6.263)
Observations	10,039	2,382
Control	Yes	Yes
Industry FE	Yes	Yes
Province FE	Yes	Yes
Year FE	Yes	Yes
Adj. R^2	0.168	0.224

Panel C. Managerial ability

	High	Low
	(1)	(2)
Variables	ET	ET
DF	0.021*	0.008
	(2.025)	(0.785)
Constant	0.941***	0.836***
	(15.827)	(25.643)
Observations	7,148	5,273
Control	Yes	Yes
Industry FE	Yes	Yes
Province FE	Yes	Yes
Year FE	Yes	Yes
Adj. R^2	0.169	0.206

Panel D. CEO power

	High	Low
	(1)	(2)
Variables	ET	ET
DF	-0.009	0.019*

	(-0.451)	(1.879)
Constant	1.002***	0.836***
	(8.207)	(21.759)
Observations	3,487	8,934
Control	Yes	Yes
Industry FE	Yes	Yes
Province FE	Yes	Yes
Year FE	Yes	Yes
Adj. R^2	0.130	0.200

This table reports results of subsample tests in terms of *state ownership*, and factors of corporate governance, which are *managerial ability, board independence* and *CEO duality*. All variables are defined in the Appendix A1. Robust *t*-statistics are reported in parentheses. The symbols ***, **, and * denote significance level at the 1%, 5%, and 10% levels, respectively.

Table 12. Further test – Trend of corporate digital transformation and increasing demand for high-skilled labour

Panel A. Corporate digital transformation

Variables	(1) ET	(2) DT	(3) ET
DF	0.014**	0.073***	0.012**
	(2.214)	(6.162)	(2.139)
DT			0.035***
			(3.803)
Constant	0.883***	-0.041	0.763***
	(23.250)	(-0.629)	(22.677)
Observations	12,421	12,421	12,421
Control	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Indirect effect through DT			0.003
Sobel test for indirect effect			3.661***
Adj. R^2	0.180	0.451	0.181

Panel B. Practice in artificial intelligence

Variables	(1) ET	(2) AI	(3) ET
DF	0.014**	0.328***	0.014**
	(2.214)	(3.946)	(2.375)
AI			0.002*
			(1.665)
Constant	0.883***	-0.545	0.598
	(23.250)	(-1.224)	(1.558)
Observations	12,421	12,421	12,421
Control	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes

Year FE	Yes	Yes	Yes
Indirect effect through AI			0.001
Sobel test for indirect effect			1.775*
Adj. R^2	0.180	0.203	0.176

Panel C. Demand for high-skilled labour

Variables	(1) ET	(2) Skill	(3) ET
DF	0.014**	0.213***	0.012**
	(2.214)	(8.755)	(2.189)
Skill			0.010**
			(2.106)
Constant	0.883***	-0.370***	0.764***
	(23.250)	(-2.920)	(22.648)
Observations	12,421	12,421	12,421
Control	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Indirect effect through Skill			0.002
Sobel test for indirect effect			2.095**
Adj. R^2	0.180	0.433	0.181

This table reports results of channel tests. The potential channels through which DF affects employee treatment are trend of corporate digital transformation, adaption of AI technology and increasing demand for high-skilled employees. All variables are defined in the Appendix. Robust *t*-statistics are reported in parentheses. The symbols ***, **, and * denote significance level at the 1%, 5%, and 10% levels, respectively.

Appendix A1. Variable definitions

Variables	Definitions
Independent variable	
DF	The index of digital finance of the city in the year divided by 100.
Dependent variables	
ET	Employee treatment, measured as employee health and safety index of a firm in the year divided by 100, which is obtained from Huazheng ESG database.
Compensation	Employee Compensation, measured as the natural logarithm of the total average employee compensations, which is calculated as the total salary expenses for all employees minus that of management, divided by the total number of ordinary employees following Dong et al. (2020).
ES	Employee score, measured as employee treatment index of a firm in the year, which is obtained from Hexun CSR database.
Control variables	
Firm Size	The natural logarithm of total assets of a firm.
Firm Age	The natural logarithm of listing age of a firm.
Leverage	Total debt divided by total assets.
Concentration	Top one shareholding, which is the largest shareholding.
Q	Tobin's Q, measures as the ratio of market value and book value of total assets.
ROA	Return on assets, measured as net income divided by total assets.
Growth	Annual sales growth rate of a firm.
SOE	Dummy variable equal to 1 if the firm is state-owned, and 0 otherwise.
Independence	The number of independent directors as a percentage of total number of board directors.
Board Size	The natural logarithm of the total number of directors on the board.
Duality	Dummy variable equal to 1 if a firm's CEO is also the chairman of the board, and 0 otherwise.
EmChange	Annual change rate of total number of employees.
Marketization	Fangang marketization index, the higher the index, the higher the marketization of provinces.
Unemployment	The unemployment rate of the province.
GDP Growth	The annual GDP growth rate in a province during the fiscal year.
Other variables	
IV-Distance	Instrumental variable, calculated as the interaction term between the mean of the DF index at the national level (except for the specific city) and the distance to Hangzhou city.
IV-Intel	Instrumental variable, measured as the interaction term between the number of Internet users in year t-1 at the national level and the number of fixed-line phones per 100 people per city in 1984.
KZ index	A measure of financial constraint as per Kaplan and Zingales (1997). A firm with a high KZ index is considered more financially constrained.
WW index	A measure of financial constraint as per Whited and Wu (2006). A firm with a high WW index is considered more financially constrained.
IT	Information transparency, measured as information transparency index of a firm in the year, which is obtained from CSMAR database
ID	Information disclosure, measured as information disclosure index of a firm in the year, which is obtained from Huazheng database
AQI	Air quality index, which is the natural logarithm of the average daily AQI (the concentration level of six atmospheric pollutants, namely, SO_2, NO_2,

	PM_{10}, $PM_{2.5}$, CO, and O_3) for a given year and city. The higher the AQI, the heavier the air pollution the city has.
MA	Managerial ability, the proxy of the ability of the managerial team, which is constructed as per Demerjian et al. (2012).
DT	Index of corporate digital transformation, obtained from CSMAR, the higher the index, the higher level of digital transformation within firm.
AI	Artificial intelligence index, measured as the total frequency of artificial intelligence technology words in the annual report after excluding MD&A content.
Skill	The proportion of skilled labour, which is the number of employees who have a bachelor's degree or higher divided by the total number of employees in a firm.

Appendix A2. Balanced tests after PSM

Variables	Sample	Treated	Control	%bias	bias	*t*-statistics	p>t
Firm Size	Unmatched	22.199	22.323	-10.7		-4.84	0.000
	Matched	22.187	22.191	-0.3	97.0	-0.11	0.915
Firm Age	Unmatched	2.828	2.876	-15.0		-6.81	0.000
	Matched	2.872	2.861	3.4	77.1	1.07	0.283
Leverage	Unmatched	0.403	0.399	2.5		1.13	0.257
	Matched	0.389	0.392	-1.2	50.2	-0.40	0.692
Concentration	Unmatched	0.332	0.323	6.7		3.04	0.002
	Matched	0.323	0.324	-0.5	92.3	-0.17	0.868
Q	Unmatched	2.194	2.077	9		4.08	0.000
	Matched	2.148	2.162	-1.1	87.4	-0.35	0.725
ROA	Unmatched	0.055	0.053	3.1		1.40	0.160
	Matched	0.054	0.056	-2.6	17.2	-0.80	0.426
Growth	Unmatched	0.203	0.187	3.9		1.79	0.073
	Matched	0.198	0.194	0.9	76.3	0.29	0.775
SOE	Unmatched	0.204	0.324	-27.6		-12.54	0.000
	Matched	0.222	0.221	0.2	99.2	0.08	0.939
Independence	Unmatched	0.379	0.372	13.7		6.22	0.000
	Matched	0.373	0.373	0.6	95.6	0.19	0.849
Board Size	Unmatched	2.100	2.136	-18.5		-8.39	0.000
	Matched	2.116	2.119	-1.3	92.8	-0.44	0.663

Duality	Unmatched	0.341	0.258	18.3		8.32	0.000
	Matched	0.312	0.314	-0.4	97.5	-0.14	0.890
EmChange	Unmatched	0.123	0.098	7.3		3.32	0.001
	Matched	0.103	0.107	-1.4	81.3	-0.44	0.659
Marketization	Unmatched	10.431	9.487	79.9		36.31	0.000
	Matched	10.201	10.196	0.4	99.5	0.13	0.894
Unemployment	Unmatched	2.842	3.095	-54.7		-24.85	0.000
	Matched	2.930	2.923	1.6	97.1	0.46	0.644
GDP Growth	Unmatched	0.084	0.077	17.4		7.90	0.000
	Matched	0.086	0.086	-0.3	98.5	-0.09	0.928

Appendix A3. Comparison of means before and after entropy balancing

	Before entropy balancing			After entropy balancing		
Variables	Treatment (n=6,185)	Control (n=6,236)	Diff	Treatment (n=6,185)	Control (n=6,236)	Diff
Firm Size	22.340	22.380	0.040*	22.340	22.340	0.000
Firm Age	2.821	2.880	0.059***	2.821	2.821	0.000
Leverage	0.406	0.412	0.005	0.406	0.407	0.000
Concentration	0.339	0.332	-0.007***	0.339	0.339	0.000
Q	2.183	2.042	-0.141***	2.183	2.183	0.000
ROA	0.054	0.051	-0.003***	0.054	0.054	0.000
Growth	0.196	0.180	-0.015**	0.196	0.196	0.000
SOE	0.273	0.372	0.099***	0.273	0.274	0.000
Independence	0.380	0.372	-0.008***	0.380	0.380	0.000
Board Size	2.108	2.143	0.035***	2.108	2.108	0.000
Duality	0.324	0.238	-0.085***	0.324	0.323	0.000
EmChange	0.123	0.092	-0.031***	0.123	0.123	0.000
Marketization	10.310	8.913	-1.399***	10.310	10.310	0.000
Unemployment	2.709	3.188	0.478***	2.709	2.710	0.000
GDP Growth	0.086	0.073	-0.013***	0.086	0.086	0.000