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# How Digital Finance Shapes ESG Outcomes: The Mediating Roles of Productivity and Analyst Coverage

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**Abstract**

This paper investigates how digital finance affects corporate ESG performance through the following mediation paths. Based on agency theory and a resource-based view, we hypothesize that digital finance benefits ESG performance not only directly but also indirectly through enhancing TFP and analyst coverage. We test our hypotheses using 22,576 firm-year observations of Chinese listed firms from 2011 to 2023 by employing a fixed-effects mediation model. The empirical results support our hypotheses. Digital finance improves ESG performance directly, and part of its effect goes through higher TFP and better analyst monitoring. The results show that digital finance plays dual roles in improving efficiency and market monitoring, which is beneficial to corporate sustainability. By identifying the above two mediation paths, this paper enriches the theoretical understanding of the relationship between financial digitalization and sustainability and provides practical implications for policymakers and managers to improve ESG performance.

**Keywords:** digital finance; ESG performance; total factor productivity

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Academic Editor: Francesco Tajani

Received: 18 September 2025
Revised: 16 October 2025
Accepted: 18 October 2025
Published: 23 October 2025

**Citation:** Su, R.; Liang, D. How Digital Finance Shapes ESG Outcomes: The Mediating Roles of Productivity and Analyst Coverage. *Sustainability* **2025**, *17*, 9431. https://doi.org/10.3390/su17219431

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## 1. Introduction

The development of digital technology and finance has greatly changed how firms obtain capital, operate, and handle Environmental, Social and Governance (ESG) performance challenges. As a new type of financial development, digital finance, which uses big data, artificial intelligence, and platform-based innovations to alleviate financing constraints, improve information transparency, and enhance the allocation efficiency of resources, creates new opportunities to promote corporate sustainability [1–3]. On the other hand, it is important to measure firm value and stakeholders' trust using ESG performance to meet the challenge of intensive regulations and growing awareness of sustainability.

Previous studies have investigated the impact of digitalization on firm performance from the perspective of innovation efficiency, corporate governance, and investment optimization [4] but still have many gaps. The majority of the literature on productivity and ESG has studied how strong ESG performance can improve productivity through better investment efficiency and resource allocation [5–7], while few have focused on the potential reverse effect. Similarly, most capital market studies have studied how ESG can attract analyst coverage, improve information transparency, and alleviate financing constraints [8], while few have studied how digital finance can affect ESG. Recently, evidence showed that digital finance can bridge the gaps. It can increase total factor productivity (TFP) by reducing capital misallocation and promoting technological innovation [9,10] and can also

improve information transparency to attract more attention from analysts [11,12]. This dual pathway through internal efficiency improvement and stronger external monitoring provides a new perspective to understand how firms can make further ESG performance progress under ESG resource constraints.

In addition, the influence of digital finance is not uniform across ESG dimensions. The empirical results show that the influence of digital finance is significant and positive on social and governance performance, while the influence of digital finance on environmental performance is weak or insignificant [1,13]. The above results suggest that the two mechanisms through which digital finance operates, such as improvements in internal efficiency (TFP) and external monitoring (analyst coverage), may play an important role in explaining the effect of financial digitalization on ESG performance, especially social and governance performance.

Therefore, these ideas inspire the study to construct a dual-channel mediation model in which digital finance influences ESG performance directly and indirectly through TFP and analyst coverage. This study makes the following three main contributions. First, this study finds the reverse mechanism through which the improvement of TFP drives ESG performance. In this way, TFP is a precondition for ESG performance rather than being seen as a result, which extends the research on the relationship between digital finance, TFP and ESG. Second, this study finds that analyst coverage is an important transmission channel for the effect of digital finance on ESG outcomes. Third, this study provides practical implications on how firms and policymakers can use digital finance to improve efficiency, enhance market supervision and then improve ESG performance.

The rest of this paper is organized as follows. Section 2 reviews the related literature and constructs the research hypotheses. Section 3 presents the data sources, variable definitions, and research method. Section 4 presents the empirical results, and Section 5 discusses the main results. Section 6 concludes the paper by summarizing its main theoretical contributions and discussing the practical implications.

## 2. Literature Review

Digital finance is an important means to enhance corporate ESG performance [1,3,13–15]. A large number of studies have been undertaken on the role of digital finance in solving financing constraints [16]. Digital inclusive finance can expand the opportunity of financing for enterprises, reduce the cost of financing and improve the efficiency of financing [17]. If funds are not easily accessible, the firm is unwilling to invest in technological innovation, or any other project related to sustainable development. Recently, scholars have focused on how to solve this problem through digital finance. Online credit, supply chain finance and intelligent risk assessment can effectively ease financing constraints [1]. By improving the allocation of resources and operational efficiency, the motivation for firms to engage in green innovation, social responsibility and governance reform and further improve ESG performance can be stimulated.

The effect of digital finance is heterogeneous in terms of dimensions, ESG components, firm characteristics and regional areas. Two dimensions, including the depth of application and the degree of digitalization, are significantly associated with improved ESG performance. In contrast, the breadth of coverage does not have a significant impact [18,19]. In addition, digital finance does not exert an equal influence across all ESG components. Social and governance outcomes benefit more than environmental performance [1,13]. Looking across different firm types and regions, the impact of digital finance proves particularly significant in boosting ESG outcomes among non-state-owned enterprises, smaller firms, less market-oriented enterprises, and companies located in central and western regions [20]. Institutional and political factors also play a role. It may weaken the positive role of digital finance on ESG,

whereas better institutional development at the regional level can enhance it [21]. Institutional and political factors also play a role. It may weaken the positive role of digital finance on ESG, whereas better institutional development at the regional level can enhance it [18]. Although the literature suggests that digital finance has a positive effect on ESG performance, there are still some mixed results. The different results may result from disagreements in the measurement of ESG outcomes, differences in the indicators used to measure digital finance and some unobserved characteristics at both the regional and firm level, such as local market development, regulatory enforcement, and managerial practices. All these factors can affect the relationship between digital finance and ESG. It can be seen that the effect of digital finance on ESG may depend on some region- and firm-specific conditions, and it is necessary to conduct empirical studies considering these boundary factors. Based on the evidence above, the following hypothesis is proposed: Hypothesis 1 (H1).

**Hypothesis 1 (H1)**. *Digital finance acts as a driver of corporate ESG performance, positively influencing ESG performance.*

Previous studies have shown that digital finance positively impacts TFP, which constitutes an important channel through which digital finance affects corporate ESG performance. These effects can be classified into three groups: agriculture, financial institutions and enterprises, and green development and energy efficiency. Specifically, in the sector of agriculture, digital inclusive finance eases farmers' access to finance and promotes technological upgrading, which in turn enhances TFP. Previous studies have indicated that digital finance significantly drives green technological innovation and improves agricultural green productivity, but these effects are not uniform across regions, and the effects in central and eastern China are stronger than those in the west [22–24]. In the case of financial institutions and enterprises, TFP improves with the help of technology spillovers, supply chain finance and optimal allocation of resources, which can alleviate financing constraints and promote corporate innovation, adjust capital flow and internal financing strength [25]. In terms of green development and energy efficiency. Digital finance improves green TFP by alleviating financing constraints, reducing distortions, and generating spatial spillovers [26]. However, a U-shaped relationship between digital finance and green TFP was found in smart cities, and the impact of digital finance on green TFP was stronger after passing the turning point [27]. In summary, the previous literature has consistently found that digital finance has a significant positive impact on TFP in agriculture, financial institutions, enterprises, and the green economy.

While most prior studies emphasize that improvements in ESG performance drive productivity, there is also a theoretical basis for considering TFP as a factor that promotes ESG engagement.

Improving firms' ESG ratings can significantly increase TFP through the following channels: easing financing constraints [28], promoting green technological innovation [24,26,29]. Studies show that improvement in ESG performance depends on capacities such as green R&D efficiency (GRDE), green technology transformation efficiency (GTTE), improvements in energy efficiency and supply chain [26,30]. These capacities are closely related to the process of enhancing TFP, and therefore, the relationship between them may not be one-way. Although most previous studies have focused on the fact that improvements in ESG performance promote TFP, TFP can be seen as a factor that promotes ESG from a theoretical perspective. The resource-based view suggests that these capabilities are valuable, rare, and inimitable resources that form the foundation of a firm's sustainable competitive advantage. A higher TFP level indicates not only that the firm has technological strength, but also that its managerial efficiency is high enough to use resources to achieve better ESG performance. In line with this theoretical reasoning, research conducted by Geng, Zheng,

Yuan and Jiménez-Zarco [28] also finds that digitization positively moderates the effect of ESG in alleviating financing constraints, hence raising TFP, and that TFP growth gives more resources to practice ESG, creating a virtuous cycle. It is attested that digitization raises TFP through ESG improvement [31]. Furthermore, higher levels of digitalization create more opportunities to raise TFP through ESG improvement [28]. Thus, the results suggested that there exists a virtuous cycle between digitalization, TFP, and ESG. Based on the above evidence, digital finance enables firms to improve their productive capacity and green production through better financing conditions and technological advancement, as well as optimal resource use. The capabilities shown in the TFP gains, such as green innovation, energy efficiency, and optimal resource use, are prerequisites for practicing ESG. In this sense, TFP represents not only the outcome of digital finance but also the precondition for ESG engagement. This makes TFP a possible mediator in the relationship between digital finance and ESG performance. Based on this, the following hypothesis is proposed:

**Hypothesis 2 (H2)**. *The positive relationship between digital finance and corporate ESG performance is mediated by TFP.*

The expansion of digital finance has created a new informational and technological environment that facilitates analyst coverage. By easing corporate financing constraints, digital finance makes good use of both internal and external information effects [2]. Digital finance enables operational, financial, and even non-financial information of firms to be captured and analyzed with far greater efficiency. This greatly reduces the costs analysts face when collecting and processing information. As for firms with small market capitalization, limited disclosure, or remote geographic locations, digital finance provides more accessible data resources and digital transaction records. In this way, digital finance not only broadens the scope of analyst coverage but also enhances its depth and precision. The study done by Cai, Tu and Li [11] confirms that digital transformation can attract more analysts' attention to improve corporate ESG performance. According to agency theory, analyst coverage can be viewed as an important external governance mechanism that alleviates agency problems caused by information asymmetry between managers and investors. As key information intermediaries in capital markets [32], analysts have stronger expertise and better skills in collecting and interpreting information; they can provide adequate information for the market [33]. More attention from analysts can reduce asymmetries and provide external monitoring pressure on firms to improve their information processing and even social responsibilities [11]. Panel data analysis on Chinese listed firms also supports this view. Analyst coverage can significantly improve corporate ESG performance, and the effect is more significant for state-owned enterprises or firms with tighter financing constraints [34]. When a company receives greater attention from analysts, it sends a positive signal to the market. As a result, investors tend to see the firm as more transparent and develop higher expectations regarding its future performance and value. [11]. This trust brings benefits, such as higher market value, lower financing cost, and stronger ability to undertake ESG behaviors [35]. Therefore, it can be inferred that digital finance can increase the transparency and evaluability of corporate information and attract more analyst coverage. The increased analyst coverage spurs companies to improve their ESG practices and disclosure levels through external supervision. Based on this, the following hypothesis is proposed:

**Hypothesis 3 (H3)**. *The positive relationship between digital finance and corporate ESG performance is mediated by analyst coverage.*

## 3. Materials and Methods

### *3.1. Data Sources and Sample*

Companies on the main board at Shanghai and Shenzhen Stock Exchanges in China from 2011 to 2023 are taken as research samples in this paper to explore the relationship between ESG performance and digital finance development. The financial and market data are retrieved from China Stock Market & Accounting Research (CSMAR), Shenzhen, China. The digital financial inclusion index is obtained from the Institute of Digital Finance, Peking University, Beijing, China. ESG is taken from the Sino-Securities Index Information Service Co., Shanghai, China. We use the following steps to refine the sample and exclude observations that may cause bias. First, Companies from the financial industry and the real estate industry are excluded. This is because these industries operate under distinct regulatory frameworks and financial reporting practices, leading to differences in their ESG disclosure patterns. Such differences could distort the comparability of results in the empirical analysis. Second, companies labelled as ST and PT are excluded, because they are under special treatment due to financial distress or abnormal operating conditions, which may significantly affect their ESG reporting behavior and distort the analysis. Third, companies with missing data are deleted. Fourth. All continuous variables are winsorized at the 1% and 99% levels. Our final sample consisted of 22,576 observations.

We employ a panel fixed effects model to control for unobserved heterogeneity across industry and over time. In addition, we incorporate a mediation framework proposed in the prior work [36] to test the indirect effects of total factors productivity and analyst coverage between digital finance and ESG.

### *3.2. Variables*

#### 3.2.1. Dependent Variables

Huazheng ESG Index is used to measure corporate ESG performance. This index is a specialized evaluation system developed for Chinese A-share listed companies, providing broad coverage and incorporating indicators consistent with the Chinese regulatory and disclosure context. ESG performance is represented by quantitative scores derived from this index. The Huazheng ESG draws on international standards, using a top-down construction and bottom-up aggregation approach. It starts with environmental, social, and governance dimensions, gradually breaking them down into more specific evaluation indicators. The design of these indicators and the weight distribution take industry differences into account. However, the Huazheng Index differs from international standards in its scope and focus on underlying indicators. Global raters typically maintain consistent evaluation methods across countries to ensure comparability. In contrast, the Huazheng Index incorporates national features, such as indicators related to poverty alleviation and rural revitalization, which show more attention to the national development rather than high cross-comparability [37].

#### 3.2.2. Independent Variables

Digital finance development. We use the digital financial inclusion index to measure the development of digital finance in the region. The index could be measured at the provincial level, prefectural level and county level. In this paper, we use an index at the prefecture level. In addition to the overall index, the digital financial inclusion index includes three dimensions: depth of coverage, depth of usage and level of digitization. Depth of coverage reflects the range of digital financial services, such as user count and service network coverage. It reflects the depth of digital finance penetration into different groups, especially small and micro enterprises, rural areas. Depth of usage reflects the degree to which the digital financial service is used, including payment, insurance, credit, money market fund, and

investment. It reflects to what extent do users depend on digital finance and how often they use digital finance. Level of digitization reflects the level of technological empowerment of digital finance, including the indicators related to mobility, convenience and security. This sub-index reflects how digital technologies empower financial services and improve efficiency and user experience. In robustness analysis, we select the index at the provincial level and the three dimensions as alternative explanatory variables.

#### 3.2.3. Mediating Variables

There are two widely used approaches to measure total factor productivity (TFP) for firms, Olley–Pakes (OP) and Levinsohn–Petrin (LP). OP methods would cause sample loss problem because this method could not estimate enterprises' TFP which have zero investment. The LP method uses intermediate inputs as a proxy for investment in TFP estimation so that sample loss is reduced and it is more effective than OP method in solving endogeneity problem [38,39]. In measuring Total Factor Productivity (TFP) for firms, the following variables are used. The nominal values of output, capital, labor, and intermediate inputs are used directly in the estimation process:

$$\text{Output (Y)} = \text{Annual operating revenue}$$

$$\text{Capital Input (K)} = \text{Net value of fixed assets at the end of the year}$$

$$\text{Labor Input (L)} = \text{Number of employees}$$

Intermediate Input (M) = Operating costs + Selling expenses + Financial expenses + Administrative expenses − Depreciation expenses − Cash payments to employees and for employees' benefits.

Each variable is logged before being used in regression analysis, which results in the calculation of the Total Factor Productivity indicator (_TFP).

$$\ln Y_{i,t} = \lambda_0 + \lambda_1 \ln L_{i,t} + \lambda_2 \ln K_{i,t} + \lambda_3 \ln M_{i,t}$$

The Total Factor Productivity indicator is logged to obtain TFP:

$$\text{TFP} = \ln(\text{_TFP})$$

In terms of Analyst coverage. We calculate analyst coverage as the natural logarithm of one plus the number of analysts following the same sample firm.

#### 3.2.4. Control Variables

Based on the extant literature [40–42], this paper selects firm size, firm age, growth rate, liquidity ratio, cash flow, intangible assets, financial leverage and share concentration as control variables. The details of control variables are summaried in Table 1.

**Table 1.** Summary of the definitions of specific variables.

| Variables | Name | Definition | Source |
| --- | --- | --- | --- |
| ESG performance | ESG | Huazheng ESG score | Wind |
| Digital finance development | DF | Digital financial inclusion index/100 | the Institute of Digital Finance, Peaking University |
| Total Factor Productivity | TFP | Calculated by input in log based on LP method | CSMAR; Authors' calculation |

**Table 1.** *Cont.*

| Variables | Name | Definition | Source |
|---|---|---|---|
| Analyst coverage | AC | ln (number of analysts following + 1) | CSMAR |
| Size | Size | ln(total asset) | CSMAR |
| Age | Age | ln(Year-year of listed + 1) | CSMAR |
| Growth rate | Growth | Annual growth rate of operating revenue | CSMAR |
| Liquidity ratio | LR | current assets/current liabilities | CSMAR |
| Cash flow | CF | net cash flow from operations to total assets | CSMAR |
| Intangible asset | IA | Intangible assets/total assets | CSMAR |
| Leverage ratio | Lev | Total debts/total assets | CSMAR |
| Share concentration | Top1 | ratios of shares held by the largest shareholder | CSMAR |

## 4. Results

### *4.1. Descriptive Statistics and Correlation Analysis*

To better understand the basic features of each variable for the sample firms, this paper first conducted a descriptive statistical analysis of the main variables, with the results shown in Table 2. The statistical sample covers annual observation data from 22,576 companies, spanning the period from 2011 to 2023.

**Table 2.** Summary statistics.

| Variables | Observation | Mean | SD | Min | Median | Max |
|---|---|---|---|---|---|---|
| ESG | 22,576 | 73.62 | 4.690 | 60.12 | 73.66 | 84.41 |
| DF | 22,576 | 2.49 | 0.797 | 0.59 | 2.67 | 3.63 |
| TFP | 22,576 | 8.59 | 1.047 | 4.68 | 8.48 | 13.11 |
| Size | 22,576 | 22.52 | 1.288 | 20.26 | 22.32 | 26.43 |
| Age | 22,576 | 2.28 | 0.753 | 0.69 | 2.40 | 3.40 |
| Growth | 22,576 | 0.22 | 0.533 | −0.60 | 0.10 | 3.27 |
| LR | 22,576 | 2.16 | 1.832 | 0.34 | 1.58 | 11.72 |
| CF | 22,576 | 0.06 | 0.063 | −0.12 | 0.05 | 0.24 |
| IA | 22,576 | 0.05 | 0.053 | 0.00 | 0.04 | 0.36 |
| Lev | 22,576 | 0.43 | 0.187 | 0.07 | 0.43 | 0.84 |
| Top1 | 22,576 | 35.50 | 15.162 | 8.88 | 33.47 | 75.10 |

The mean value of the ESG score, the dependent variable, is 73.62, with a standard deviation of 4.69, a maximum value of 84.41, and a minimum value of 60.12, indicating that the overall ESG performance of the sample companies is relatively high but with some disparities. The proximity of the median (73.66) to the mean (73.62) suggests a relatively symmetric distribution of ESG performance within the sample, though some firms exhibit lower levels of responsibility fulfilment.

The mean value of TFP is 8.59, the standard deviation is 1.047, the maximum value is 13.11, and the minimum value is 4.68. The inter-firm variation in this variable shows the large gap in production efficiency and capacity of resource allocation. The average value of digital finance is 2.49, and the standard deviation is 0.797, ranging from 0.59 to 3.63, showing regional differences in development levels of digital finance, which provides evidence for this study to explore the differentiated mechanisms through which digital finance influences corporate ESG performance.

Table 3 presents a correlations matrix that examines the relationships among various variables in the study, along with their corresponding variance-inflation factors (VIFs). In addition to the average VIF value (1.39), the VIF values for the variables are relatively low (ranging from 1.01 to 2.38), which are less than standard value (10), indicating that multicollinearity is not a severe issue.

**Table 3.** Correlation matrix.

| Variables | ESG | DF | Size | Age | Growth | LR | CF | IA | Lev | Top1 | VIF |
|---|---|---|---|---|---|---|---|---|---|---|---|
| ESG | 1.000 | | | | | | | | | | |
| DF | 0.071 *** | 1.000 | | | | | | | | | 1.05 |
| Size | 0.235 *** | 0.157 *** | 1.000 | | | | | | | | 1.59 |
| Age | −0.039 *** | 0.092 *** | 0.369 *** | 1.000 | | | | | | | 1.23 |
| Growth | −0.026 *** | −0.024 *** | −0.052 *** | 0.005 | 1.000 | | | | | | 1.01 |
| LR | 0.048 *** | −0.010 | −0.358 *** | −0.256 *** | 0.016 ** | 1.000 | | | | | 2.01 |
| CF | 0.114 *** | 0.043 *** | 0.077 *** | −0.034 *** | −0.093 *** | 0.045 *** | 1.000 | | | | 1.09 |
| IA | −0.014 ** | −0.051 *** | 0.068 *** | 0.048 *** | −0.007 | −0.124 *** | 0.056 *** | 1.000 | | | 1.03 |
| Lev | −0.056 *** | −0.004 | 0.487 *** | 0.272 *** | 0.022 *** | −0.695 *** | −0.165 *** | 0.033 *** | 1.000 | | 2.38 |
| Top1 | 0.067 *** | −0.062 *** | 0.158 *** | −0.119 *** | −0.009 | −0.002 | 0.107 *** | 0.042 *** | 0.014 ** | 1.000 | 1.08 |
| Mean Vif | | | | | | | | | | | 1.39 |

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

### *4.2. Baseline Regression*

The baseline regression adopts fixed effect model which would control for industry and time-fixed effects.

$$ESG_{i,t} = \alpha_0 + \alpha_1 DF_{i,t} + \gamma_k X_{i,t} + \delta_i + \mu_t + \varepsilon_{i,t} \quad (1)$$

In Equation (1), $ESG_{i,t}$ is the explained variable, $DF_{i,t}$ is the explanatory variable, $X_{i,t}$ are control variables that have been identified in Table 1. $\delta_i$ and $\mu_t$ represent industry and time effect. In addition, we cluster robust standard errors in firm level to ensure the robustness of conclusion.

Table 4 presents the baseline regression results on the relationship between digital finance and corporate ESG performance. To examine the impact of digital finance, three progressively specified regression models were estimated. Model (1) includes only digital finance as the explanatory variable; Model (2) adds control variables; and Model (3) further includes industry and year fixed effects.

**Table 4.** Baseline regression.

| Variables | ESG (Model 1) | ESG (Model 2) | ESG (Model 3) |
|---|---|---|---|
| DF | 0.419 *** | 0.116 *** | 1.157 *** |
| | (0.0391) | (0.0379) | (0.303) |
| Size | | 1.348 *** | 1.520 *** |
| | | (0.0289) | (0.0590) |
| Age | | −0.758 *** | −0.712 *** |
| | | (0.0434) | (0.0839) |
| Growth | | 0.0263 | −0.0733 |
| | | (0.0557) | (0.0894) |
| LR | | 0.0469 ** | 0.0277 |
| | | (0.0228) | (0.0387) |
| CF | | 3.879 *** | 3.888 *** |
| | | (0.487) | (0.683) |

**Table 4.** *Cont.*

| Variables | ESG (Model 1) | ESG (Model 2) | ESG (Model 3) |
|---|---|---|---|
| IA | | −2.353 *** | 0.712 |
| | | (0.566) | (1.418) |
| Lev | | −4.539 *** | −4.845 *** |
| | | (0.243) | (0.456) |
| Top1 | | −0.00219 | 0.00216 |
| | | (0.00202) | (0.00419) |
| Constant | 72.58 *** | 46.53 *** | 39.85 *** |
| | (0.102) | (0.583) | (1.398) |
| Observations | 22,576 | 22,576 | 22,575 |
| R-squared | 0.005 | 0.110 | 0.166 |
| Industry Fixed Effect | NO | NO | YES |
| Year Fixed Effect | NO | NO | YES |

Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The results from Model (1) indicate that digital finance exerts a significant positive effect on ESG performance. The coefficient is 0.419 ($p < 0.01$). Given that ESG scores in the sample range approximately from 60.12 to 84.81 (see Table 2), this suggests that a one-unit increase in digital finance is associated with a modest, yet meaningful, improvement in ESG outcomes.

When controls are introduced in Model (2), the coefficient of digital finance is dropped to 0.116 ($p < 0.01$), which represents the partial explanatory power of firm size, age and growth. As for control variables, firm size has significant positive effect on ESG performance, while firm age has negative effect on ESG performance. When industry fixed effects and year fixed effects are introduced into Model (3), the coefficient of digital finance is raised to 1.157 ($p < 0.01$). The 10-times rise highlights the specification sensitivity and shows that omitting industry and temporal heterogeneity can obscure the true effect of digital finance. By controlling for unobserved, time-invariant differences across industries and temporal shocks that have impacts on ESG practices, the model better isolates the partial effect of digital finance. Overall, the consistently positive and significant coefficients confirm the positive impact of digital finance on corporate ESG performance, supporting Hypothesis 1.

As for control variables, firm size and cash flow have significant positive effect on ESG performance, while leverage and firm age have negative effect on ESG performance. The coefficient of intangible assets (IAs) changes sign across models. In Model (2), IAs have a significant negative relationship with ESG performance, while in Model (3), when controlling for industry and year fixed effects, the coefficient of IAs becomes positive but insignificant. The significant negative relationship in Model (2) is probably because firms with fewer intangible assets, typically in capital-intensive or highly regulated industries such as utilities and manufacturing, are more likely to be involved in environmental and social concerns and thus make stronger ESG initiatives and disclosures. In contrast, firms with high intangible intensity, such as technology or pharmaceutical companies, may prioritize innovation and intellectual property over formal ESG reporting, resulting in a lower ESG score. Once industry and year effects are controlled in Model (3), these cross-industry differences are absorbed, and the within-industry variation shows no significant association. Thus, the change in the IA coefficient shows that the negative correlation results from cross-industry structural factors rather than a consistent firm-level relationship between intangibles and ESG performance.

### *4.3. Endogeneity Analysis*

To address potential endogeneity concerns arising from reverse causality and omitted variable bias, we introduce a lag period of digital finance (L.DF) as a regressor and construct a Bartik instrument variable.

First, we employ a lagged digital finance index as the primary explanatory variable. As the result in Table 5 shows, the coefficient of L.DF is significantly positive at the 1% level, which is consistent with the result in baseline regression.

**Table 5.** Endogeneity test results.

| Variables | ESG | First Stage DF | Second Stage ESG |
|---|---|---|---|
| L.DF | 1.209 *** | | |
| | (0.311) | | |
| DF | | | 0.823 * |
| | | | (0.428) |
| Bartik IV | | 0.829 *** | |
| | | (0.0381) | |
| Kleibergen–Paap rk LM statistic *p*-value | | | 0 |
| Kleibergen–Paap rk Wald F statistic | | | 474.17 |
| Cragg–Donald Wald F | | | 5675.73 |
| 10%maximal IV size | | | 16.38 |
| Control variables | YES | YES | YES |
| Industry Fixed Effect | YES | YES | YES |
| Year Fixed Effect | YES | YES | YES |
| Observations | 20,100 | 17,725 | 17,725 |
| R-squared | 0.171 | | 0.142 |

Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Second, we estimate a two-stage least squares (2SLS) model using Bartik instrument variable, constructed as the interaction between the one-period lagged digital finance index and its first-difference. As demonstrated in Table 5, the regression results of the first stage show that the regression coefficient Bartik instrument variable is significantly positive at the 1% level, indicating a significant positive correlation between the instrumental variable and Digital Finance. The regression results of the second stage reveal that the Cragg–Donald Wald F value is much larger than the critical value (10% maximal IV size), which reject the null hypotheses of "weak identification of instrumental variables". The estimated coefficient of digital finance on ESG performance is significantly positive. This suggests that, after mitigating the endogeneity issue, the conclusion that digital finance enhances corporate ESG performance still holds.

### *4.4. Robustness Tests*

#### 4.4.1. Alternative Explanatory Variables

This study further uses an index at the province level (Pindex) and three dimensions of digital finance, such as digitization level, coverage breadth, and usage depth, as alternative explanatory variables. As shown in Table 6, no matter which alternative variable is used, the impact is still significantly positive. Among the three dimensions, the coefficient of usage depth is the largest (0.0110) and the coefficient of digitization level is smallest (0.00701). That is, the usage depth of digital finance exerts more influence on ESG than digitization level. In practice, the deeper usage of digital financial services can improve information transparency, make capital allocation more efficient and promote sustainable investment. While simply

expanding the level of digitization cannot bring about meaningful ESG outcomes unless firms deeply use these digital tools in their financial management and operations.

**Table 6.** Robust test 1: alternative explanatory variables.

| Variables | ESG (Model 1) | ESG (Model 2) | ESG (Model 3) | ESG (Model 4) |
|---|---|---|---|---|
| digitization_level | 0.00701 ** | | | |
| | (0.00284) | | | |
| coverage_breadth | | 0.00717 *** | | |
| | | (0.00248) | | |
| usage_depth | | | 0.0110 *** | |
| | | | (0.00319) | |
| Pindex | | | | 0.00960 *** |
| | | | | (0.00211) |
| Constant | 40.74 *** | 40.90 *** | 41.84 *** | 39.83 *** |
| | (1.437) | (1.342) | (1.708) | (1.336) |
| Control variables | YES | YES | YES | YES |
| Industry Fixed Effect | YES | YES | YES | YES |
| Year Fixed Effect | YES | YES | YES | YES |
| Observations | 22,575 | 22,575 | 15,472 | 22,575 |
| R-squared | 0.164 | 0.165 | 0.151 | 0.167 |

Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

#### 4.4.2. Quantile Regression

Considering that digital finance may affect the ESG performance of firms differently in different quantiles of distribution, Table 7 presents the regression results at the 25th, 50th, and 75th percentiles. The coefficients of digital finance are 1.201, 1.067, and 0.966, respectively, and are all significantly positive at the 1% level. Thus, it is confirmed that digital finance benefits firms' ESG performance across all levels.

**Table 7.** Robust test 2: Quantile regression.

| Variables | 25th Percentile | 50th Percentile | 75th Percentile |
|---|---|---|---|
| | (1) ESG | (2) ESG | (3) ESG |
| DF | 1.201 *** | 1.067 *** | 0.966 *** |
| | (0.319) | (0.326) | (0.353) |
| Control variables | YES | YES | YES |
| | YES | YES | YES |
| Industry Fixed Effect | YES | YES | YES |
| Year Fixed Effect | YES | YES | YES |
| Observations | 22,576 | 22,576 | 22,576 |

Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

#### 4.4.3. Lagged Effect

Considering that the impact of digital finance on ESG performance may have a time lag, this research delays the dependent variable by 1–3 periods and explores the results of the lagged effect based on the benchmark model. Table 8 reveals that across all lag lengths, the coefficients of digital finance are positive and statistically significant (1.236, 1.380, and 1.434, respectively). Although the coefficients rise slightly over time, this phenomenon may be due to other reasons rather than a true intensification of the effect. Overall, the results suggest that the influence of digital finance on ESG performance is persistent, but the apparent upward trend in the coefficients should be interpreted cautiously.

**Table 8.** Lagged item.

| | (1) | (2) | (3) |
|---|---|---|---|
| **Variables** | **ESG + 1** | **ESG + 2** | **ESG + 3** |
| DF | 1.236 *** | 1.380 *** | 1.434 *** |
| | (0.312) | (0.323) | (0.343) |
| Size | 1.569 *** | 1.535 *** | 1.554 *** |
| | (0.0619) | (0.0648) | (0.0680) |
| Age | −0.613 *** | −0.515 *** | −0.455 *** |
| | (0.0882) | (0.0919) | (0.0966) |
| Growth | 0.160 * | 0.0182 | 0.0176 |
| | (0.0929) | (0.100) | (0.102) |
| LR | 0.00332 | −0.00380 | −0.0132 |
| | (0.0413) | (0.0427) | (0.0442) |
| CF | 5.976 *** | 7.622 *** | 7.628 *** |
| | (0.716) | (0.761) | (0.822) |
| IA | 0.929 | 1.117 | 0.972 |
| | (1.496) | (1.591) | (1.666) |
| Lev | −5.081 *** | −4.738 *** | −4.429 *** |
| | (0.485) | (0.507) | (0.534) |
| Top1 | 0.000940 | 0.00147 | 0.00201 |
| | (0.00440) | (0.00460) | (0.00482) |
| Constant | 38.47 *** | 38.62 *** | 38.03 *** |
| | (1.440) | (1.480) | (1.530) |
| Observations | 20,099 | 17,750 | 15,515 |
| R-squared | 0.172 | 0.170 | 0.169 |
| Industry Fixed Effect | YES | YES | YES |
| Year Fixed Effect | YES | YES | YES |

Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

### *4.5. Mechanism Analysis*

$$M_{i,t} = \beta_0 + \beta_1 DF_{i,t} + \gamma_k X_{i,t} + \delta_i + \mu_t + \varepsilon_{i,t} \quad (2)$$

$$ESG_{i,t} = \lambda_0 + \lambda_1 DF_{i,t} + \lambda_2 M_{i,t} + \gamma_k X_{i,t} + \delta_i + \mu_t + \varepsilon_{i,t} \quad (3)$$

To further explore how digital finance affects corporate ESG outcomes, this paper introduces two mediating variables, including TFP and analyst coverage. Following the steps of Baron and Kenny [36], we construct models (1)–(3) to test the mediating effect.

The regression result of model (1) is shown in Table 4; the impact of digital finance on ESG has been verified. Table 9 shows the results of the model (2)–(3). The coefficient of digital finance in columns (1) and (3) reveals that digital finance exerts a significant positive impact on both mediating variables. Specifically, the regression coefficient for digital finance on TFP is 0.285 ($p < 0.01$), which means that digital finance raises TFP. The coefficient for digital finance's impact on analyst coverage is 0.257 ($p < 0.01$), which means that digital finance raises analyst coverage. The results of the Sobel test and bootstrap method (1000 repetitions) suggest that digital finance may affect ESG performance through TFP and analyst coverage, through which the proportion of mediating effect is 7.80% and 12.38%, respectively.

**Table 9.** Mediating effect.

| Variables | (1) TFP | (2) ESG | (3) AC | (4) ESG |
|---|---|---|---|---|
| DF | 0.285 *** | 1.067 *** | 0.257 *** | 1.014 *** |
| | (0.0495) | (0.303) | (0.0732) | (0.301) |
| TFP | | 0.316 *** | | |
| | | (0.101) | | |
| AC | | | | 0.557 *** |
| | | | | (0.0523) |
| Size | 0.591 *** | 1.333 *** | 0.605 *** | 1.183 *** |
| | (0.00970) | (0.0854) | (0.0142) | (0.0674) |
| Age | 0.00478 | −0.713 *** | −0.288 *** | −0.551 *** |
| | (0.0145) | (0.0839) | (0.0204) | (0.0846) |
| Growth | −0.0627 *** | −0.0535 | 0.00981 | −0.0788 |
| | (0.0133) | (0.0897) | (0.0235) | (0.0874) |
| LR | 0.00289 | 0.0268 | −0.0337 *** | 0.0465 |
| | (0.00670) | (0.0384) | (0.00918) | (0.0377) |
| CF | 1.304 *** | 3.475 *** | 3.478 *** | 1.951 *** |
| | (0.111) | (0.685) | (0.173) | (0.664) |
| IA | −0.985 *** | 1.024 | −0.373 | 0.920 |
| | (0.203) | (1.413) | (0.287) | (1.406) |
| Lev | 0.692 *** | −5.064 *** | −1.260 *** | −4.144 *** |
| | (0.0877) | (0.454) | (0.111) | (0.454) |
| Top1 | 0.00228 *** | 0.00144 | −0.00450 *** | 0.00467 |
| | (0.000702) | (0.00418) | (0.00101) | (0.00415) |
| Sobel Z value | 5.745 *** | | 7.383 *** | |
| Bootstrap(1000 times) | [0.0596, | | [0.1058, | |
| 95% conf. Interval | 0.1208] | | 0.1806] | |
| Proportion of total effect that is mediated | 0.0780 | | 0.1238 | |
| Direct effect | 0.0902 | | 0.1432 | |
| Indirect effect | 1.0666 | | 1.0136 | |
| Industry Fixed Effect | YES | YES | YES | YES |
| Year Fixed Effect | YES | YES | YES | YES |
| Constant | −5.848 *** | 41.70 *** | −11.57 *** | 46.29 *** |
| | (0.234) | (1.511) | (0.338) | (1.528) |
| Observations | 22,575 | 22,575 | 22,575 | 22,575 |
| R-squared | 0.714 | 0.168 | 0.391 | 0.179 |

Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

In columns (2) and (4), both TFP and analyst coverage have a significant positive effect on corporate ESG performance. The coefficient of TFP on ESG is 0.316 ($p < 0.01$), which means the improvement of TFP will promote ESG performance. The coefficient of analyst coverage is 0.557 ($p < 0.01$), which shows that in a more transparent environment, firms are more inclined to take on their social responsibilities.

After incorporating the two mediators, the direct effect of digital finance on ESG is still significant (coefficient = 1.067 and 1.014, $p < 0.01$) and only slightly lower than in the baseline regression. This indicates the partial mediation effect and validates Hypothesis 2 and Hypothesis 3. Digital finance affects ESG through direct and indirect effects by enhancing TFP and analyst coverage.

### *4.6. Heterogeneity*

Based on two typical firm's characteristics, ownership structure (state-owned enterprises [SOEs] versus non-SOEs) and environmental sensitivity (high-pollution versus

non-high-pollution industries), we conduct subsample analyses to explore the possible heterogeneity of the relationship between digital finance and ESG performance. The classification follows Guidelines on Industry Classification of Listed Companies, with high-pollution sectors identified based on the List of Industry Classification Management for Environmental Protection Verification of Listed Companies. Ownership status is determined based on actual controlling shareholders per the CSMAR database definitions.

#### 4.6.1. Ownership Structure

From the results in Table 10, in both the SOE sample group and the non-SOE sample group, the regression estimation coefficients of digital finance are significantly positive at the 1% and 5% level. This further confirms that digital finance has a significant positive effect on improving the ESG performance of enterprises, which is consistent with previous research conclusions. It is worth noting that the regression estimation coefficient of digital finance in the SOE sample group is larger than that in the non-SOE sample group. The results indicate that, under different ownership structures, there are differences in the impact of digital finance on corporate ESG performance. That is, compared with non-SOE, digital finance has a greater promoting effect on the ESG performance of SOE. This is because SOEs are more likely to benefit from preferential access to policy-driven financing and digital finance infrastructure, enabling more efficient adoption of ESG-aligned financial tools. Moreover, SOEs may face stricter ESG compliance requirements, making them more responsive to digital finance, which streamlines reporting and monitoring.

**Table 10.** Heterogeneity analysis result.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Variables** | **ESG** | | **ESG** | |
| | **SOEs** | **Non-SOEs** | **High-Pollution** | **Non-High-Pollution** |
| DF | 1.5500 *** | 0.9932 ** | 0.6647 | 1.4326 *** |
| | (3.36) | (2.43) | (1.36) | (3.77) |
| Control variables | YES | YES | YES | YES |
| | YES | YES | YES | YES |
| Industry Fixed Effect | YES | YES | YES | YES |
| Year Fixed Effect | YES | YES | YES | YES |
| Observations | 9442 | 12,849 | 7143 | 15,430 |
| Chow test | 108.93 | | 10.86 | |
| *p*-value | 0.0000 | | 0.0000 | |

Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

#### 4.6.2. Environmental Sensitivity

As shown in columns (3) and (4) of Table 10, there is a significant difference in the effect of digital finance on the ESG performance of firms in different industries. Although the regression coefficient of the high-pollution firm is positive, it cannot reach a significant level ($p > 0.10$). Digital finance has a significantly stronger effect on the ESG performance of firms in the non-high-pollution industry ($\beta = 0.147$, $p < 0.01$). Generally, a high-pollution industry has heavy assets and high dependence on technology. There is a certain contradiction between its production model and the requirement of environmental protection. The financial convenience brought by digital finance may be preferentially used to maintain the existing production capacity rather than for green transformation. Thus, the improvement in ESG is limited.

## 5. Discussion

The positive impact of digital finance on ESG can be explained by the fact that it can alleviate financing constraints in conventional financial systems with online risk control and intelligent credit assessment, and provide funds required for ESG-related investments, such as green transformation and environmental equipment purchase. In addition, the transparency and traceability of fintech can improve market supervision of corporate responsibility and force firms to actively improve ESG compliance and disclosure [43]. It is more difficult for firms to evade responsibility and improve the credibility of information disclosed, and this thus forces them to enhance ESG.

A key mechanism is that digital finance can greatly increase the TFP of firms, which further positively affects their ESG scores. Digital finance can effectively reduce the misallocation of capital and enhance the technological innovation of firms' TFP [9]. The efficiency gains from the production side can free managerial resources and funds for ESG investment. This explains why companies can improve their ESG performance despite having limited resources. This result complements the study of Cheng [10]. He also demonstrates that digitalization can improve both productivity and ESG performance. Different from previous studies focusing on the positive effect of ESG performance on TFP [5–7], this paper suggests and tests a reverse mechanism: that digital finance can improve firms' TFP, thereby providing conditions for firms to improve ESG performance. Theoretically, treating TFP as a precondition for ESG extends the resource-based view by focusing on productivity as an organizational capability. By using digital finance, firms can obtain efficiency advantages that are difficult for competitors to imitate and then develop the capacity to implement ESG strategies. In this way, ESG performance becomes an extension of firms' productive resources, enhancing their long-term competitive advantage.

Empirical results from this study show that analyst coverage exerts significant mediating effects between digital finance and corporate ESG performance. Specifically, digital finance can improve the transparency and accessibility of corporate information and reduce information asymmetry to attract more attention from analysts. As key information intermediaries in capital markets [32], analysts not only monitor and evaluate companies regularly but also urge companies to fulfill more ESG responsibilities. This transmission mechanism has been supported by the existing literature. Zhang and Wu [34] find that analyst coverage improves corporate ESG performance, especially environmental performance and social performance. Similarly, it has been shown that digital transformation reduces financing constraints and improves analyst attention, furthering an increase in ESG performance [11]. Their finding is similar to the transmission mechanism found in this study, that is, that digital finance influences ESG performance through channeling analyst coverage. However, some scholars propose an opposite causal direction. For example, in the study of Hou [8], ESG performance attracts more attention from analysts, which reduces information asymmetry and improves business credit, furthering a decrease in firms' financing constraints. This is different from the transmission path found in the present study, where digital finance is the starting point. It does not negate the validity of our proposed mechanism. The reason may lie in the fact that the expansion and application of digital finance represent some of the preconditions for improving the external information environment of firms. Through technological advancements, digital finance significantly increases the breadth and depth of corporate information disclosure, stimulates market attention, and then subsequently enhances ESG performance. Agency theory can explain the mediating effect of analyst coverage. Analyst coverage is external governance. It can solve agency problems induced by information asymmetry between managers and investors. By monitoring managers' behaviors and publicly releasing their evaluations, analysts motivate and constrain managers' opportunistic behaviors. Digital finance creates

the institutional environment of a more transparent information environment, which helps analysts monitor managers better. Thus, agency costs will be reduced, and firms have an incentive to adopt a strategy to improve their ESG performance.

## 6. Conclusions

Based on 22,576 observations of Chinese listed companies from 2011 to 2023, we have studied the mechanism through which digital finance is related to corporate ESG performance. We constructed a mediation model with two mediating variables, TFP and analyst coverage. The results show that there is a positive association between digital finance and ESG outcomes, which exists directly and indirectly. The indirect associations pass through improved productivity and more analyst coverage.

By emphasizing TFP as the prerequisite for ESG improvement, we challenge the mainstream view that ESG improves productivity and offer a reverse mechanism to enrich understanding of the relationship between digital finance, TFP and ESG. Furthermore, we find that analyst coverage plays the role of an external monitoring channel. Digital finance reduces information asymmetry, attracts more attention from analysts and further improves ESG performance. This transmission pathway shows how digital finance simultaneously strengthens internal efficiency and external oversight, providing both theoretical contributions and practical guidance for future research.

The findings of this study have the following practical implications. Firstly, firms could use digital finance to promote sustainability, for example, by adopting digital disclosure platforms and fintech to improve transparency, efficiency, and ESG reports. Second, policymakers can consider the promotion of digital finance in the institutional environment to improve corporate transparency, resource allocation and external monitoring.

This study still has the following limitations. First, this study uses overall ESG scores and does not separately analyze the three dimensions of ESG. Since digital finance may affect three dimensions differently, future research can use disaggregated scores or use specialized databases to test the effect. Second, industry, ownership, and institutional heterogeneity are not considered. Firms are heterogeneous in their ability to use digital finance and sensitivity to ESG pressures. Future studies can test high- and low-pollution industries and state-owned and private firms. Regional policies may vary, and regulatory intensity may also exist, which may have moderating effects. Future studies can construct institutional indices across regions to test these variations. Third, this study has potential methodological limitations. The use of the static panel model may not capture how the impact of digital finance on ESG evolves. In addition, the results may be affected by omitted variables or ESG score measurement errors. It is also possible that digital finance exerts a non-linear impact on ESG. Therefore, future research can test models that consider such complexities. Fourth, ESG performance is measured using Huazheng ESG Index. Although this index is well-known, using a single ESG database may introduce bias due to differences in rating methodologies and disclosure. Future research can address this limitation by using multiple ESG databases or applying harmonization methods. Fifth, it should be noted that the mediation analysis uses sequential exogeneity, that is, digital finance affects the mediators, which in turn affect ESG performance. This assumption may be subject to endogeneity concerns since previous research finds possible reverse causality between ESG performance and analyst coverage [8]. In addition, since Huazheng ESG Index uses localized evaluation framework, its indicator system may not be fully comparable with global ESG datasets such as Refinitiv or MSCI. Therefore, ESG performance across countries should be interpreted with caution. Finally, it is important to acknowledge that the sample in this study is Chinese firms operating within a unique institutional and regulatory environment. The development of digital finance and the ESG standards in China may

differ from those in other countries. Therefore, the results should be interpreted with some caution when applied beyond the Chinese context. Future cross-country research would be valuable in examining whether the mechanisms identified here hold in other settings.

**Author Contributions:** Conceptualization: R.S.; methodology: D.L.; software: D.L.; validation: D.L.; formal analysis: R.S.; investigation: D.L.; resources: R.S.; data curation: D.L.; writing—original draft preparation: R.S. and D.L.; writing—review and editing: D.L.; supervision: D.L.; project administration: R.S. and D.L.; funding acquisition: R.S. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was funded by the Key Research Base of Philosophy and Social Sciences of Sichuan Province–Research Center for System Science and Enterprise Development (grant number Xq24B07).

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** The financial and market data are retrieved from China Stock Market & Accounting Research (CSMAR) https://data.csmar.com/ (accessed on 12 August 2025). The digital financial inclusion index is obtained from the Institute of Digital Finance, Peaking University https://en.idf.pku.edu.cn/ (accessed on 12 August 2025). Huazheng ESG scores are obtained from WIND database https://www.wind.com.cn/portal/zh/Home/index.html (accessed on 12 August 2025).

**Conflicts of Interest:** The authors declare no conflicts of interest.

## References

1. Mo, Y.; Che, Y.; Ning, W. Digital finance promotes corporate ESG performance: Evidence from China. *Sustainability* **2023**, *15*, 11323. [CrossRef]
2. Liu, Y.; Chen, L. The impact of digital finance on green innovation: Resource effect and information effect. *Environ. Sci. Pollut. Res.* **2022**, *29*, 86771–86795. [CrossRef] [PubMed]
3. Wu, K.; Zhang, Y.; Chen, Y.; Li, M. Impact of digital finance on corporate ESG. *Int. Rev. Financ. Anal.* **2025**, *104*, 104259. [CrossRef]
4. Zhou, B.; Ge, J. Does corporate digitization affect investment efficiency? Evidence from China. *Appl. Econ. Lett.* **2024**, *31*, 2144–2149. [CrossRef]
5. Ge, G.; Xiao, X.; Li, Z.Z. ESG performance, investment efficiency, and total factor productivity of enterprises. *Enterp. Econ.* **2024**, *43*, 40–49.
6. Guo, H.; Wang, J. The relationship between corporate ESG performance and total factor productivity: An empirical test based on listed companies. *J. Tangshan Univ.* **2023**, *36*, 71–78.
7. Sheng, M.; Li, Z.; Wang, S. ESG information disclosure and total factor productivity of enterprises. *Stat. Inf. Forum* **2024**, *39*, 88–100.
8. Hou, X.Y. Corporate ESG performance and financing constraints: Empirical evidence from Chinese listed companies. *J. Appl. Financ. Bank.* **2023**, *13*, 77–96. [CrossRef]
9. Xu, X. The impact of digital finance on total factor productivity of enterprises. *BCP Bus. Manag.* **2022**, *32*, 1–16. [CrossRef]
10. Cheng, Q. Digital transformation as a catalyst for high-quality development: Examining total factor productivity and ESG performance in China's manufacturing sector. *J. Ecohumanism* **2025**, *3*, 12426–12442. [CrossRef]
11. Cai, C.; Tu, Y.; Li, Z. Enterprise digital transformation and ESG performance. *Financ. Res. Lett.* **2023**, *58*, 104692. [CrossRef]
12. Zhang, J.; Li, Y.; Xu, H.; Ding, Y. Can ESG ratings mitigate managerial myopia? Evidence from Chinese listed companies. *Int. Rev. Financ. Anal.* **2023**, *90*, 102878. [CrossRef]
13. Luo, Z.; Yip, P.S.; Brooks, R. Bridging digital finance and ESG success: The role of financing constraints, innovation, and governance. *Int. J. Financ. Stud.* **2025**, *13*, 109. [CrossRef]
14. Ren, X.; Zeng, G.; Zhao, Y. Digital finance and corporate ESG performance: Empirical evidence from listed companies in China. *Pac.-Basin Financ. J.* **2023**, *79*, 102019. [CrossRef]
15. Wu, Y.; Wu, B.; Liu, X.; Zhang, S. Digital finance and agricultural total factor productivity–From the perspective of capital deepening and factor structure. *Financ. Res. Lett.* **2025**, *74*, 106449. [CrossRef]
16. Teng, L. The mechanism and path of digital inclusive finance in alleviating financing constraints of small and medium-sized enterprises. *Surv. World* **2020**, *9*, 27–35.
17. Lang, X.; Zhang, M.; Wang, J. Digital inclusive finance, financing constraints, and innovation in small and medium-sized enterprises: Evidence from New Third Board enterprises. *South. Financ.* **2021**, *11*, 13–25.

18. Xiang, S.; Deng, L.; Zhou, Z.; Zhang, Z. Digital finance, ESG performance, and financial performance in Chinese firm levels: The pathway to sustainability. *Sustainability* **2024**, *16*, 7976. [CrossRef]
19. Xue, R.; Wang, H.; Yang, Y.; Linnenluecke, M.K.; Jin, K.; Cai, C.W. The adverse impact of corporate ESG controversies on sustainable investment. *J. Clean. Prod.* **2023**, *427*, 139237. [CrossRef]
20. Mu, W.; Liu, K.; Tao, Y.; Ye, Y. Digital Finance and Corporate ESG. *Financ. Res. Lett.* **2022**, *51*, 103426. [CrossRef]
21. Xue, L.; Dong, J.; Zha, Y. How does digital finance affect firm environmental, social and governance (ESG) performance?-Evidence from Chinese listed firms. *Heliyon* **2023**, *9*, e20800. [CrossRef]
22. Jin, S.; Zhong, Z. Impact of digital inclusive finance on agricultural total factor productivity in Zhejiang Province from the perspective of integrated development of rural industries. *PLoS ONE* **2024**, *19*, e0298034. [CrossRef]
23. Xiao, Q.; Wang, Y.; Liao, H.; Han, G.; Liu, Y. The Impact of Digital Inclusive Finance on Agricultural Green Total Factor Productivity: A Study Based on China's Provinces. *Sustainability* **2023**, *15*, 1192. [CrossRef]
24. Ma, X.; Zhou, A.; Chi, C. ESG performance and green total factor productivity. *Financ. Res. Lett.* **2025**, *73*, 106630. [CrossRef]
25. Li, W.; Pang, W. The impact of digital inclusive finance on corporate ESG performance: Based on the perspective of corporate green technology innovation. *Environ. Sci. Pollut. Res.* **2023**, *30*, 65314–65327. [CrossRef] [PubMed]
26. Wu, S.; Fan, M.H.; Wu, L.; Liu, Z.Q.; Xiang, Y.C. Path to green development: How do ESG ratings affect green total factor productivity? *Sustainability* **2024**, *16*, 10653. [CrossRef]
27. Yu, H.; Liang, C.; Liu, Z.; Wang, H. News-based ESG sentiment and stock price crash risk. *Int. Rev. Financ. Anal.* **2023**, *88*, 102646. [CrossRef]
28. Geng, Y.; Zheng, Z.; Yuan, X.; Jiménez-Zarco, A.I. ESG performance and total factor productivity of enterprises: The role of digitization. *Res. Int. Bus. Financ.* **2025**, *77*, 102920. [CrossRef]
29. Yu, Y.; Wang, L.; Wu, Y.; Zhang, J.Z.; Li, H.; Zhang, Y. How ESG governance affects total factor productivity: Evidence from Chinese listed companies. *Environ. Impact Assess. Rev.* **2026**, *116*, 108074. [CrossRef]
30. Gu, Y.; Zeng, S.; Peng, Q. The Mutual Relationships Between ESG, Total Factor Productivity (TFP), and Energy Efficiency (EE) for Chinese Listed Firms. *Sustainability* **2025**, *17*, 2296. [CrossRef]
31. Song, C.; Han, M.; Yuan, H. The impact of digital transformation on firm productivity: From the perspective of sustainable development. *Financ. Res. Lett.* **2025**, *75*, 106912. [CrossRef]
32. Wu, Z.; Zhang, K.; Li, R. ESG score, analyst coverage and corporate resilience. *Financ. Res. Lett.* **2024**, *62*, 105248. [CrossRef]
33. Khan, M.A. ESG disclosure and Firm performance: A bibliometric and meta analysis. *Res. Int. Bus. Financ.* **2022**, *61*, 101668. [CrossRef]
34. Zhang, C.; Wu, X. Analyst coverage and corporate ESG performance. *Sustainability* **2023**, *15*, 12763. [CrossRef]
35. Hu, J.; Zou, Q.; Yin, Q. Research on the effect of ESG performance on stock price synchronicity: Empirical evidence from China's capital markets. *Financ. Res. Lett.* **2023**, *55*, 103847. [CrossRef]
36. Baron, R.M.; Kenny, D.A. The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *J. Personal. Soc. Psychol.* **1986**, *51*, 1173–1182. [CrossRef]
37. Sino-Securities Index ESG Information Service (Shanghai) Co., Ltd. *Sino-Securities Index ESG Ratings Methodology*; Sino-Securities Index ESG Information Service: Shanghai, China, 2024.
38. Levinsohn, J.; Petrin, A. Estimating production functions using inputs to control for unobservables. *Rev. Econ. Stud.* **2003**, *70*, 317–341. [CrossRef]
39. Lu, X.; Lian, Y. Estimation of Total Factor Productivity of Chinese Industrial Enterprises: 1999–2007. *Economics* **2012**, *11*, 541–558.
40. Hu, Y.; Liu, Q. Local Digital Economy and Corporate Social Responsibility. *Sustainability* **2023**, *15*, 8487. [CrossRef]
41. Li, H.; Lu, L.; Lin, Z.; Meng, T. Digital innovation and corporate social responsibility performance: Evidence from firms' digital patents. *Technol. Forecast. Soc. Change* **2024**, *207*, 123626. [CrossRef]
42. Zeng, J.; Avila-Romero, F.; Ren, J.; Ribeiro-Navarrete, S. Shaping effect of digitalisation on corporate social responsibility: Evidence from Born Global Entrepreneurial firms. *Int. Entrep. Manag. J.* **2025**, *21*, 55. [CrossRef]
43. Zhao, W.L. FinTech enhances the quality of ESG information disclosure. *China Financ.* **2023**, *14*, 69–70.


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