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Research Article

Digital Transformation and ESG Performance: A Quasinatural Experiment Based on China's Environmental Protection Law

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The bioeconomy model provides an alternative view of global economic systems by putting sustainable practices combined with digital approaches at the forefront to tackle issues such as climate change. To address this new business trends, financial institutions began to set up the environmental, social, and governance (ESG) business units to evaluate their business strategies. This paper is aimed at examining the nonfinancial effect created by the digital transformation (DT) activities, highlighting the role of enterprise heterogeneity after the implementation of Environmental Protection Law (EPL) in China. We employ the panel data of A-share listed companies from 2010 to 2020, selecting DT and ESG indicators as the important representations of "Industry 5.0." Our empirical results demonstrate a positive impact of EPL on the ESG performance in sight of resource enterprises (REs), environmental enterprises (EEs), and polluting enterprises (PEs), but a negative impact of EPL on the DT indicators among those environmental related industries. Additional causal relationship regression reveals that enterprise DT has an intrinsic promoting effect on the ESG performance, emphasizing on the high risk of digitization process being the shock transmitters to enterprise nonfinancial indices. Notably, the connectedness of environmental policy illustrates dynamic patterns by parallel trend test and propensity score matching (PSM) DID regression. This paper is prone to benefit lawmakers, regulators, and firm executives responsible for analyzing and assessing enterprise digitization behavior by exploring the influence of macrolevel environmental policy.

1. Introduction

The world is currently confronting with increasingly serious environmental problems such as climate change, rapid deforestation, and land desertification, which are seriously troubling and threatening social resilience. A new industrial development paradigm of "Industry 5.0" is directed to humanization of digital transformation, social resilience, and sustainable development of industrial ecosystems. "Industry 5.0" is not a new technological revolution, but a value-driven initiative that drives green transformation to bring about a significant increase in human well-being. Countries around the world continue to set new demands and goals concerning environmental issues, transforming environmental sustainability into one of the critical challenges encountered by the global community [1]. The United Nations formulated the "Agenda 2030" and Sustainable Development Goals (SDGs) in 2015, where many of their goals potentially correlate with or diverge from one another [2, 3]. The SDGs emphasize on the critical role of digital technology [4] and the holistic development in the economic, social, and environmental spheres [5]. To maximize synergies and minimize trade-offs within and among the SDGs, incorporating advanced social sciences into sustainability efforts poses a daunting challenge [6–8]. Chinese central government also officially implemented the Environmental Protection Law (EPL) in 2015, which has been defined as the strictest administrative law the in environmental field [9–11]. Empirical examples available show that enterprises' digital transformation (DT) activity is increasingly being exploited for improving environmental resilience, which can enable enterprises' convergence toward the SDGs. Although most studies indicate that DT is an effective tool for achieving SDGs (e.g., [4, 12]), some scholars still believe that the impact mechanism of DT on SDGs is unclear yet (e.g., [13, 14]), especially controversial regarding social and environmental aspects (e.g., [15, 16]). Inspired by SDGs and EPL, we have directed our research interest toward searching for approaches to sustainable digitization for the environment as well as measuring its impact for policy-makers.

From the perspective of enterprises, their long-term orientation of enterprises is closely related to their environmental [17, 18] and social responsibility [19] performance. And the real effects of socially responsible investment initiatives and the refinement of environment, social, and governance (ESG) type ratings are the influential forces for reducing climate risks [20]. ESG scores can measure the contribution and effectiveness of relevant aspects from the firm's annual report, reflecting the enthusiasm of corporate executives toward ESG rating [21, 22]. Investors in the capital market are increasingly integrating ESG risks into their investment strategy [23, 24], particularly for those institutional investors [25, 26]. This ESG concerning of institutional investors will inevitably attract more institutional analysts on a company's ESG performance, which can facilitate the executives for integrating ESG indicators into their long-term strategy [27]. Furthermore, stakeholders of the listed companies would pay more attention on the sustainable strategy of improving their social responsibility level to attract more institutional investors and analysts [28, 29]. Based on that, the "Governance Standards for Listed Companies" issued by China Securities Regulatory Commission (CSRC) in 2018 preliminary established the basic framework of ESG demands for Chinese listed companies. Later in 2020, Shenzhen Stock Exchange (SSE) further revised the "Assessment Measures for Information Disclosure of Listed Companies," which is the first proposal for China's listed companies to actively disclose ESG information as well as assess the quality of ESG disclosure. Subsequently, the State-owned Assets Supervision and Administration Commission (SASAC) proposed clear requirements for all state-owned listed companies to fully disclose ESG information by 2023. Combining the upcoming context of "Industry 5.0," our major research problem lies in the uncertainty of DT activity within the relationship between environmental policy and sustainable indices. Referring to Song et al. [30], both DT and ESG performance are selected as the important representations of "Industry 5.0" for our empirical research.

Our paper is aimed at addressing a unique quasinatural experimental design that can contribute to harmonious and sustainable development, and the key aspect here is to determine the internal impact of enterprises' DT activity on the ESG performance. We investigate the inherent mechanisms by which EPL influences the DT to reveal the drivers of and paths toward enhancing sustainable performance, providing theoretical support and empirical evidence for scholars and practitioners. The main contributions of this study are as follows. First, we integrate the "Industry 5.0" indicators of DT and ESG performance into the same analytical framework to explore the nonfinancial impact of DT from the perspective of enhancing ESG practices, broadening the current scope of research in corporate finance. Second, we examine the impact of the EPL on resource enterprises (REs), environmental enterprises (EEs), and polluting industries (PEs) to explore more microlevel empirical evidence of environmental policy in achieving SDGs. Third, the "black box" of causal relationship between DT and ESG performance is partially revealed by examining the intrinsic mechanism of DT after the implementation of the EPL. Our finding contributes to presenting the internal driving mechanisms and effect of DT activity, filling the research gap of the enhancement of overall ESG practice for the upcoming era of "Industry 5.0."

2. Literature Review

2.1. EPL and ESG Performance. Stemming from the 2015 SDGs and EPL, stricter environmental policies and external governance are particularly influential for improving enterprises' ESG awareness. From the perspective of environmental scanning theory [31], enterprises will frequently conduct "environmental scans" to identify the external economic, social, legal, and political situation, making strategic decisions on adapting the new environmental regulations. In this context, stakeholders of listed companies would pay more attention on their sustainable strategy, improving their level of social responsibility and green governance to attract more institutional investors and analysts [22, 28, 29]. There are mainly three views that EPL can promote ESG performance. First, the EPL increases the punishment intensity of violation for enterprises, and its deterrent effect can compel them on abandoning short-sighted strategies [11]. Second, the EPL increases the social responsibility risk and cost on environmental pollution of enterprises [10]. Third, the EPL increases firm's investment on environmental protection to strengthening the environmental compliance and information disclosure [32].

Further, since the new institutional constraints and rules of EPL, the social responsibility costs of environmental related industries are sensibly higher than before. Particularly, polluting enterprises (PEs) attach great importance on environmental regulatory policies to avoid the excessive polluting cost [33]. Resource enterprises (REs) and environmental enterprises (EEs) also strengthen the green transformation to expand the existing advantages for green policies [21]. In this case, EPL significantly increased the corporate tax avoidance of pollution emissions in PEs [34], pushing PEs to disclose the specific environmental information [10]. And the financial rewards and penalties of EPL may motivate the stakeholders of EEs and REs to deepening their green production. Under the dual pressure of institutional constraints and financial penalties, we suppose EPL can positively impact on ESG indices of environmental related industries including REs, EEs, and PEs; thus, the following hypothesis is proposed.

H1. Compared with other industries, EPL can positively affect the ESG performance of REs, EEs, and PEs.

2.2. EPL and DT. Another concern is that enterprises may symbolically conform to environmental policies without actual efforts on pursuing the environmental goals [35], such as digital progression. So this promotion on social responsibility can significantly affect the policy effect of digital progression [36]. On the basis of "insurance effect" [37], enterprises tend to pursue the maximum financial returns and benefits with the lowest investment on social responsibility. China's listed companies still had insufficient green investment scale due to the negative externalities of environmental regulation [9]. From the perspective of EPL, China's firms have insufficient inherent motivation and external regulatory environment to driving the digital process under the high pressure of maximizing their financial returns. As a result, the additional costs and environmental constraints imposed by EPL may bring more challenges on DT activities for environmental related industries of REs, EEs, and PEs. Along with this, there may exist more negative externalities of a different kind, so the search for a compromise and consistency of interests is of fundamental importance here. In such circumstances, the following hypothesis is proposed.

H2. Compared with other industries, EPL can negatively affect the DT of REs, EEs and PEs.

2.3. DT and ESG Performance. On the on hand, enterprises' DT in industry is part of the overall digitalization process, which mainly focuses on the disruptive restructuring of digital resources [38]. The resource allocation theory [39] suggests enterprises to effectively allocate and integrate digital resources for fully exploiting the resources value as well as improving the operational efficiency. Taking the advantages of digital resources, the resource structural evolution on natural ecosystem and corporate governance may reshape to the ecological balance [40]. And those digital resources provide more possibilities for enterprises to solve environmental problems when the digitization process embedded into the internal governance structure [41]. So it is possible to achieve low-carbon production and the resource utilization by digitization process, providing environmental information in real time [42, 43].

On the other hand, enterprises' DT can also improve the information transparency in social and environmental aspects [28]. With regard to signal transmission theory, DT enable the traceability of enterprise operational process to reducing information asymmetry and transaction costs [44, 45] and reducing the interaction costs between enterprises and stakeholders [46]. Therefore, DT accounts for the greatest impact on the ESG indices [41], and it is fundamental elements in achieving high-quality and sustainable development [47]. Based on the above analysis, the following hypothesis can be proposed, and our theoretical framework is presented in Figure 1.

H3. Enterprises' DT positively affects the ESG performance.

3. Methodology

3.1. Data Source. This paper selects A-share listed companies in Shanghai and Shenzhen Stock Exchange from 2010 to 2020, regarding the application of China's EPL in 2015 as the exogenous event. Our firm-level data are obtained from the listed companies databases of China Stock Market & Accounting Research (CSMAR) and Wind China Financial Database (WIND). We conducted the following data processing: (1) excluding samples with missing data, (2) excluding financial and real estate samples, and (3) excluding ST and PT samples during the research period. All continuous variables are winsorized by 1% and 99% quantiles to control the influence of extreme values. Finally, 27,338 observations can be acquired for the following empirical regression.

3.2. Variables

3.2.1. Explained Variable. Referring to the researches of Tang [48] and Zhong et al. [47], this paper employs Huazheng ESG ratings to measure the enterprise' ESG performance, which divides ESG ratings into nine grades (C-AAA) and assigns points (1–9) for each observation. Huazheng ESG scoring system mainly consists of 14 secondary-level indicators, 26 third-level indicators, and more than 130 underlying data indicators.

3.2.2. Explanatory Variable. Drawing on the practice of Xue et al. [43] and Wu et al. [49], this paper adopts the method of text frequency analysis to construct the DT score. Keyword matching was performed on the text content of annual reports, where the total DT frequency was calculated by the summation of each company after taking the natural logarithm value.

3.2.3. Grouping Variables

(1) EEs and REs. Based the classification of the China Statistics Bureau (CSB), a total number of 80 subclassifications were screened due to the availability of relevant data. In line with the classification of Zhang and Xu [50] and Chen et al. [27], 16 subindustries were identified from 22 industrial subcategories as the EEs and REs after the consolidation of analogous industries (see Table 1). Finally, a sampling group of 7719 observations from 1098 EEs and REs can be acquired.

(2) PEs. Since the polluting companies are more affected by environmental regulations, evaluating the policy's effect is more important for this group [32]. Drawing upon the methodology of Deschenes et al. [51] and Zhou et al. [52], 12 subindustries were identified from 14 industrial subcategories to investigate the effect of the EPL on PEs (see Table 2). Finally, an experimental group of 6131 observations from 852 polluting firms can be acquired.

3.2.4. Control Variables. Referring to the previous researches [53, 54], our control variables include firm size (SIZE), debt to asset (LEV), return on assets (ROA), cash to assets (CASH), fixed assets (FIXED), independent board (INEDP), book to market value (BM), and firm age (AGE). Moreover, our models also introduce the firm and year fixed effects. Table 3 demonstrates the definition of each variable in this study.

3.3. Model Setting

3.3.1. Parallel Trend Models. An important prerequisite for valid DID estimation is that the treatment and control groups have a parallel trend before the event impact [55,

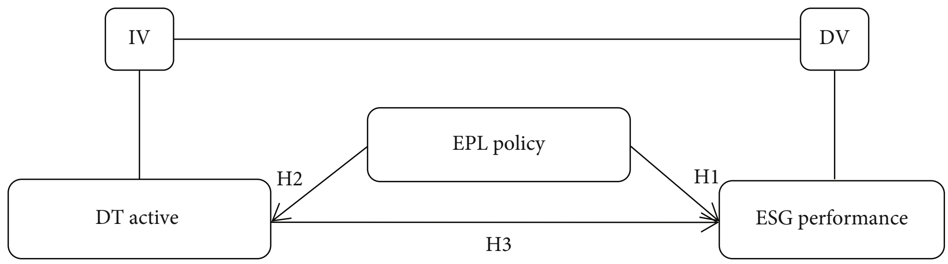

Figure 1: Theoretical framework.

Table 1: Subcategories of EEs and REs.

N	Code	Industry	Number of samples	Percent (%)
1	B06, B08, B09, B10, B11	Mining	639	8.28%
2	C15	Beverage, liquor, and refined tea manufacturing	375	4.86%
3	C19	Fur, feathers, leather, and their products	76	0.98%
4	C20, C21	Wood processing	189	2.45%
5	C22	Papermaking and paper products	253	3.28%
6	C23	Printing and recording media copying	91	1.18%
7	C25, B07	Coking, oil and gas processing, nuclear fuel processing	207	2.68%
8	C26	Chemical materials and products	1862	24.12%
9	C28	Chemical fibers	235	3.04%
10	C31	Metallurgy of black metals	305	3.95%
11	C32	Metallurgy of nonferrous metals	572	7.41%
12	C33	Metallic mineral products	463	6.00%
13	C35	Special equipment manufacturing sector	1513	19.60%
14	D44	Electric power and hot power production	673	8.72%
15	D45	Gas production and supply industry	132	1.71%
16	D46	Waste resource and material recycling and processing	134	1.74%
Total			7719	100%

Table 2: Subcategories of PEs.

N	Code	Industry	Number of firms	Percent (%)
1	B08, B09	Mining	264	4.31%
2	C17	Textiles	389	6.34%
3	C19	Leather, fur, feathers, and their products	76	1.24%
4	C22	Papermaking and paper products	253	4.13%
5	C25, B07	Oil and gas processing, coking, and nuclear fuel processing	207	3.38%
6	C26	Chemical materials and products	1862	30.37%
7	C28	Chemical fibers	235	3.83%
8	C29	Rubber and plastic products	545	8.89%
9	C30	Nonmetallic mineral products	750	12.23%
10	C31	Metallurgy of black metals	305	4.97%
11	C32	Metallurgy of nonferrous metals	572	9.33%
12	D44	Electric power and hot power production	673	10.98%
Total			6131	100%

56]. In order to verify the grouping differences before and after the event year, the parallel trend test has become the necessary prerequisite for DID research when sample sizes are sufficiently large. According to Zhang et al. [11], Yu et al. [34], Liu et al. [10], and Huang and Lei [9], this paper takes the EPL formally implemented by the Chinese central government on January 1, 2015, as a quasiexperimental design. Referring to model setting of Seltzer et al. [57] and

Table 3: Variable definition.

Type	Symbol	Variable	Description
Dependent variable	ESG	Environmental, social, and governance performance	ESG score from 1 to 9
Explanatory variable	DT	Degree of digital transformation	DT score from 0 to 1
Grouping variable	EERE	Resource enterprises and environmental enterprises	REs and EEs = 1, else = 0
	POLLUT	Polluting industries	PEs = 1, else = 0
	POST	Year of policy event	After 2015 = 1, else = 0
Control variable	SIZE	Firm size	Natural logarithm of total assets
	LEV	Debt to asset	Corporate liabilities/total assets
	ROA	Return to assets	Net profit/total assets
	CASH	Cash to assets	Cash flow/total assets
	FIXED	Fixed asset ratio	Fixed assets/total assets
	INDEP	Independent board	Natural logarithm of numbers of independent board directors
	BM	Book to market value	Equity/market capitalization
	AGE	Firm age	Natural logarithm of firm age

Fan et al. [58], this paper adopts the consecutive difference-in-differences (DID) model to ensure the uniqueness of the event and examine the grouping difference during the complete study period from 2010 to 2020. Models (1) and (2) were established as a quasinatural experiment to test the parallel trend of the EPL.

$$\mathrm{ESG}_{it}=\sum_{k=-5}^{5}\beta_k[(t=k)\times \mathrm{TREAT}_i]+\gamma \mathrm{Controls}_{it}+\mu_i+\omega_t+\varepsilon_{it}, \tag{1}$$

$$\mathrm{DT}_{it}=\sum_{k=-5}^{5}\beta_k[(t=k)\times \mathrm{TREAT}_i]+\gamma \mathrm{Controls}_{it}+\mu_i+\omega_t+\varepsilon_{it}. \tag{2}$$

The explanatory variable of ESG_{it} in Model (1) represents the ESG performance of company i at year t, and the explanatory variable of DT_{it} in Model (2) represents the DT of company i at year t, where Controls involve a serious of control variables that affect ESG and DT and ε_{it} is the random error term. In order to mitigate the external influence of macroeconomic policy on the variables, we also introduce the industry fixed effect μ_i and year fixed effect ω_t into DID regression. Furthermore, $t=0$ denotes the implementation year of the policy which is 2015, $t=-5$ to 5 denotes the 5 consecutive years before and after the application of the EPL, collapsing the data into pre- and postperiods. TREA T_i is the grouping variable of green and polluting industries, and the coefficients of $(t=k)\times \mathrm{TREAT}_i$ are concerning those changes on coefficient β_k reflecting the dynamic impact of the EPL on REs, EEs, and PEs.

3.3.2. Difference-in-Differences Models. In line with the researches of Bertrand and Schoar [59] and Seltzer et al. [57], this paper constructs the following DID model setting to investigate the impact of the EPL on DT and ESG performance, where POST_t is the year dummy variable for the implementation of the 2015 EPL, and other model setting are consistent with the previous Models (1) and (2).

$$\begin{aligned}\mathrm{ESG}_{it}=\beta_0+\beta_1\mathrm{TREAT}_i+\beta_2\mathrm{POST}_t+\beta_3\mathrm{TREAT}_i\\ \times \mathrm{POST}_t+\gamma \mathrm{Controls}_{it}+\mu_i+\omega_t+\varepsilon_{it},\end{aligned} \tag{3}$$

$$\begin{aligned}\mathrm{DT}_{it}=\beta_0+\beta_1\mathrm{TREAT}_i+\beta_2\mathrm{POST}_t+\beta_3\mathrm{TREAT}_i\\ \times \mathrm{POST}_t+\gamma \mathrm{Controls}_{it}+\mu_i+\omega_t+\varepsilon_{it}.\end{aligned} \tag{4}$$

3.3.3. Internal Mechanism Impact. With regard to the model setting of Preacher and Hayes [60] and Cao et al. [61], we further introduce the Models (5) and (6) to explore the intrinsic mechanisms of DT within the relationship between EPL and ESG performance.

$$\mathrm{ESG}_{it}=\beta_0+\beta_1\mathrm{DT}_{it}+\gamma \mathrm{Controls}_{it}+\mu_i+\omega_t+\varepsilon_{it}, \tag{5}$$

$$\begin{aligned}\mathrm{ESG}_{it}=\beta_0+\beta_1\mathrm{TREAT}_i\times \mathrm{POST}_t+\beta_2\mathrm{DT}_{it}\\ +\gamma \mathrm{Controls}_{it}+\mu_i+\omega_t+\varepsilon_{it}.\end{aligned} \tag{6}$$

4. Empirical Results

4.1. Descriptive and Correlation Statistics. In Table 4, the mean value of ESG is 6.485 with a standard deviation of 1.154, indicating that most of China's listed companies have relevant high ESG performance in view of Huazheng ESG scoring system. And the mean value of DT is 0.099 with a standard deviation of 0.227, implying that the overall digital

Table 4: Descriptive statistics.

Var.	Obs	Mean	Std. dev.	Min	Max
ESG	27,338	6.485	1.154	3	9
DT	27,338	0.099	0.227	0	1
EERE	27,338	0.282	0.450	0	1
POLLUT	27,338	0.224	0.417	0	1
POST	27,338	0.645	0.479	0	1
SIZE	27,338	22.204	1.284	19.525	26.398
LEV	27,338	0.432	0.207	0.027	0.925
ROA	27,338	0.039	0.066	-0.398	0.244
CASH	27,338	0.046	0.069	-0.224	0.257
FIXED	27,338	0.216	0.162	0.002	0.736
INDEP	27,338	0.375	0.054	0.273	0.600
BM	27,338	1.055	1.178	0.051	10.142
AGE	27,338	2.869	0.341	1.099	3.555

transformation of our sample companies is quite low with large variance. The mean value of EERE is 0.282, and that of POLLUT is 0.224, representing that both green and polluting enterprises account for a relatively low proportion in our samples. Moreover, it can be seen that there are no abnormal values in our sample description, and the descriptive statistics of financial indicators in Table 4 are highly consistent with the existing literature.

We apply the variance inflation factor (VIF) test to find that there is no multicollinearity issue on the further regression analysis (all results of VIF are less than the threshold value of 10). As indicated, all Pearson correlation coefficients between variables reported in Table 5 are less than 0.6, suggesting that each variable can be clearly distinguished. Furthermore, the correlation between DT and ESG is positive at the 1% significance level, suggesting that enterprises' digital transformation may affect their ESG performance.

4.2. Regression Results

4.2.1. Parallel Trend Test. The dynamic regression results of EPL on the ESG performance are shown in Figures 2 and 3. The coefficients ($\beta_{-5} - \beta_{-2}$) of ESG performance before 2015 are generally negative and all 95% confidence intervals contain 0, indicating the grouping differences are not significant at the 5% level before 2015 [55, 56]. Meanwhile, the 95% confidence intervals of $\beta_0 - \beta_5$ do not contain 0, implying a significant grouping difference after the implication of EPL. Thus, the parallel trend assumption for Model (1) is valid, and EPL has a notable influence on the ESG performance of REs, EEs, and PEs.

The dynamic regression results of EPL on the DT are shown in Figures 4 and 5. The 95% confidence intervals contain 0 and the coefficients ($\beta_{-5} - \beta_{-2}$) of *DT* are typically negative before 2015, indicating the grouping differences of DT are not significant at the 5% level. In contrast, the coefficients ($\beta_0 - \beta_5$) are significantly different from 0 after the implementation of EPL, also supporting the parallel trend assumption for Model (2).

4.2.2. Main Results

(1) Benchmark DID Test. Based on the previous parallel trend test, Table 6 reports the impact of EPL on REs, EEs, and PEs, where the coefficients of the interaction term TREAT*POST in columns (1) and (2) are 0.117 and 0.072, respectively, both are significantly positive at the 1% level after controlling the year and industry fixed effects. The results indicate that the implementation of EPL has a positive impact on the ESG performance of REs, EEs, and PEs, thus supporting the H1 (in-line with [9, 10, 34]). Meanwhile, the coefficients of the interaction term TREAT*POST in columns (3) and (4) are -0.013 and -0.012, which also pass the significance tests at the 1% level. The benchmark results also preliminarily verify that the implementation of EPL has a negative impact on the DT in REs, EEs, and PEs, fully supporting our H2.

(2) PSM-DID Regression. Ignoring the time series variation altogether allowing for an arbitrary covariance matrix over time has been shown to be a simple viable solution to deal with the serial correlation problem in DID regression [62]. In this paper, the logit model was adopted with the grouping dummy variable as the dependent variable and the SIZE, LEV, ROA, CASH, FIXED, INDEP, BM, AGE, and other variables as the covariates. Drawing upon the nearest neighbor matching method of Zhu et al. [63], Wang et al. [64], and Guan et al. [65], we examine the average treatment effect of the covariates between the treatment and control groups. Table 7 reports the average treatment results by nearest neighbor matching approach with a 1 : 1 ratio to match a control company for each treatment company. The average treatment effect on the treated (ATT) values of ESG performance are 2.220 and 2.600 after nearest neighbor matching, and the ATT values corresponding to DT are -22.760 and -19.310 after matching. All absolute values of ATT are greater than the critical value of 1.96, indicating that there is still a significant difference between the treatment and control samples after matching. That is, EPL have a significant treatment effect on both indicators of China's REs, EEs, and PEs.

In line with Jin et al. [55] and Guo et al. [66], the similarity between treatment and control groups can be further measured by a nearest neighbor matching estimator in PSM regression. Figures 6 and 7 plot the figure before matching on the left and the figure after matching on the right. Both figures demonstrate that the probability density of the propensity score value is closer after matching, displaying a good matching effect of our benchmark DID Model (3) and (4), also indicating the feasibility and rationality of the following PSM-DID method.

In order to control the systematic differences and estimation error of the DID regression, PSM-DID method can solve the problems of reverse causality and sample selection bias [65]. This paper conducts the PSM-DID regression for sampling estimation to reduce the sample selection bias and estimation error of the benchmark model. The significance and direction of the interaction terms TREAT*POST

Table 5: Correlation matrix.

	ESG	DT	EERE	POLLUT	POST	SIZE	LEV	ROA	CASH	FIXED	INDEP	BM	AGE
ESG	1												
DT	0.046***	1											
EERE	-0.008	-0.178***	1										
POLLUT	-0.030***	-0.164***	0.529***	1									
POST	-0.044***	0.069***	-0.019***	-0.043***	1								
SIZE	0.333***	-0.048***	0.066***	0.056***	0.139***	1							
LEV	0.067***	-0.003	0.024***	0.048***	-0.039***	0.496***	1						
ROA	0.153***	-0.047***	-0.010*	-0.018***	-0.065***	0.009	-0.344***	1					
CASH	0.067***	-0.062***	0.072***	0.079***	0.069***	0.056***	-0.170***	0.373***	1				
FIXED	-0.007	-0.245***	0.307***	0.389***	-0.086***	0.086***	0.076***	-0.072***	0.235***	1			
INDEP	-0.011*	0.037***	-0.030***	-0.039***	0.061***	0.001	-0.010*	-0.028***	-0.009	-0.050***	1		
BM	0.187***	-0.015**	0.055***	0.075***	0.011*	0.645***	0.552***	-0.201***	-0.092***	0.076***	0.008	1	
AGE	0.032***	0.032***	-0.017***	0.008	0.370***	0.172***	0.167***	-0.104***	0.022***	-0.003	-0.012**	0.170***	1

Notes: $N = 27{,}338$. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

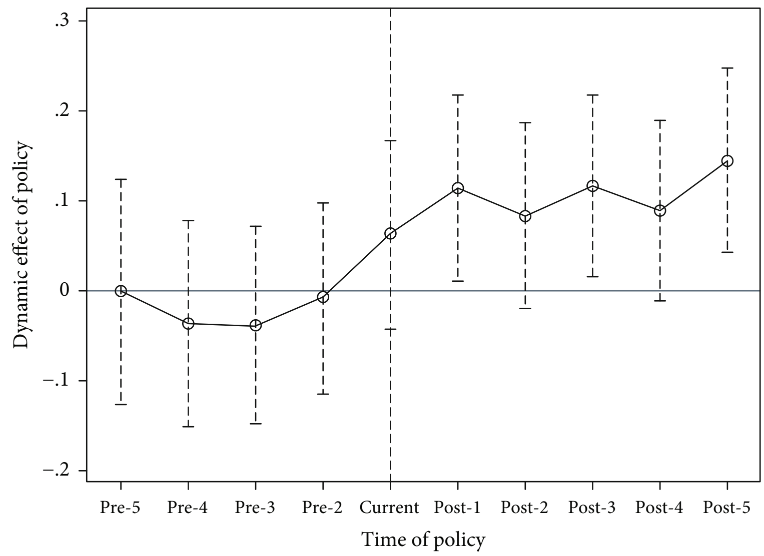

Figure 2: Dynamic impact of EPL on the ESG performance of EEs and REs.

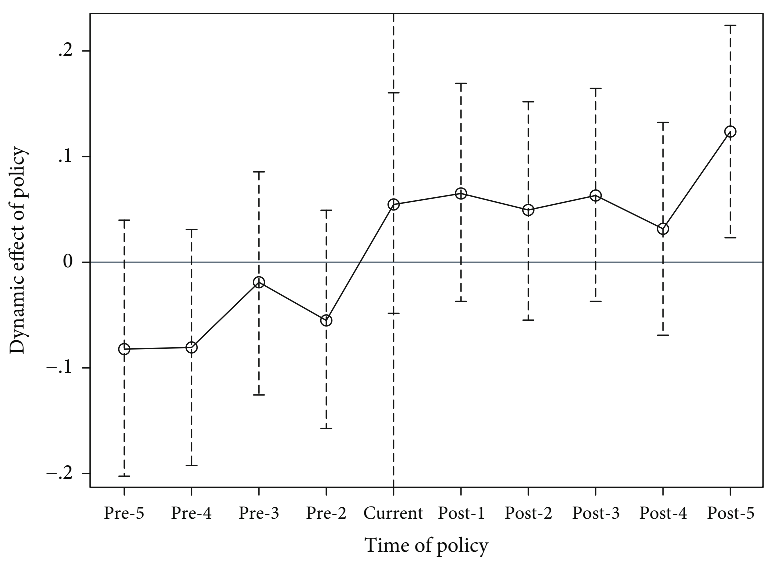

Figure 3: Dynamic impact of EPL on the ESG performance of PEs.

in Table 8 are highly consistent with the benchmark DID models, fully supporting our H1 and H2. Moreover, the absolute value of the coefficient increases compared with benchmark regression, implying that the impact of EPL on ESG and DT is more significant within those green and polluting samples after propensity score matching.

4.2.3. DT and ESG Performance. The results in Table 9 can reflect the causal relationship of enterprises' DT on ESG performance. We conduct the Hausman test before the regression, and the result shows that the *p* value is 0.000. Thus, the random effects (RE) model with a null hypothesis is rejected, and the fixed effects (FE) model is chosen for the following regression analysis. The coefficient on DT in column (1) is 0.154 and statistically significant at the 1% level, which fully supports H3 (in-line with [41, 46, 47]), indicating that DT has a positive impact on ESG performance. As mentioned before, this may be because enterprise digitization can strengthen the connection between enterprises and stakeholders, pushing top managers to fulfill the social responsibilities and maximize the noneconomic value of digital transformation activities.

We further explore the internal mechanism of EPL on DT and ESG by models (5) and (6), where the coefficient of interaction term TREAT*POST in column (2) is 0.119 and significant at the 1% level, and the coefficient of TREA T*POST in column (3) is 0.074 and significant at the 1% level. Those results can imply that the internal mechanism effect of DT on promoting ESG performance is stronger among REs, EEs, and PEs in comparison with other industries, and EPL can affect enterprises' ESG performance though the potential pathway of DT activities [61].

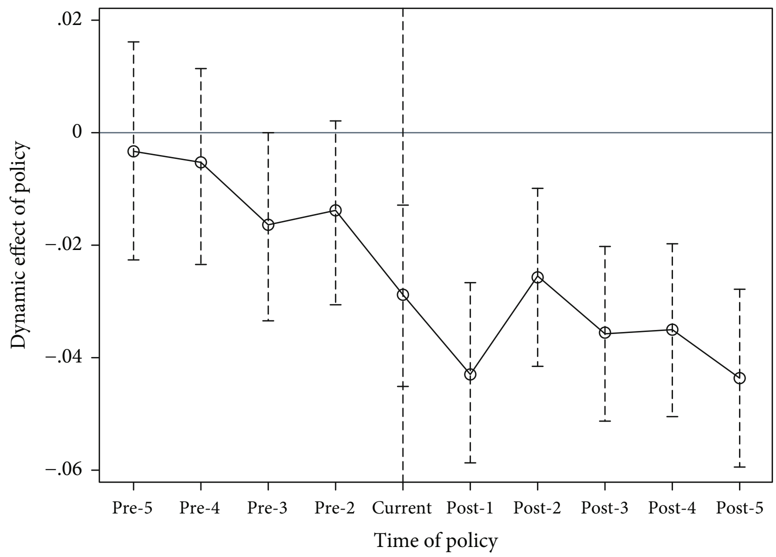

Figure 4: Dynamic impact of EPL on the DT of EEs and REs.

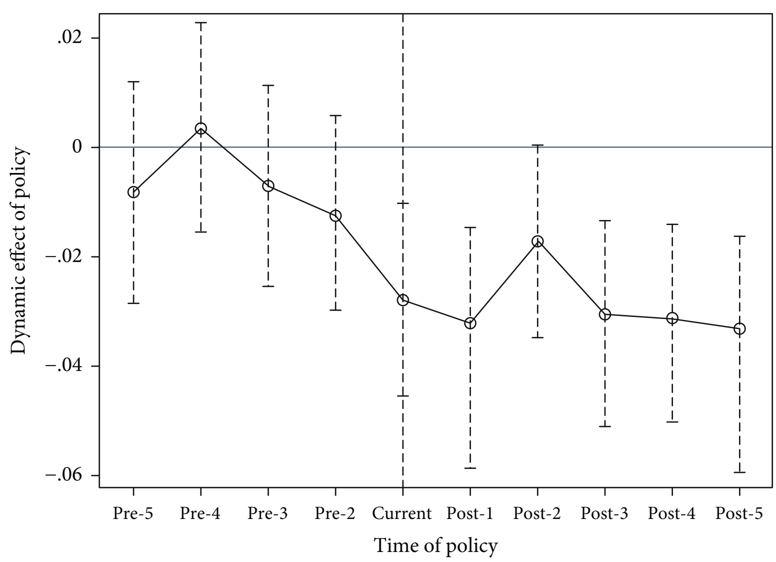

Figure 5: Dynamic impact of EPL on the DT of PEs.

4.3. Robustness Test

4.3.1. Kernel Propensity Score Matching DID and QDID Estimation. Based on Villa [67] and Chen et al. [21], we additionally combined the kernel propensity score matching DID and quantiles difference-in-differences (QDID) approaches as robustness test for the DID regression. Kernel DID can estimate the common support of the propensity score [67], and QDID can identify the treatment effect at different quantiles from various covariate distributions [68]. All directions and significance of interaction term in Tables 10 and 11 are consistent with our previous findings in the main test.

4.3.2. Endogeneity Treatment. Since there may be endogeneity issue caused by reverse causality between enterprises' DT and ESG performance, this paper adopts the instrumental variable with two-stage least squares (2SLS) regression to weaken the influence of endogeneity issues in FE approach. Referring to the practice of Hs and Fei [69] and Chen et al. [27], we introduce the one-period lagged variable of DT_{-1} as the instrumental variable, which can effectively satisfy the homogeneity requirement. Further, the general method of moment (GMM) regression is more applicable for the panel data research in comparison with the traditional 2SLS and 3SLS method [70]. Our personal scientific contributions involve the GMM approach on this basis of the weak instrumental variable test in2SLS first-order regression. The results are appropriate and in agreement with the research tools used, respectively, and emphasize the innovative elements of an applied scientific nature.

Table 12 reports the regression results for the 2SLS and GMM methods. In the first stage regression of 2SLS regression, the coefficient of DT_{-1} in column (1) is 0.361 and

Table 6: Benchmark DID test.

	Model 3		Model 4	
	(1) EERE	(2) POLLUT	(3) EERE	(4) POLLUT
TREAT	0.139 (0.355)	0.297 (0.280)	0.039 (0.064)	0.023 (0.050)
POST	0.238*** (0.055)	0.253*** (0.055)	0.047*** (0.010)	0.046*** (0.010)
TREAT*POST	0.117*** (0.022)	0.072*** (0.024)	-0.013*** (0.004)	-0.012*** (0.004)
SIZE	0.188*** (0.014)	0.185*** (0.014)	-0.008*** (0.002)	-0.007*** (0.002)
LEV	-0.694*** (0.053)	-0.693*** (0.053)	0.002 (0.009)	0.001 (0.009)
ROA	1.021*** (0.100)	1.025*** (0.100)	-0.083*** (0.018)	-0.083*** (0.018)
CASH	-0.280*** (0.085)	-0.284*** (0.085)	0.005 (0.015)	0.006 (0.015)
FIXED	0.138** (0.069)	0.145** (0.069)	-0.091*** (0.012)	-0.092*** (0.012)
INDEP	-0.217 (0.139)	-0.214 (0.139)	0.024 (0.025)	0.023 (0.025)
BM	0.041*** (0.008)	0.042*** (0.008)	-0.008*** (0.001)	-0.009*** (0.001)
AGE	-0.321*** (0.080)	-0.313*** (0.080)	-0.026* (0.014)	-0.027* (0.014)
Cons	3.051*** (0.429)	3.079*** (0.429)	0.366*** (0.077)	0.366*** (0.077)
Year fix	Yes	Yes	Yes	Yes
Industry fix	Yes	Yes	Yes	Yes
N	27,338	27,338	27,338	27,338
Adj. R^2	-0.084	-0.084	-0.099	-0.099

Notes: standard errors in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 7: Average treatment effect test.

Variable		Sample	Treated	Controls	Difference	S.E.	T-statistic
ESG	EERE	Unmatched	6.539	6.464	0.075	0.015	4.840
		ATT	6.514	6.478	0.037	0.016	2.220
	POLLUT	Unmatched	6.521	6.475	0.046	0.017	2.770
		ATT	6.496	6.448	0.049	0.019	2.600
DT	EERE	Unmatched	0.037	0.124	-0.087	0.003	-29.090
		ATT	0.036	0.084	-0.048	0.002	-22.760
	POLLUT	Unmatched	0.033	0.118	-0.085	0.003	-26.230
		ATT	0.031	0.075	-0.044	0.002	-19.310

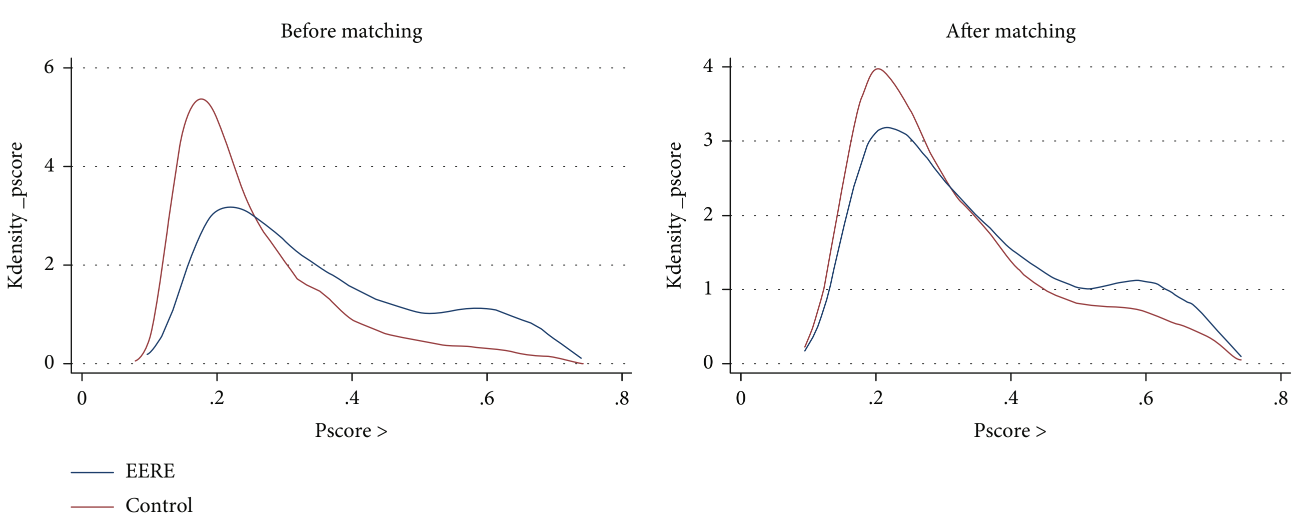

Figure 6: Probability distribution density estimation of the propensity score value grouped by EERE.

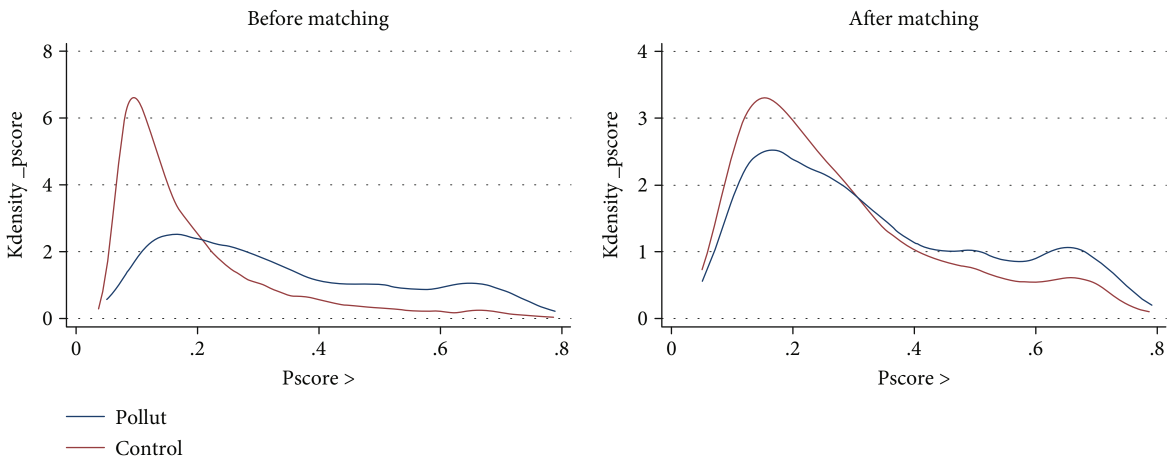

Figure 7: Probability distribution density estimation of the propensity score value grouped by POLLUT.

Table 8: PSM-DID regression.

	ESG		DT	
	(1) EERE	(2) POLLUT	(3) EERE	(4) POLLUT
TREAT	-0.163*** (0.029)	-0.189*** (0.033)	-0.061*** (0.005)	-0.055*** (0.005)
POST	-0.327*** (0.027)	-0.287*** (0.031)	0.027*** (0.005)	0.024*** (0.005)
TREAT*POST	0.151*** (0.037)	0.085** (0.041)	-0.025*** (0.007)	-0.021*** (0.007)
Cons	-0.781*** (0.223)	-0.844*** (0.252)	0.175*** (0.040)	0.004 (0.042)
Control	Yes	Yes	Yes	Yes
Year fix	Yes	Yes	Yes	Yes
Industry fix	Yes	Yes	Yes	Yes
N	15029	11641	15029	11641
Adj. R^2	0.134	0.134	0.102	0.090

Notes: standard errors in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 9: Internal mechanism impact of DT on ESG.

	Model (5)	Model (6)	
	(1) ESG	(3) ESG (EERE)	(3) ESG (POLLUT)
TREAT*POST		0.119*** (0.022)	0.074*** (0.024)
DT	0.154*** (0.036)	0.158*** (0.036)	0.156*** (0.036)
SIZE	0.183*** (0.014)	0.189*** (0.014)	0.186*** (0.014)
LEV	-0.700*** (0.053)	-0.695*** (0.053)	-0.693*** (0.053)
ROA	1.054*** (0.100)	1.034*** (0.100)	1.038*** (0.100)
CASH	-0.286*** (0.085)	-0.280*** (0.085)	-0.285*** (0.085)
FIXED	0.164** (0.069)	0.153** (0.069)	0.160** (0.069)
INDEP	-0.220 (0.139)	-0.221 (0.139)	-0.217 (0.139)
BM	0.042*** (0.008)	0.042*** (0.008)	0.043*** (0.008)
AGE	-0.310*** (0.080)	-0.317*** (0.080)	-0.309*** (0.080)
Cons	3.084*** (0.429)	2.993*** (0.429)	3.022*** (0.429)
Year fix	Yes	Yes	Yes
Industry fix	Yes	Yes	Yes
N	27,338	27,338	27,338
Adj. R^2	0.061	0.062	0.061

Notes: standard errors in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 10: Kernel propensity estimation.

	ESG		DT	
	(1) EERE	(2) POLLUT	(3) EERE	(4) POLLUT
TREAT	-0.117*** (0.024)	-0.164*** (0.023)	-0.044*** (0.003)	-0.050*** (0.003)
POST	-0.056** (0.022)	-0.047** (0.022)	0.023*** (0.003)	0.019*** (0.003)
TREAT*POST	0.110*** (0.031)	0.099** (0.031)	-0.014*** (0.004)	-0.011** (0.004)
Cons	6.592*** (0.017)	6.587*** (0.017)	0.070*** (0.002)	0.074*** (0.002)
Control	Yes	Yes	Yes	Yes
Year fix	Yes	Yes	Yes	Yes
Industry fix	Yes	Yes	Yes	Yes
N	22,685	22,610	22,685	22,604
Adj. R^2	0.001	0.003	0.027	0.031

Notes: standard errors in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 11: QDID estimation at the 0.5 quantile.

	ESG		DT	
	(1) EERE	(2) POLLUT	(3) EERE	(4) POLLUT
TREAT	-0.162*** (0.025)	-0.233*** (0.023)	-0.004*** (0.001)	-0.003*** (0.001)
POST	-0.251*** (0.018)	-0.247*** (0.015)	0.016*** (0.000)	0.017*** (0.000)
TREAT*POST	0.153*** (0.031)	0.167*** (0.028)	-0.011*** (0.001)	-0.014*** (0.001)
Cons	-1.907*** (0.172)	-1.914*** (0.144)	0.010** (0.004)	0.007* (0.004)
Control	Yes	Yes	Yes	Yes
Year fix	Yes	Yes	Yes	Yes
Industry fix	Yes	Yes	Yes	Yes
N	27,338	27,338	27,338	27,338
Adj. R^2	0.050	0.060	0.020	0.020

Notes: standard errors in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 12: 2SLS and GMM estimation.

	2SLS		GMM
	First stage (1) DT	Second stage (2) ESG	(3) ESG
DT_{-1}	0.361*** (23.230)		0.635*** (43.610)
DT		0.290** (2.410)	0.210*** (4.000)
Control	Yes	Yes	Yes
Year fix	Yes	Yes	Yes
Industry fix	Yes	Yes	Yes
N	23,409	23,409	23,520
AR (1)			0.000
AR (2)			0.023
Hansen			1.000
Kleibergen-Paap rk LM statistic	159.540		
Cragg-Donald Wald F statistic	5231.088		
Kleibergen-Paap rk Wald F statistic	541.079		

Notes: T-statistics in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

passes the significance test at the 1% level. Meanwhile, the Kleibergen–Paap LM statistic of 159.540 is corresponding to a p value of 0, thus indicating that our instrumental variables can be fully identified. And the Cragg–Donald Wald F -statistic of 5231.088 is much higher than the Stock-Yogo critical judgment value of 16.38 at the 10% level, also illustrating that there is no weak instrumental variable problem within our endogeneity treatment. Both coefficients of DT in column (2) and (3) are significantly positive; therefore, the results of the robustness tests by 2SLS and GMM regression are highly consistent with the FE regression.

5. Conclusion and Implication

5.1. Conclusion. Based on the panel data of China's A-share listed companies from 2010 to 2020, this paper examine the intrinsic impact of EPL on ESG performance and DT, mainly concerning on the grouping difference of environmental related enterprises. In comparison with other industries, our empirical results show that the implementation of the EPL significantly improved ESG performance of REs, EEs, and PEs but inhibited the DT activities among those industries. Further research reveals that the internal mechanism effect of enterprises' DT in driving ESG performance is more potent among REs, EEs, and PEs when considering the influence of environmental policy and industry disparities. The above findings clarify the economic consequences of EPL while extending the intrinsic mechanism of DT to provide empirical evidence on how to improve corporate ESG and sustainability performance.

5.2. Practical Implication. Striking a balance between enterprise digitization and environmental protection will be an ongoing challenge, so our findings have obvious consequences for legislators and regulators regarding furthering global economic integration and should therefore be of interest to the public, special-interest groups, and others. The authors believe that our findings will also help academics who want to do more research in this relatively unexplored field, as well as policy-makers and corporate bodies in long-term planning.

At the policy level, governments should further improve the effect of the market incentive by building more flexible standards and convenient channels for the public to participate in environmental supervision. Enterprises' DT is becoming an essential approach to promote the green economy and achieve China's dual carbon goals (DCGs) of carbon neutrality and carbon peak. But the inherent limitations of current green policies may hinder enterprises from fully supporting their DT and ESG performance. The rigorous environmental policies imposed penalties on polluters who fail to meet specific standards, compelling them to introduce more ecofriendly technologies which can affect their digitalization process, especially for the environmental related industries. Since China's EPL significantly inhibited the DT performance of those environmental related enterprises, the central government should provide more environmental policies to support the green development by facilitating the digitalization activities of REs, EEs, and PEs.

At the enterprise level, emerging new business models should include elements of socially responsible policy, such as EPL. Increasing digitalization has pressured enterprises to reflect on their current strategy and systematically explore new business opportunities. Our results show that the 2015 EPL has a positive effect on ESG performance of REs, EEs, and PEs. In the context of stricter supervision regulation, PEs should deepen their green transformation by adopting more digital technologies to reduce the cost of pollution control and improve the corporate social responsibility. And EEs and REs are easier to obtain benefits from environmental policies, highlighting the importance of top managers' motivations to obtain higher ESG ratings within those industries. Our results also reveal that the internal mechanism effect of enterprises' DT in driving ESG indicator is more potent among the environmental related industries when considering the influence of environmental policy and industry disparities. Since EPL can strengthen the environmental protection system on promoting green and sustainable development, it offers more opportunity for REs, EEs, and PEs to realize their ESG strategy by digitalization. And China's enterprises need to further integrate their DT with sustainability goals if their decisions must be data-driven. In general, enterprises and investors should adopt the two-pronged green governance and DT-integrated strategy for achieving the sustainable financial performance. In the upcoming era of "Industry 5.0," DT in industrial markets can create an idea of introduction mechanisms for substantiate successful strategies at industrial enterprises.

5.3. Limitation and Future Prospects. This paper assessed the current state and analyzed the prospects, solutions, methods, and approaches that will contribute to a sustainable digital transition. In terms of our study's limitation and future direction, we focused on Chinese listed firms so that future research may extend to green development studies of unlisted companies and compare the findings (i.e., high-tech or state-owned enterprises). Meanwhile, future studies may consider other impact mechanism (i.e., spillover effect along the supply chain and regression discontinuity design) for Chinese or international enterprises. Finally, EPL provides a unique quasinatural experimental setting, and future researchers can alter the pandemic scenario to empirically investigate how COVID-19 will affect enterprises' digitization and sustainable performance.

Today's technology-driven DT is not limited to the implementation and operation of new technologies within organizations [71–73]. In the new era of digital economy, the amount of data accumulated by an enterprise's business operations will determine its financing status. As the digital economy quickly expands, enterprises' DT offers substantial opportunities to accelerating the transition to industrial Internet of Things (IIoT) [74]. A new industrial development paradigm of "Industry 5.0" is directed to humanization of social resilience and sustainable development of industrial ecosystems. Addressing the importance of incorporating sustainability strategies into DT roadmaps entails thinking beyond profit and placing social and environmental considerations on the same footing alongside financial purpose. In the field of humanities and social sciences, future researchers are encouraged to employing more social resilience and sustainable development indicators as representatives of "Industry 5.0" into the empirical studies.

Data Availability

The datasets used and analyzed during the current study will be made available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Authors' Contributions

LC and YG contributed to the conception and design of the study. YC organized the database. LC performed the statistical analysis. YC and YG wrote the first draft of the manuscript. LC wrote sections of the manuscript. All authors contributed to manuscript revision and read and approved the submitted version.

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