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Corporate FinTech and Environmental Information Disclosure: Evidence from Chinese A-Share Listed Firms

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Abstract

As climate governance and low-carbon transition continue to advance, environmental information disclosure (EID) has become an important tool for strengthening corporate environmental accountability. Based on a sample of Chinese A-share listed firms from 2008 to 2023, this study constructs a firm-level FinTech index by employing a BERT large language model and examines its relationship with EID via a two-way fixed effects model. The results show that FinTech development is positively associated with EID levels, with stronger effects observed in non-high-tech and non-manufacturing firms. In addition, mechanism tests suggest that FinTech may enhance EID by promoting internal green innovation and reducing external information asymmetry. Further analysis indicates that stronger environmental regulation and higher internal control quality may reinforce the positive relationship between FinTech and EID. These findings provide empirical evidence for understanding how FinTech supports the modernization of corporate environmental governance.

Keywords: firm-level FinTech; environmental information disclosure; BERT; green innovation channel; information asymmetry channel

1. Introduction

Recently, global climate change has intensified significantly, rendering environmental protection an extremely important issue that needs to be addressed. In light of China's national Dual Carbon policy, Environmental information disclosure (EID) has become a crucial institutional tool for evaluating environmental governance capabilities and firms' sustainability performance. Corporate EID links environmental performance to stakeholder decisions, strengthens accountability, supports the low-carbon transition, and advances high-quality economic development. In practice, Chinese enterprises continue to encounter numerous challenges in EID. On the one hand, corporate sustainability disclosures remain predominantly qualitative, exhibiting issues such as fragmented information presentation and limited thematic coverage [1]. On the other hand, the absence of a unified disclosure framework, coupled with insufficient internal governance and external oversight, has led to the frequent occurrence of corporate greenwashing [2]. Consequently, a systematic examination of the determinants that improve corporate EID quality has significant practical ramifications for strengthening environmental governance.

Existing studies mainly explain the differences in enterprises' EID from two aspects: internal characteristics of the enterprises and external institutional pressures [3,4]. In recent

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years, more and more studies have begun to explore the impact of digital technology on corporate sustainable governance and its mechanism of action [5]. However, most existing studies rely on traditional governance and institutional frameworks, overlooking how firm-level FinTech affects EID. In particular, there is still a limited understanding of FinTech's role with firms' internal capabilities and external conditions, and the pathways to shape EID.

FinTech has grown to be a significant result of digital transformation due to the financial industry's close integration with digital technology [6]. According to the definition of the Financial Stability Board (FSB), FinTech refers to the use of technology to drive innovation in financial services and to form new business models, applications, processes, or products. This study further defines enterprise-level FinTech as the process in which enterprises apply digital technologies such as artificial intelligence, big data, blockchain, and cloud computing to their management and operation, financing activities, and resource allocation, to enhance information processing efficiency and promote digital transformation. Official statistics indicate that China's FinTech market is projected to exceed RMB 4.8 trillion in 2023, representing a year-on-year growth of 12.3%. Concurrently, the number of FinTech enterprises at the national level demonstrates a consistent upward trend in Figure 1. Moreover, the main provinces and municipalities are experiencing notably vigorous growth, as illustrated in Figure 2. Compared with traditional financial instruments, FinTech reduces information acquisition costs, enhances the traceability and transparency of data, and establishes a new pathway for capital allocation. This serves to mitigate information asymmetry and promote green innovation [7].

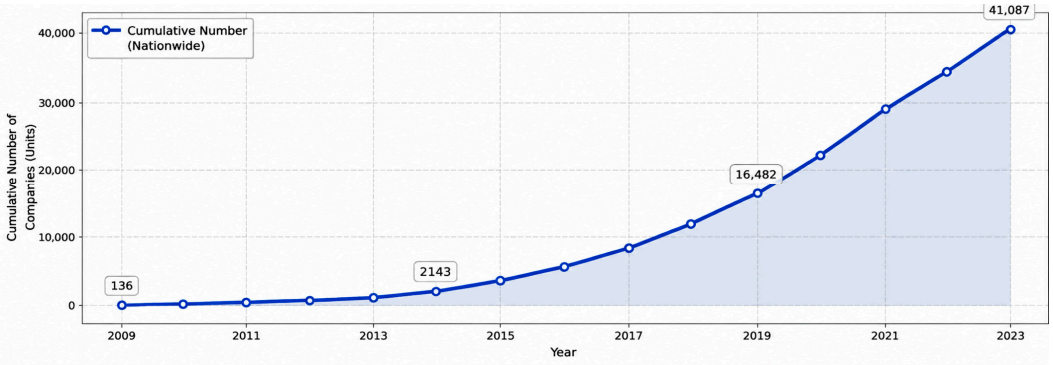


Figure 1. FinTech companies registered from 2009 to 2023.

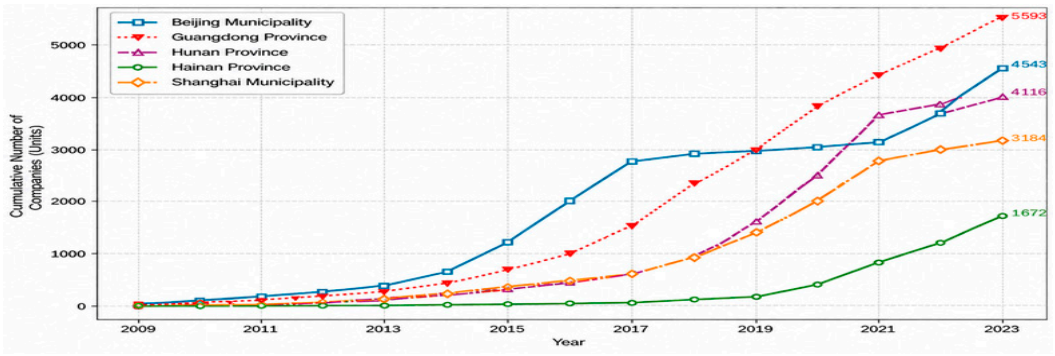


Figure 2. FinTech companies registered in provinces from 2009 to 2023.

FinTech reshapes the information environment and resource allocation logic of enterprises. From an internal perspective within enterprises, by precisely determining the value of green projects, FinTech might raise the bar for corporate green innovation, effectively reducing financing barriers for green R&D, and optimizing resource allocation according to the resource-based view [8,9]. From the external perspective of enterprises, FinTech

may reduce the acquisition and verification cost of environmental information, enhance the credibility and traceability of data according to the theory of information asymmetry, and thus reduce the degree of information asymmetry of stakeholders with the help of big data and blockchain technologies [10]. The above analysis shows that FinTech may provide content support for EID through the two-way path of internally promoting enterprises' green innovation and externally alleviating information asymmetry.

Then, could FinTech improve the corporate EID? What are the specific impact paths? Is there heterogeneity in this effect across different types of enterprises? This study attempts to address these questions. We first construct a corporate FinTech indicator by employing a BERT large language model. Then, using a sample of Chinese A-share listed enterprises from 2008 to 2023, we conduct an empirical investigation into the impact of FinTech on EID. The empirical results demonstrate that FinTech significantly promotes EID, and non-manufacturing and non-high-tech firms benefit more. In addition, mechanism analysis reveals that this promotion is achieved through stimulating internal green innovation and alleviating external information asymmetry. Furthermore, our analysis confirms that stringent external environmental regulations and robust internal controls significantly strengthen the positive effect of FinTech on EID.

The marginal contribution lies in the following: First, it expands the research boundary of EID influencing factors. This paper incorporates firm-level FinTech into the EID analysis framework, which makes up for the existing literature that only focuses on traditional corporate characteristics and governance dimensions, but pays less attention to the unique role of FinTech. It emphasizes the deep integration of financial functions and digital technology, which can have a more targeted impact on corporate environmental governance behavior by improving information processing efficiency. Second, innovation in FinTech measurement methods could be achieved. This paper introduces the BERT large language model to conduct semantic parsing of the MD&A of the annual report and constructs a FinTech index at the enterprise level. Compared with traditional methods such as the regional digital finance index, patent number, or keyword word frequency statistics, the BERT model captures contextual semantic information through a self-attention mechanism, more accurately identifies the real FinTech application, and effectively alleviates the limitations of the word frequency method in semantic ambiguity and context neglect. Third, this paper systematically identifies the transmission mechanism and moderating roles of FinTech on EID. This paper constructs an integrated analysis framework of internal capability and external power, reveals the transmission logic of FinTech improving EID level from the paths of internal green innovation and external information asymmetry, and further examines the moderating effect of enterprise internal control and external environmental protection regulation. This paper defines micro cognition and provides empirical evidence on the impact of FinTech on the behavior of enterprise environmental information disclosure.

2. Literature Review

Existing research on the determinants of corporate EID predominantly examines organizational elements that are both internal and external. First, the internal factors cover the characteristics of the enterprise itself and the governance structure. Specifically, corporate size, financial performance, leverage level, and other characteristics form the internal driving force, which is positively correlated with EID level [11]. At the same time, effective corporate governance mechanisms, including board-related attributes [12], equity structure [13], and executive incentives [14], help maximize company value and hence raise the EID level. Second, the external factors of enterprises mainly focus on the restraint and guidance role of the government and stakeholders. Existing research shows that the

government significantly affects the EID level of enterprises through policy tools such as laws and regulations [15] and environmental systems [16]. In addition, the pressure of public opinion [17], media attention [18], and other stakeholders' supervision form continuous constraints on enterprises and promote the improvement of EID.

The rapid expansion of the digital economy has stimulated growing academic interest in the effects of digital finance and digital transformation on environmental issues and firms' disclosure behavior [19–21]. However, relatively little attention has been paid to how FinTech, an emerging form of deep integration of technology and finance, affects EID. Different from the existing research focusing on the information transformation and process optimization at the production and operation level of enterprises, FinTech is more related to the remodeling of the external information environment of enterprises and the change in the way of obtaining internal resources [22,23]. In general, even though the literature currently in publication has examined the elements that influence EID from a variety of angles, it still does not fully consider FinTech's potential role in environmental governance, particularly how it influences EID by integrating the firm's internal and external conditions.

Measurement methods and the impact effects of FinTech are another kind of literature closely related to this paper. In terms of measurement methods, since the level of FinTech is difficult to be directly observed, the existing literature usually adopts objective metrics like the quantity of FinTech companies, financing scale [24], as well as the quantity of patent applications [25]. However, single-dimensional quantitative indicators often have the defect of overestimating or underestimating the true development level of FinTech. Recently, through the integration of multi-dimensional data, the Peking University Digital Finance Index has become a proxy index for the comprehensive evaluation of regional FinTech development level, which has significantly improved the comprehensiveness of measurement [26]. With the development of text analysis technology, some scholars use the word frequency statistics method based on dictionary construction to describe FinTech at the enterprise level [27]. However, this method relies on keyword matching, which makes it difficult to capture contextual semantics and is susceptible to word ambiguity and subjective dictionary settings. To overcome the above limitations, in recent years, large language models have been introduced for text measurement. Compared with traditional methods, large language models can further understand the context meaning based on identifying keywords, thus showing significant advantages in the semantic analysis of financial texts [28].

Regarding the impact role of FinTech, existing literature primarily examines three dimensions: commercial banks, non-financial enterprises, and environmental externalities. First, at the commercial bank level, FinTech can significantly enhance banks' operational performance [29] and risk management capabilities [30], while also promoting the expansion and structural optimization of credit [31]. Second, at the level of non-financial firms, FinTech effectively addresses corporate financing challenges [32] and promotes green innovation and digital transformation [33]. Third, regarding environmental externalities, FinTech can reduce carbon emissions [34] and enhance green total factor productivity [35], thereby driving improvements in environmental governance. However, the consequences of FinTech on environmental governance from the standpoint of EID are hardly examined, and there is a lack of in-depth studies that construct specific mechanism pathways and theoretical frameworks.

In conclusion, the internal relationship between the two still needs to be further explored, even though the literature currently in publication has looked at the elements that influence EID from both internal and external perspectives. Specifically, first, from the perspective of research, the majority of current research looks at EID-influencing issues from the standpoint of traditional governance factors, such as the characteristics of

enterprises or external pressure, but pays insufficient attention to the impact of FinTech, an emerging technology. Second, in terms of measurement methods, there are problems such as insufficient accuracy and micro-suitability of FinTech measurement indicators, which limit the accurate identification of the impact of FinTech at the enterprise level. Third, while some previous research has addressed environmental externalities as an impact mechanism, there is still a lack of clear theoretical interpretation and empirical test on how FinTech has an impact on both internal and external aspects of businesses, particularly from the perspectives of internal capacity and external influence on EID.

3. Research Hypotheses and Theoretical Analysis

3.1. Direct Effect

Drawing on signaling theory, firms convey their internal attributes, strategic behaviors, and future intentions through voluntary information disclosure, thereby shaping stakeholders' decision-making processes. In the context of environmental governance, EID is a crucial signaling tool that businesses use to convey their green commitments. Implementation of environmental protection initiatives and outcomes of green innovation efforts. In addition to alleviating the information asymmetry between enterprises and external stakeholders, high-quality EID can also help enterprises convey their genuine environmental responsibility commitments and enhance their recognition among stakeholders. However, the effectiveness of environmental signals depends on their authenticity and verifiability [36]. Due to the lack of an effective data verification mechanism in traditional environmental information disclosure, stakeholders often have difficulty accurately identifying the authenticity of enterprises' environmental information, making opportunistic disclosure and greenwashing behaviors difficult to identify effectively.

By integrating advanced digital infrastructures, such as blockchain-based verification systems and intelligent analytics, FinTech improves the reliability and credibility of environmental information, thereby strengthening the effectiveness of EID and facilitating corporate signal transmission [37]. Specifically, FinTech enhances the ability of stakeholders to identify the true green behavior and opportunistic disclosure behavior of enterprises, thereby enhancing the credibility and market value of environmental signals. When the environmental information disclosed by enterprises can be effectively identified by external entities and gain market recognition, the potential benefits brought by true green behavior will further enhance the motivation of enterprises to actively disclose information. At the same time, FinTech improves the traceability of environmental information, increasing the possibility and potential costs of selective disclosure and opportunistic disclosure behaviors being detected, thereby prompting enterprises to enhance the authenticity and completeness of EID.

In summary, the promoting effect of FinTech on EID by enterprises stems not only from the improvement of information processing efficiency, but more importantly, from enhancing the credibility of environmental signals and the market recognition value, thereby improving the extent to which businesses provide environmental information. By increasing the expected benefits of genuine disclosure and constraining opportunistic disclosure behaviors, fintech drives enterprises to transform EID from a passive compliance requirement fulfillment to an active strategic behavior. Therefore, we propose:

Hypothesis 1. *FinTech can significantly improve the firms' EID.*

3.2. Indirect Effect

The resource-based view holds that a corporation's core capabilities and diverse resources serve as the basis for maintaining a competitive advantage. From an internal

corporate perspective, FinTech can provide critical support for green innovation through data integration, intelligent identification, and financing matching. On the one hand, leveraging technologies like blockchain-based supply chain financing and big data credit evaluation, FinTech can efficiently reduce corporate finance constraints and more precisely determine the value of green initiatives [38], obtaining funding for green product development, clean process enhancements, and green technology research and development. On the other hand, with FinTech's assistance, enterprises can continuously invest resources in green R&D activities, gradually accumulating heterogeneous resources such as green patents and clean technologies. This not only enhances enterprises' capacity for green transformation but also provides a more authentic and comprehensive content foundation for environmental information disclosure [39]. Consequently, enterprises gradually form an internal closed-loop process spanning from resource acquisition to capability building, which is further transformed into the foundational capacity for high-quality EID. Figure 3 shows the impact mechanism of FinTech on corporate EID in this paper.

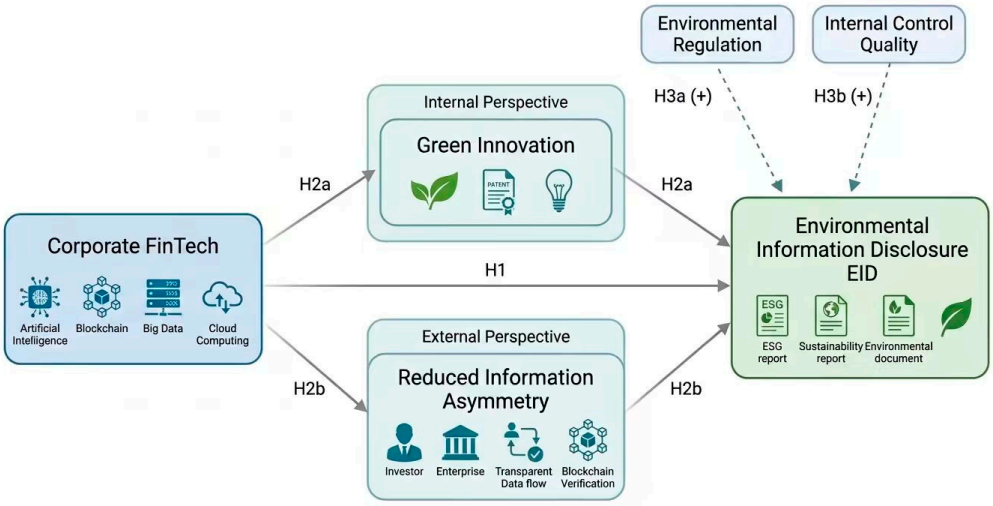


Figure 3. The impact mechanism of corporate FinTech on EID.

Market failure may result from information gaps between companies and outside investors, resulting in distortions in resource allocation. From an external perspective, FinTech successfully lowers the costs of obtaining, validating, and sharing environmental information by utilizing technologies like artificial intelligence, thereby improving the external information environment for firms [40]. Specifically, on the one hand, investors, analysts, and regulatory bodies can use FinTech to more efficiently collect, identify, and compare corporate environmental data, thereby forming a clearer assessment of corporate environmental performance [41], which reduces the scope for firms to maintain an information advantage through vague or selective disclosure. On the other hand, as external oversight capabilities strengthen, firms that continue to maintain low-quality or inadequate disclosures may face adverse consequences such as rising financing costs and reputational damage. Therefore, to send positive signals to stakeholders, firms could have greater incentives to improve transparency, accuracy, and enhance corporate EID levels.

Therefore, these two mechanisms do not replace each other but rather function jointly from two dimensions: the internal capabilities of the enterprise and the external governance environment. Green innovation provides a substantive foundation for environmental information disclosure, while enhanced information transparency facilitates the transformation of green achievements into external information dissemination. Together, they promote the improvement of the level of environmental information disclosure by enterprises. Therefore, we propose.

Hypothesis 2a. *FinTech could enhance corporate EID by fostering green innovation.*

Hypothesis 2b. *FinTech could enhance corporate EID by mitigating information asymmetry.*

3.3. Moderation Effect

In accordance with institutional theory, corporate business decisions and disclosure practices are profoundly influenced by the external institutional environment. A higher intensity of environmental regulations creates stronger external constraints and compliance pressures [42]. Environmental regulations not only impose compliance pressure on enterprises but also change the cost–benefit structure of enterprises' EID by increasing the cost of violations and regulatory requirements. As environmental regulations continue to strengthen, enterprises need to provide more genuine, accurate, verifiable, and traceable environmental information to meet regulatory requirements and maintain the legitimacy of the system, thereby significantly increasing the demand for high-quality environmental data processing capabilities. FinTech can improve the efficiency of environmental data collection, integration, and verification, enhance information transparency and traceability, and reduce the compliance costs for enterprises to meet regulatory requirements. Therefore, environmental regulations have created the institutional demand for enterprises to conduct high-quality EID, while FinTech provides the technical capabilities to meet this demand. The two form a complementary relationship of demand and technology. The stricter the environmental regulations, the higher the marginal value of FinTech in improving the quality of EID.

To maintain institutional legitimacy and secure policy support, companies are often more motivated to enhance the caliber of their EID. In this context, the value of FinTech becomes particularly evident, on the one hand, FinTech can optimize the processes of collecting, processing, and disclosing environmental data, thereby improving the timeliness, accuracy, and traceability of disclosures, effectively meeting regulatory requirements, and reducing the costs of non-compliance; on the other hand, by leveraging the green and trustworthy image fostered by FinTech, policy incentives like government green subsidies and tax cuts are easier for firms to get. Consequently, the greater the incentive for enterprises to improve their environmental disclosure standards, the more readily the governance effects of FinTech can be fully realized.

The internal control system of enterprises is an important cornerstone to ensure the operational efficiency of enterprises, the accuracy of financial records, and adherence to legal requirements [43]. According to the organizational control theory, high-quality internal control can provide a good governance environment for the effective absorption, integration, and application of FinTech, thus strengthening its promotion effect on environmental information disclosure. Specifically, a sound internal control system usually means that enterprises have a more standardized institutional process, a clearer division of rights and responsibilities, and a more effective risk management mechanism, which helps promote the deep integration of FinTech and the enterprise disclosure system. In the process of environmental information management, sound internal control can standardize the process of data collection, processing, and reporting, and guarantee the quality of information processed by FinTech from the source. On the contrary, even if FinTech is introduced, if an organization's internal governance is inadequate, it may be difficult to play the expected role due to data distortion, execution deviation, or insufficient department coordination, and even induce new governance risks such as technical greenwashing [4]. Therefore, a high level of internal control can ensure that the FinTech governance process is controllable, reliable, and effective. Therefore, we propose.

Hypothesis 3a. *The stronger the regional environmental regulations intensity, the greater the impact of FinTech on the corporate EID.*

Hypothesis 3b. *The higher the corporate internal controls, the greater the impact of FinTech on the corporate EID.*

4. Experimental Design

4.1. Data Source

The year 2008 is chosen as the starting year because the Shanghai Stock Exchange's 2008 guidelines on EID for listed companies offer a standardized framework suitable for empirical analysis. The dataset integrates information from several sources, including annual reports collected from the Juchao Information network, EID, and corporate financial and governance data, which are sourced from the CSMAR and Wind databases. The following criteria are used in the construction of the sample: (1) eliminate the samples with unusual trading conditions, like ST, *ST, and PT; (2) eliminate the observations with missing core variables; (3) continuous variables are winsorized at the 1% and 99% levels to reduce the effect of outliers. The final dataset comprises 31,998 company-year observations.

4.2. Variable Definition

4.2.1. Dependent Variable

Environmental information disclosure (EID). Following Zhao et al. [44], we use the CSMAR database to systematically sort out the disclosure of enterprise environmental information and measure it according to whether the disclosure content has monetization characteristics. Specifically, for monetized information, if it contains both quantitative and qualitative disclosure content, it is assigned a value of 2; If only qualitative description is included, the value is 1; If no relevant disclosure is made, the value is assigned to 0. For non-monetized information, the relevant indicators that have been disclosed are denoted as 2, and those that have not been disclosed are denoted as 0.

When it comes to index construction, the disclosure content of environmental governance, environmental performance, and environmental liabilities is mostly represented as quantitative financial data. The contents related to environmental management practices, environmental certification, and environmental information disclosure carriers are mainly presented in the form of non-monetized qualitative information. The above two types of information jointly cover five dimensions and 25 specific scoring indicators. On this basis, this paper summarizes the scores of each index and further uses the logarithmic transformation method to construct the EID index. This index can comprehensively describe the level of corporate EID from the overall level and be used for subsequent empirical analysis. Table 1 presents the specific scoring items.

Table 1. Classification of indicators of EID.

Type	Items	Scoring Explanation
Disclosure carrier	Annual reports of listed companies	Disclosure: 2 points None: indicates 0 points
	Social Responsibility Report	
	Environmental Report	
Certification disclosure	ISO14001 certification [45]	Yes: 2 points No: 0 points
	ISO9001 certification [46]	

Table 1. *Cont.*

Type	Items	Scoring Explanation
Environmental Management disclosure	Environmental philosophy	Disclosed: 2 points Not disclosed: 0 points
	Environmental targets	
	Environmental protection management system	
	Environmental education and training	
	Emergency response system for environmental disasters	
	Environmental awards or accolades	
	Three simultaneous systems	
	Special protection actions	
Environmental liability disclosure	Wastewater discharge	Quantitative and qualitative description: 2 points Only qualitative: 1 point Not disclosed: 0 points
	COD emissions	
	SO2 emissions	
	CO2 emissions	
	Soot and dust emissions	
	Production of industrial solid waste	
Environmental performance and governance disclosure	Emission reduction and management of exhaust gas	
	Wastewater treatment and emission reduction	
	Situation of dust and soot control	
	Solid waste utilization and disposal	
	Control of noise, light pollution, and radiation	
	Implementation of cleaner production	

4.2.2. Explanatory Variable

Referring to Lin et al. [47], this paper utilizes the BERT model to construct a FinTech index at the enterprise level. This indicator aims to measure the actual application, construction, and deployment degree of FinTech-related technologies and systems by enterprises in their management and operation processes. The specific construction process is as follows:

Step 1: Build a keyword library for FinTech development and extract relevant texts. Firstly, based on the technical attributes and business application scenarios of FinTech, we construct a FinTech keyword library with 124 terms encompassing six dimensions: big data, cloud computing, blockchain, artificial intelligence, and going mobile, as shown in Table 2. On this basis, we also extract all sentences containing the above keywords from the MD&A section to form a candidate sentence set. It should be noted that keyword matching is only used for candidate text screening and does not directly measure the level of enterprise FinTech development. Since annual reports may contain industry trends, policy backgrounds, or technical descriptions that are not related to the enterprise's own applications, directly counting the frequency of keywords may overestimate the extent of enterprise FinTech applications. Therefore, this paper further utilizes the BERT model for

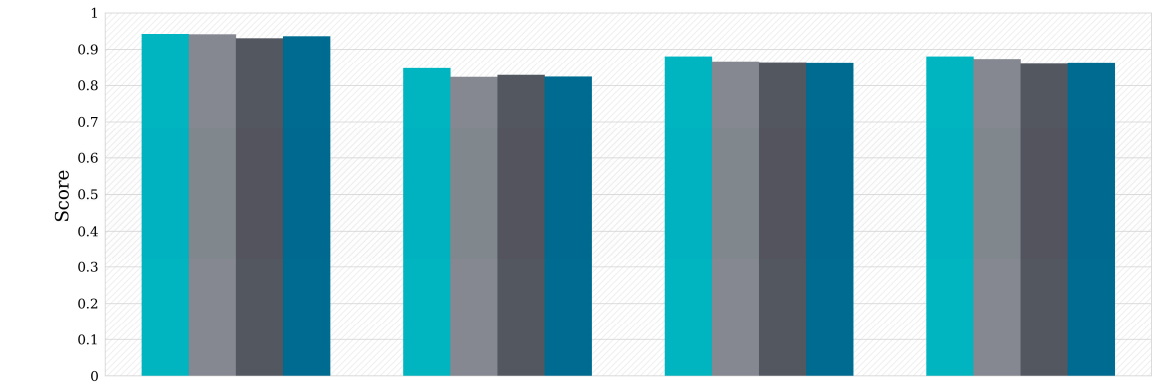
semantic recognition to distinguish between the actual FinTech activities carried out by the enterprise and non-substantive expressions.

Table 2. Keywords dictionary of FinTech.

Dimensions	Keywords
Artificial intelligence	Robotics, machine learning, deep learning, neural networks, facial recognition, biometrics, voiceprint recognition, pattern recognition, image recognition, face payment, virtual reality, augmented reality, knowledge graphs, smart finance, smart deposits, smart counters, smart branches, smart credit, smart banking, smart marketing, smart risk control, automation, and natural language processing.
Blockchain	Digital and electronic money, blockchain, near-field communication, quantum technology, distributed ledger technology, supply chain, Internet of Things (IoT), and quantum transmission.
Cloud computing	Financial cloud, trusted cloud, public cloud, private cloud, virtualization, cloud services, cloud platforms, cloud computing, cloud architecture, cloud systems, cloud disaster recovery, distributed systems, distributed storage, distributed computing, distributed architecture, distributed databases.
Big data	Digitalization, digital transformation, digital finance, digital signatures, digital ecology, digital credit cards, digital banking, digital marketing, big data, big data analytics, big data services, big data technology, big data model, big data mining, data warehouse, data technology, data model, data mining, data governance, and data center.
Going online	Online finance, online wealth management, online financing, online consumer loans, online banking, online payment, online transactions, electronization, Internet finance, FinTech, digital technology, networking, e-channel, e-commerce, e-banking, and e-payments.
Going mobile	open banking, software development kit, mobile banking, mobile payment, Program interface, open platform, barcode payment, mobile e-commerce, mobile Internet, digital finance, digital payment, application programming interface, and direct banking.

Step 2: Build training samples and perform semantic annotation. We randomly select 10% of the sentences from the keyword-filtered sentence set as annotation samples to determine whether each sentence reflects the enterprise's FinTech, providing annotated data for subsequent model training. It is necessary to admit that the above-mentioned steps inevitably introduce subjective judgment factors: the selection and classification of keywords, and the definition of semantic annotation standards. To minimize the influence of subjective factors, this paper has constructed a three-layer quality assurance system of multi-model preannotation—manual review and adjudication—consistency verification. Specifically, we selected two large language models, GPT-5 and ChatGLM-5.1, to independently pre-annotate the annotation samples by asking questions such as "Does this statement reflect the actual application, construction, research and development, launch, operation, or external provision of FinTech-related technologies, systems, platforms, products, or services by the enterprise?" We obtain the judgment results of the two models. For samples with inconsistent conclusions, they are uniformly verified and adjudicated by humans to ensure the consistency and credibility of the annotation. Finally, sentences that can truly reflect the enterprise's FinTech behavior are marked as 1, otherwise marked as 0. In addition, 10% of the labeled samples are randomly selected for rechecking. The Cohen's Kappa value was 0.86, indicating a high level of consistency in labeling.

Step 3: Model training and semantic prediction. We annotated 110,478 sample sentences, and the distribution of the annotated categories is as follows: approximately 41.6% of the sentences are labeled as 1, and approximately 58.4% are labeled as 0. Subsequently, the annotated sentences are converted into a binary classification dataset suitable for training a text recognition model and are divided into a training set, validation set, and test set in a ratio of 0.8:0.1:0.1. We fine-tune the pre-trained BERT model to enable the model to better adapt to the semantic recognition task of this financial technology. After the model training is completed, we benchmark its performance against a series of machine learning algorithms, including Support Vector Machine (SVM), Random Forest (RF), and Naive Bayes (NB). Each model is evaluated using four standard classification metrics: Precision, Accuracy, Recall, and F1-score. The specific performance indicators of the models are shown in Figure 4, and the results indicate that BERT achieved the highest overall performance. The final trained model is used to conduct semantic prediction for all candidate sentences, thereby identifying the sentences that truly reflect FinTech and the corresponding keyword sets, and counting their occurrence frequencies at the enterprise-year level. Compared with traditional word frequency methods, this approach can effectively eliminate non-substantive expressions. Therefore, it can more accurately depict the FinTech level at the enterprise level.



	BERT	SVM	RF	NB
Accuracy	0.942252	0.847015	0.880597	0.880597
Precision	0.941390	0.822888	0.866560	0.873612
Recall	0.930488	0.828414	0.864200	0.859581
F1-score	0.935918	0.824256	0.863393	0.863378

Figure 4. Comparison of classification performance among different models.

Step 4: Establish the enterprise-level FinTech index. This study takes the number of FinTech keywords identified by the model at the enterprise-year level as the base variable. Considering that the distribution of the text usually has a right-skewed characteristic, and to avoid the value issues caused by zero-value samples during the logarithmic transformation process, the final approach adopted in this study is to take the number of FinTech keywords identified plus 1 and calculate the natural logarithm. This way, the larger the value of the index, the higher the level of enterprise FinTech development.

4.2.3. Control Variable

Following to Sun et al. [48] and Peng and Lin [49], this study controls for corporate governance factors and firm-level attributes, specifically including: firm size (Size), firm age (Age), profitability (Roa), financial leverage (Lev), board size (Board), total executive compensation (Lnpay), ownership type (Soe), and the largest shareholder's ownership ratio (Top1). Table 3 provides these variables' definitions.

Table 3. Variable definitions and measurement.

Variable	Name	Symbol	Definitions and Measurement
Dependent variable	environmental information disclosure	EID	Take the logarithm of the aggregating scores of the enterprise plus 1
Explanatary variable	FinTech index	FinTech	According to the calculation method described in Section 4.2.2
Mechanism variable	Information asymmetry	ASY	Composite indicator of information asymmetry
	Green innovation	GI	The natural logarithm of one plus the annual number of green patent applications filed by the firm.
Moderation variable	Intensity of environmental regulation	ER	According to the calculation method described in Section 4.2.5
	Internal control quality of enterprises	IC	Take the logarithm of the Dibbo internal control index plus 1
Control variable	Company size	Size	Take the logarithm of the total assets of the business
	Age of the company	Age	Take the logarithm of the year minus the year of listing and add 1
	Profitability	Roa	Net profit/total assets
	Financial leverage	Lev	Earnings before interest and tax (EBIT)÷(EBIT- interest expense)
	Board size	Board	The board's entire membership is a natural logarithm
	Total executive compensation	Lnpay	Log total executive compensation
	Nature of shareholding	Soe	1 for SOEs and 0 for non-SOEs
	The largest shareholder's shareholding ratio	Top1	Total number of shares owned by the company's largest trading shareholder divided by the total number of shares

Note: The detailed definitions of each variable are provided in Section 4.2.

4.2.4. Mechanism Variable

Green Innovation (GI). Referring to Wu et al. [50], this study gauges a listed company's level of green innovation by counting the number of green patent applications. The measure is the natural logarithm of one plus the number of green patent applications, including the total number of green patents (Total), green invention patents (Inva), and green utility model patents (Uma).

Information asymmetry (ASY). Following Yu et al. [51], we first construct three stock liquidity indicators: the liquidity ratio (LR), the illiquidity ratio (ILL), and the return reversal indicator (GAM). Then, we perform principal component analysis on LR, ILL, and GAM to create a comprehensive ASY index. Specifically:

$$LR_{it} = -\frac{1}{D_{it}} \sum_{k=1}^{D_{it}} \sqrt{\frac{V_{it}(k)}{|r_{it}(k)|}} \quad (1)$$

$$ILL_{it} = \frac{1}{D_{it}} \sum_{k=1}^{D_{it}} \sqrt{\frac{|r_{it}(k)|}{V_{it}(k)}} \quad (2)$$

Among them, $V_{it}(k)$ represents the daily trading volume, $r_{it}(k)$ represents the stock return of enterprise i on the kth trading day of year t, and D_{it} represents the number of trading days in that year.

$$GAM_{it} = |\gamma_{it}| \quad (3)$$

γ_{it} is estimated by the following

$$r^e_{it}(k) = \theta_{it} + \varphi_{it} r_{it}(k-1) + \gamma_{it} V_{it}(k-1) sign[r^e_{it}(k-1)] + \varepsilon_{it}(k) \quad (4)$$

Among them, $r^e_{it}(k) = r_{it}(k) - r_{mt}(k)$ represents the excess return. $r_{mt}(k)$ represents the market return weighted by market capitalization. We first conduct Z-score standardization processing on the three original indicators, namely LR, ILL, and GAM. Then, we use the principal component analysis method to extract the first principal component for the three indicators (LR, ILL, and GAM) to capture their common variation information, which is also related to the asymmetric information. The final ASY index is composed of the weight coefficients corresponding to the first principal component and the weighted sum of the three standardized variables. The specific calculation formula is as follows:

$$ASY = \lambda_1 LR^{std}_{it} + \lambda_2 ILL^{std}_{it} + \lambda_2 GAM^{std}_{it} \quad (5)$$

where LR^{std}_{it}, ILL^{std}_{it}, GAM^{std}_{it} represent the LR, ILL, and GAM indicators after Z-score standardization processing; λ_1, λ_2, and λ_3 are the weight coefficients used when constructing the first principal component score, and they are: 0.3996, 0.6993, and 0.5928, respectively.

The eigenvalue of the first principal component is: 1.3823 (greater than 1); the loadings of the first principal component are: LR = 0.4698, ILL = 0.8222, GAM = 0.6970, and the explained variance of the first component is: 46.08%.

4.2.5. Moderation Variable

Environmental regulatory intensity (ER). Following Li et al. [52]. This paper measures the intensity of environmental regulation (ER) by the proportion of environmental-related terms in the city government work reports. Specifically, we first collect the government work reports issued by each city over the years; then, we segment the reports and identify the environmental-related terms within them. Based on this, this paper takes the ratio of the number of environmental-related terms in the government work reports to the total number of terms as the environmental regulation intensity indicator and scales it by multiplying by 100. The higher the value of this index is, the stronger the local government's attention to and regulation of environmental problems in that year is. The specific calculation formula is as follows:

$$ER_{it} = \frac{Environmental\ Words_{it}}{Total\ Words_{it}} * 100 \quad (6)$$

Internal controls quality (IC). Following Tan [53], this paper employs the Dibbo internal control index to measure the Ic. This index is derived from the five fundamental elements of internal control: internal environment, risk assessment, control activities, information and communication, and internal monitoring. We take the natural logarithm of the Dibbo score plus 1 to comprehensively evaluate the effectiveness of the company's internal control system. The higher the score, the better the quality of internal control.

4.3. Model Design

To account for firm-specific characteristics that remain constant over time and macroeconomic factors that are uniform across firms, both company and year fixed effects are included in the regression analysis of this study's two-way fixed effects model. The specific model is as follows:

$$EID_{it} = \alpha_0 + \alpha_1 FinTech_{it} + \alpha_2 Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (7)$$

Among them, the firm and year are indicated by the subscripts i and t, respectively. The dependent variable EID_{it} represents the level of corporate EID. The independent variable $FinTech_{it}$ captures the degree of corporate FinTech adoption, and Controls are control variables. μ_i and λ_t respectively, represent the firm and year fixed effects, while ε_{it} is the error term.

4.4. Descriptive Statistics

Table 4 displays the descriptive statistics for the main variables. The average EID score is approximately 1.668, with a standard deviation of 0.975. The substantial variation across firms indicates significant heterogeneity in EID practices, reflecting the absence of a fully standardized and systematic disclosure mechanism across the market [54]. FinTech, the main explanatory variable, has a standard deviation of 1.032 and an average value of 0.784, demonstrating significant variations in the level of FinTech adoption among organizations. This variation may reflect disparities in firms' technological capabilities, digital transformation strategies, and access to financial technology infrastructure. In addition, Table 4 reports the descriptive statistics for firms' financial characteristics and corporate governance-related control variables. All variables lie within reasonable ranges, and the observed distributions are broadly consistent with prior literature [55]. The data further suggest that variations in financial resources, governance structures, and firm size may contribute to differences in both FinTech adoption and environmental information disclosure behavior, supplying a strong basis for further regression analysis.

Table 4. Descriptive statistics.

Variable	N	Mean	Sd	Min	Max
EID	31,998	1.668	0.975	0.000	3.367
FinTech	31,998	0.784	1.032	0.000	4.174
ASY	31,947	−0.204	0.597	−6.652	30.526
GI	31,998	0.375	0.795	0.000	3.951
ER	28,733	0.940	0.280	0.000	2.977
IC	27,754	6.354	0.918	0.000	6.894
Size	31,998	22.362	1.419	19.934	27.116
Age	31,998	2.077	0.908	0.000	3.367
Soe	31,998	0.290	0.454	0.000	1.000
Roa	31,998	0.037	0.063	−0.245	0.200
Board	31,998	2.121	0.203	1.609	2.708
Lnpay	31,998	15.091	0.836	13.102	17.278
Lev	31,998	1.437	1.228	0.288	9.493
Top1	31,998	33.601	14.807	8.140	73.650

5. Empirical Results

5.1. Correlation and Multicollinearity

The variance inflation factors (VIF) and correlation coefficients among the variables are presented in Table 5. FinTech and EID exhibit a correlation of 0.061, providing preliminary

evidence in support. Among the control variables, factors such as firm size and firm age also show positive correlations with EID, in line with theoretical expectations [56]. This observation further validates the appropriateness of the selected control variables. Moreover, all variables display VIF values below the widely recognized cutoff of 10, suggesting that multicollinearity is not an issue in the model. This ensures that the subsequent regression results are not distorted by inter-variable correlations and can be interpreted with confidence [57]. The observed correlation patterns also suggest that firms with more extensive resources and governance structures may be better positioned, highlighting the interplay between corporate characteristics and the effectiveness of FinTech in promoting EID.

Table 5. Correlation and multicollinearity results.

Variable	EID	FinTech	Size	Age	Soe	Roa	Board	Lnpay	Lev	Top1	VIF
EID	1.000										
FinTech	0.061 ***	1.000									1.11
Size	0.399 ***	0.129 ***	1.000								1.95
Age	0.170 ***	0.030 ***	0.430 ***	1.000							1.49
Soe	0.098 ***	−0.056 ***	0.352 ***	0.388 ***	1.000						1.37
Roa	0.047 ***	−0.054 ***	−0.021 ***	−0.218 ***	−0.053 ***	1.000					1.19
Board	0.099 ***	−0.0342 ***	0.282 ***	0.138 ***	0.260 ***	0.020 ***	1.000				1.14
Lnpay	0.356 ***	0.253 ***	0.530 ***	0.144 ***	0.094 ***	0.136 ***	0.178 ***	1.000			1.59
Lev	0.012 *	−0.090 ***	0.088 ***	0.170 ***	0.115 ***	−0.297 ***	0.058 ***	−0.107 ***	1.000		1.15
Top1	0.062 ***	−0.096 ***	0.148 ***	−0.106 ***	0.200 ***	0.162 ***	−0.002	−0.026 ***	−0.062 ***	1.000	1.18

Note: *, *** show significance at the relevant 10%, and 1% levels.

5.2. Benchmark Regression

Table 6 displays the results for Equation (1). Column (1) controls only for firm and year fixed effects, without including any other control variables. The findings indicate that since the FinTech coefficient is notably positive at the 1% level, FinTech contributes to a higher degree of enterprises' EID. In columns (2) and (3), we examine scenarios with and without control variables to further account for firm-specific fixed effects. The FinTech coefficient is still significantly positive, supporting the earlier conclusions. Finally, the analysis incorporates both firm and year fixed effects, along with all control variables, to ensure a comprehensive estimation. According to the findings in Column (4), the FinTech coefficient is 0.015 and remains positive at the 1% level, indicating that after controlling for other potential factors, for every 1% increase in FinTech, EID typically increases by approximately 0.015%. From the perspective of discrete changes, both FinTech and EID in this paper are transformed in logarithmic form. According to Table 4, the standard deviation of FinTech is 1.032. Therefore, an increase of one standard deviation in the numerical value of FinTech could result in an increase of $0.015 \times 1.032 = 0.01548$ in the numerical value of EID, corresponding to an actual increase in EID level of $[\exp(0.01548) - 1] \times 100\% \approx 1.56\%$. The above results support Hypothesis 1.

Furthermore, the estimation results are consistent with the existing research conclusions regarding the impact of digital transformation, digital finance, and information technology on enterprises' environmental governance behaviors. Relevant studies have generally found that digital technologies promote corporate green governance and information disclosure mainly through channels such as improving information acquisition efficiency, alleviating information asymmetry, and optimizing resource allocation [58,59]. One possible explanation is that FinTech enhances the efficiency and accuracy of data collection, processing, and verification, thereby reducing both the cost and complexity of EID. This improvement not only facilitates easier reporting but also strengthens firms' capacity and motivation to provide comprehensive and timely environmental data. Additionally, FinTech makes it possible to integrate internal and external information flows more effectively, improves transparency, and allows firms to respond more proactively to regulatory requirements and stakeholder expectations. Furthermore, the regression results for control variables reveal that larger firms and those with longer listing histories

tend to disclose more environmental information, likely due to increased public scrutiny, reputational concerns, and more established governance structures. Conversely, firms with higher debt ratios display lower levels of EID, possibly reflecting financial constraints and the prioritization of short-term financial obligations over environmental reporting, which is consistent with prior studies [60].

Table 6. Baseline regression results.

Variable	(1) EID	(2) EID	(3) EID	(4) EID
FinTech	0.031 *** (0.006)	0.339 *** (0.006)	0.076 *** (0.006)	0.015 *** (0.006)
Size			0.193 *** (0.009)	0.118 *** (0.009)
Age			0.385 *** (0.010)	0.106 *** (0.012)
Soe			−0.197 *** (0.022)	−0.060 *** (0.020)
Roa			−0.102 (0.070)	0.184 *** (0.068)
Board			−0.152 *** (0.034)	−0.052 (0.033)
Lnpay			0.136 *** (0.009)	0.051 *** (0.009)
Lev			−0.008 ** (0.004)	0.000 (0.004)
Top1			−0.000 (0.001)	0.001 ** (0.001)
Constant	1.644 *** (0.005)	1.402 *** (0.006)	−5.148 *** (0.200)	−1.885 *** (0.214)
Controls	×	×	√	√
Firm FE	√	√	√	√
Year FE	√	×	×	√
N	31,998	31,998	31,998	31,998
Adj R^2	0.692	0.566	0.668	0.697

Note: **, *** show significance at the relevant 5% and 1% levels. The standard errors are firm-level clustered in parentheses.

5.3. Robustness Test

5.3.1. One-Period Lag of the Independent Variable

Given that the impact of FinTech on corporate EID could be vulnerable to a time lag, we re-perform the regression analysis with the primary independent variable, FinTech, lagged by one period, in accordance with the methodology of Li et al. [61]. The robustness of the baseline findings is further supported by the FinTech coefficient's continued positivity at the 1% level, as indicated in column (1) of Table 7. This implies that the positive effect of FinTech demonstrates a certain degree of durability.

Table 7. The robustness test results.

Variable	(1) EID	(2) EID	(3) EID	(4) EID	(5) EID	(6) EID
FinTech		0.015 ** (0.007)	0.029 *** (0.006)	0.016 *** (0.006)	0.015 ** (0.007)	0.015 * (0.008)
L.FinTech	0.013 ** (0.006)					
Controls	√	√	√	√	√	√
Firm FE	√	√	√	√	√	√
Year FE	√	√	×	√	√	√
Ind#year	×	×	√	×	×	×
N	27,431	22,320	31,901	31,419	25,602	31,998
Adj R^2	0.702	0.687	0.710	0.700	0.691	0.697

Note: *, **, *** show significance at the relevant 10%, 5%, and 1% levels. Variable notations remain the same as those in Table 6. Ind#year indicates the inclusion of industry–year fixed effects.

5.3.2. Modify Sample Observations

To account for the possible influence of COVID-19 on the estimation outcomes, and following Hu et al. [62], observations from 2019 to 2022 were excluded, and the regression was re-estimated. Table 7's column (2) demonstrates that the FinTech coefficient is still substantially positive, indicating that its positive effect on corporate environmental information disclosure persists outside the pandemic period. This confirms that the main findings are robust and not driven by extraordinary events, reinforcing their generalizability across different time frames and economic conditions.

5.3.3. Adjust Fixed Effects

To further enhance the robustness of the model, this study introduces fixed effects for the interaction between industry and year to control for industry-specific time-varying effects and joint industry-year shocks, thereby eliminating potential biases arising from these unobserved factors. The regression findings in Table 7's column (3) demonstrate that FinTech's coefficient is still noticeably positive, suggesting that the estimation results are not sensitive to unobserved joint industry-year shocks.

5.3.4. Exclude Financial Sector Samples

As the financial industry itself is an important participant and application of FinTech, its financial status and EID behavior may be systematically different from that of non-financial enterprises. Since the financial sector is both a major user and driver of FinTech, its financial condition and environmental information disclosure practices may systematically differ from those of non-financial firms. The FinTech coefficient is still significantly positive. Table 7's Column (4) presents the results, suggesting that the study's conclusions are independent of the financial sector sample.

5.3.5. Exclude Directly Administered Municipalities' Samples

Municipalities directly under the central government may differ from ordinary provinces in terms of policy environments and economic structures. Referring to Cao et al. [63], we further excluded sample firms located in Beijing, Shanghai, Tianjin, and Chongqing. As reported in Column (5) of Table 7, the coefficient of FinTech remains positive and statistically significant after excluding special provinces, suggesting that the impact of FinTech on corporate environmental disclosure is robust and applicable beyond specific regional contexts.

5.3.6. Change the Clustering Standard Error

To address potential correlation and heteroskedasticity at both the firm and year levels, this study adopts the approach of Cheng and Vyas [64] and re-estimates the results using robust standard errors with double clustering by firm and year. The statistical inferences from the baseline regression are unaffected by the correlation structure of the disturbance terms, as seen by the FinTech coefficient's continued significant positive value at the 1% level in Table 7's column (6). This further ensures the robustness of the study's conclusions.

5.3.7. Other Robustness Tests

In addition, we further supplement the robustness test by replacing the measurement of explanatory variables, adding additional control variables, and adding joint fixed effects. The results are shown in Table 8. Column (1) reports replacing the measurement of FinTech. Specifically, this paper uses the ratio of keyword numbers identified based on the large language model to the total number of sentences in the MD&A section of the annual report of the enterprise as an alternative explanatory variable. This treatment aims to test whether the conclusions are sensitive to the way of index construction, to exclude the possible

interference of the choice of measurement method on the estimation results. Column (2) reports the regression results of the second alternative FinTech indicator. A robustness test is conducted by using the logarithm of the number of FinTech companies in the location of the enterprise as the alternative indicator. This indicator is based on the external FinTech development environment of the enterprise and has no direct correlation with the disclosure in the enterprise's annual report text. It effectively avoids the influence of a single indicator on the estimation results. Column (3) reports the test results with additional control variables. Based on the benchmark model, this paper further controls for economic development: the per capita regional GDP of the city where the enterprise is located; Financial development is measured by the proportion of financial institution loan balance to regional GDP in the city where the firm is situated. Digital infrastructure is constructed based on urban broadband Internet penetration, measured by the logarithm of broadband users. Regional pollution intensity is evaluated using log-transformed industrial SO_2 emissions and wastewater discharge; Media attention at the enterprise level is measured by the logarithm of the number of reports of listed companies in mainstream news media in the same year. All variables are log-transformed to reduce skewness and improve the reliability of empirical estimates. Column (4) adds the joint fixed effects of industry-year, city-year, and province-year to the benchmark model, and Column (5) further incorporates the above additional control variables on this basis. This treatment aims to absorb the characteristics that do not change with time at different levels and different shocks that change with year, to strip out the possible interference of unobservable time-varying confounding factors on the estimation results at a finer dimension. The above robustness test findings reveal that the coefficients of FinTech are still significantly positive, indicating that the core conclusions of this paper are robust.

Table 8. Additional robustness test results.

Variable	(1) EID	(2) EID	(3) EID	(4) EID	(5) EID
FinTech	0.574 ***	0.022 ***	0.017 *	0.021 **	0.022 *
	(0.132)	(0.010)	(0.008)	(0.010)	(0.013)
Controls	√	√	√	√	√
Additional Controls	×	×	√	×	√
Firm FE	√	√	√	√	√
Year FE	√	√	√	√	√
Joint FE	×	×	×	√	√
N	31,795	22,441	28,368	30,012	26,770
Adj R^2	0.698	0.700	0.695	0.455	0.452

Note: *, **, *** show significance at the relevant 10%, 5%, and 1% levels. The notation of variables follows Table 6. Additional controls include regional-level economic development, financial development, digital infrastructure, and pollution intensity, as well as firm-level media attention.

5.4. Endogeneity Test

To mitigate potential endogeneity issues in the model, such as omitted variables and bidirectional causality, this study employs two-stage least squares (2SLS) for estimation. Following Nunn and Qian [65] and Akerman et al. [66], we choose the interaction term as the instrumental variable (IV) between the one-period lagged businesses' Fintech and the number of Internet users per 100 persons at the prefecture level. The construction logic of this IV is as follows. Firstly, in terms of relevance, regional internet penetration reflects the local digital infrastructure and information accessibility conditions. In addition, by interacting this regional variable with the one-period-lagged FinTech, it can simultaneously capture the joint impact of the existing technology accumulation of an enterprise and

the external digital environment, thus enhancing the correlation with the current FinTech development level. Secondly, the historical number of regional Internet users is a fact in the early stage and is not affected by the current EID decisions of enterprises, while it has also been shown how far FinTech is behind one period. Table 9 reports the instrumental variable (IV) estimation results. The first-stage regression results of Column (1) show that the IV is significantly positively correlated with FinTech, and there is no problem of insufficient identification or weak IV, so it has good validity.

Table 9. The IV test results.

Variable	(1) First FinTech	(2) Second EID	(3) Semi-Simplified Regression EID
IV	0.009 *** (0.000)		−0.0000 (0.0002)
FinTech		0.054 *** (0.016)	0.0321 *** (0.0075)
Controls	√	√	√
Firm FE	√	√	√
Year FE	√	√	√
N	25,395	25,395	25,395
Adj R^2	0.741		0.703
Kleibergen-Paap rk LM	1934.314 *** [0.0000]		
Kleibergen rk Wald F. Paap	2685.590 *** [16.38]		

Note: *** shows significance at the relevant 1% levels. All the symbols are consistent with Table 6.

To further substantiate the exclusivity constraint, we also conduct the following tests: Firstly, following the approach of Conley et al. [67], a semi-simplified regression is employed, where the IV is directly included as a control variable in the OLS regression. The regression results are shown in column (3) of Table 9. After controlling for the FinTech variables, the regression coefficient of FinTech remained significantly positive, while the coefficient of the IV did not have statistical significance. This indicates that the IV is unlikely to directly affect the enterprise EID level through channels other than FinTech, and the exclusivity constraint is preliminarily supported.

Secondly, following Acemoglu et al. [68], a placebo test is constructed. Specifically, this paper randomly selects the observed values of the IV to form a random matching relationship between the IV and the core explanatory variables. Theoretically, this randomness will cause the impact coefficient of the IV on the enterprise EID in the simple regression to tend towards zero. The above random matching and regression process is repeated 500 times in this paper. Figure 5 presents the distribution of the 500 simulated coefficients obtained from the estimation procedure. The results show that the coefficients of the placebo regression are concentrated around 0; that is, there is no significant relationship between the IV and the enterprise EID under random matching. This provides a counterargument to demonstrate the rationality of the IV used in this paper.

Thirdly, following Conley et al. [67], this method relaxes the strict assumption of exclusivity constraints, allowing the IV to have a certain degree of direct influence on the outcome variable. In this case, the confidence interval of the explanatory variable is estimated. Specifically, a semi-simplified regression is first used to obtain an estimated standard error of 0.0002, which is set as the variance of the parameter γ distribution with a variance set at 4×10^{-8}. The Local-to-Zero (LTZ) confidence interval is estimated under different variance settings (2×10^{-8}, 3×10^{-8}, 4×10^{-8}, 5×10^{-8}). The results are shown in Figure 6. Under all variance settings, the 95% confidence interval of the LTZ estimated coefficient does not include 0. This indicates that even when the exclusivity constraint

assumption is relaxed to a certain extent, the positive impact of fintech on enterprise EID remains robust, further demonstrating the rationality of the selection of IV and the reliability of the conclusion.

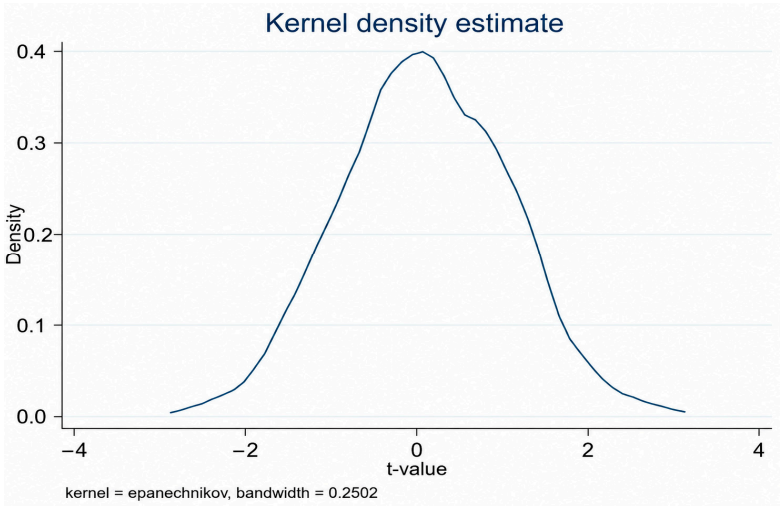


Figure 5. Placebo test for demonstrating the rationality of the IV.

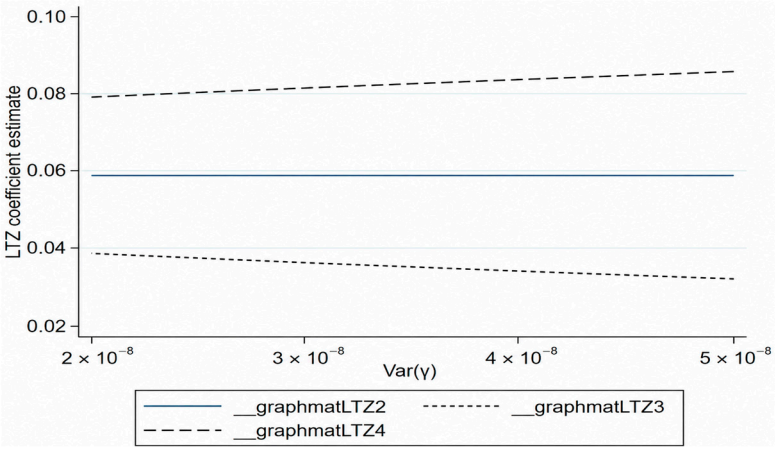


Figure 6. Coefficients and confidence intervals estimated by the LTZ method.

5.5. Mechanism Analysis

Based on theoretical analysis, FinTech indirectly influences corporate EID levels primarily through two channels: promoting green innovation and reducing information asymmetry. Thus, we adopt a two-step procedure to empirically examine the channels described above:

$$Med_{it} = \beta_0 + \beta_1 L.FinTech_{it} + \beta_2 Controls_{it} + \mu_i + \lambda_t + v_{it} \quad (8)$$

where Med_{it} represents the mechanism variable, which respectively stands for green innovation (GI) and information asymmetry (ASY). $L.FinTech_{it}$ is the level of enterprise FinTech lag behind one period, where L represents the lag operator. The remaining variables' definitions are still the same as those given previously.

5.5.1. Green Innovation Channel

Theoretical analysis suggests that while FinTech optimizes the financing environment, it also expands firms' knowledge boundaries through knowledge spillovers and information integration, thereby enhancing their capacity for green innovation and, consequently,

their willingness and ability to disclose EID [69]. In the mechanism analysis, this paper further employs a lagged one-period explanatory variable setting to alleviate potential reverse causality and contemporaneous bias. Table 10's columns (1) and (2) demonstrate how FinTech greatly encourages corporate green innovation and raises the bar for EID. Furthermore, the Sobel statistic is significant, and the confidence interval obtained from the Bootstrap test does not include 0. This indicates that the channel effect test is valid, thereby confirming Hypothesis 2a.

Table 10. Mechanism test results.

Variable	(1) EID	(2) GI	(3) ASY
L.FinTech	0.013 ** (0.006)	0.047 *** (0.006)	−0.015 *** (0.003)
Constant	−2.074 *** (0.234)	−0.167 * (0.180)	4.764 *** (0.129)
Sobel-Z		11.33	4.17
Bootstrap		[0.0067, 0.0096]	[0.0006, 0.0021]
Controls	√	√	√
Firm FE	√	√	√
Year FE	√	√	√
N	27,431	27,674	27,668
Adj R^2	0.702	0.676	0.7619

Note: *, **, *** show significance at the relevant 10%, 5%, and 1% levels. L.FinTech represents lagged one-period FinTech. Sobel-Z is the test statistic for the mediating effect; the Bootstrap confidence interval is based on 1000 repeated samplings; the other variables are the same as those in Table 6.

The possible reason is that FinTech, through technologies such as supply chain financing based on blockchain technology and big data credit evaluation, accurately identifies green vulnerabilities and innovation potential within industrial chains, thereby directing capital toward clean technologies and process upgrades [70]. Furthermore, FinTech platforms facilitate the flow of environmental knowledge among industry, academia, research institutions, and supply chains [71], making it easier for enterprises to access cutting-edge green technologies. This reduces trial-and-error costs and information barriers during the R&D process, directly incentivizing enterprises to convert financing and information advantages into substantial green R&D investments, thereby generating innovative patent outcomes [72]. In light of the extensive use of ESG investment principles and stricter regulatory oversight, firms have an incentive to disclose these achievements to demonstrate their long-term value and compliance potential, attract green investment, secure policy incentives, and enhance their brand reputation [73]. Consequently, FinTech drives green innovation, thereby incentivizing firms to improve their environmental disclosure practices.

5.5.2. Information Asymmetry Channel

Consistent with prior theoretical frameworks, FinTech incentivizes more accurate and comprehensive information disclosure by reducing the degree of information asymmetry. To address concerns regarding reverse causality and simultaneity bias, this paper further employs a lagged one-period explanatory variable setting. Table 10's column (3) demonstrates that the estimated coefficient of FinTech is significantly negative, suggesting that FinTech has a transmission effect on the enhancement of environmental information disclosure and greatly lowers the degree of information asymmetry. Furthermore, the Sobel statistic is significant, and the confidence interval obtained from the Bootstrap test does not include 0. This indicates that the channel effect test is valid, thereby confirming Hypothesis 2b.

The possible reason is that IoT sensors enable the collection of real-time energy consumption and emissions data, blockchain technology guarantees data integrity and traceability, and AI algorithms perform cross-validation and risk analysis. Together, these

technologies improve the observability, accuracy, and verifiability of environmental data, converting previously unverifiable soft information into concrete, actionable metrics. This allows stakeholders to more efficiently assess a firm's true environmental performance at lower cost, reducing information asymmetry. By enhancing the overall information environment, FinTech limits the opportunities for companies to engage in selective disclosure or greenwashing, thereby raising the potential costs of opportunistic behavior. Firms are thus incentivized to adopt more rigorous and transparent disclosure practices to maintain credibility in capital markets, avoid valuation discounts, and reduce financing constraints [74]. Furthermore, the integration of these digital technologies facilitates continuous monitoring and auditability of disclosures, strengthening internal accountability and aligning corporate behavior with external expectations.

6. Further Analysis

6.1. Moderation Effect Analysis

The strength of internal controls and the strictness of environmental rules may mitigate the beneficial effects of FinTech on a company's EID level. To test these moderating effects, this study constructs the following model:

$$EID_{it} = \delta_0 + \delta_1 FinTech_{it} + \delta_2 Fintech_{it} \times Moderator_{it} + \delta_3 Moderator + \delta_4 Controls_{it} + \mu_i + \lambda_t + \tau_{it} \quad (9)$$

In this context, $Moderator_{it}$ serves as a moderating variable, representing environmental regulation intensity (ER) and internal control quality (IC), respectively. We focus on the coefficient δ_2 of the interaction term, $Fintech_{it} \times Moderator_{it}$.

6.1.1. Stringency of Environmental Regulations

To test the moderating effect of this external contextual factor, this study incorporates the interaction between environmental regulation intensity and FinTech, where both are mean-centered before constructing the interaction term. Column (1) in Table 11 displays the results, demonstrating that FinTech's main effect coefficient remains substantial. But the interaction term FinTech × ER is positive at the 5% level and statistically significant. These findings support Hypothesis 3a, suggesting that the stringency of environmental regulation increases the beneficial effects of FinTech adoption on company EID.

Table 11. Moderation effect results.

Variable	(1) EID	(2) EID
FinTech	0.018 ***	0.017 ***
	(0.006)	(0.006)
ER	0.003	
	(0.014)	
IC		−0.003 (0.004)
FinTech × ER	0.013 ** (0.007)	
FinTech × IC		0.009 ** (0.004)
Constant	−2.066 *** (0.230)	−2.099 *** (0.234)
Controls	√	√
Firm FE	√	√
Year FE	√	√
N	28,704	27,754
Adj R^2	0.701	0.701

Note: **, *** show significance at the relevant 5%, and 1% levels. All the symbols are consistent with Table 6.

The possible reason is that in areas with strict environmental protection regulations, enterprises face higher compliance costs and violation risks. The verifiable and immutable environmental data provided by FinTech can be used as strong evidence to cope with regulatory verification, significantly reducing the accountability risk and compliance cost of enterprises [75]. Furthermore, during the implementation of environmental policies, local governments tend to allocate green financial resources to firms that can demonstrate their environmental performance. The transparent and credible green image fostered by FinTech makes firms more easily identifiable as high-quality candidates, thereby enabling them to secure scarce policy resources and market reputation, which greatly stimulates their endogenous motivation for information disclosure.

6.1.2. Quality of a Company's Internal Controls

To test the moderating role of this internal capability, this study constructs an interaction term between Bodie's internal control index and FinTech for empirical testing, where both are mean-centered before constructing the interaction term. Column (2) in Table 11 demonstrates that the main effect coefficient of FinTech is still significantly positive, and at the 5% level, the interaction term's coefficient FinTech × IC is significantly positive, thereby confirming Hypothesis 3b. The application of FinTech spans the entire process from data collection and transmission to processing and reporting. Without effective internal controls, this may lead to issues such as data distortion, departmental buck-passing, and even technological greenwashing. High-quality internal controls ensure the accuracy, completeness, and consistency of environmental data as it flows through internal systems by establishing robust procedures and clearly defining roles and responsibilities, thereby safeguarding the quality of information processed by FinTech at its source. At the same time, robust internal control mechanisms strengthen the oversight functions of the board of directors and the audit committee, effectively curbing opportunistic behavior by management that exploits technology for selective disclosure or information manipulation [76]. This creates a synergistic governance effect between technology and institutional frameworks, jointly driving improvements in the EID.

6.2. Heterogeneity Analysis

6.2.1. High-Tech and Non-High-Tech Firms

High-tech firms typically possess strong technological innovation capabilities, well-developed information systems, and transparent governance structures; their motivation and capacity for environmental disclosure are already at a relatively high level. In contrast, non-high-tech firms are mostly in traditional industries and face greater financing constraints and barriers regarding green transition and information disclosure. Following Chen and Wang [77], we further investigate whether the effects of FinTech adoption vary across different groups and classify firms into high-tech and non-high-tech categories based on the Guidelines on Industry Classification of Listed Companies (2012 Revision).

The regression results in columns (1) and (2) of Table 12 indicate that FinTech can only enhance EID among non-high-tech companies. Fisher's permutation test results indicate that the various sample groups differ significantly in terms of structure. The structural distinctions between the two kinds of businesses in terms of technology underpinnings, governance maturity, and regulatory pressures are the cause of this divergence. By alleviating financing limitations, lowering information processing costs, and strengthening external oversight, FinTech equips these firms with effective mechanisms to overcome such barriers, resulting in notable marginal improvements in disclosure. Additionally, non-high-tech firms typically have less sophisticated internal information systems and weaker

compliance cultures, making them more responsive to the efficiency and transparency gains offered by digital financial technologies [78].

Table 12. Heterogeneity analysis.

Variable	(1) High-Tech Industry	(2) Non-High-Tech Industry	(3) Manufacturing Industry	(4) Non-Manufacturing
FinTech	−0.011	0.025 ***	0.003	0.062 ***
	(0.012)	(0.007)	(0.008)	(0.009)
Constant	−2.407 ***	−1.894 ***	−1.806 ***	−3.236 ***
	(0.478)	(0.247)	(0.287)	(0.339)
Fisher's permutation test	0.037 *** [0.002]		0.060 *** [0.004]	
Controls	√	√	√	√
Firm FE	√	√	√	√
Year FE	√	√	√	√
N	8548	23,420	21,397	10,557
Adj R^2	0.697	0.704	0.689	0.730

Note: *** shows significance at the relevant 1% levels. In Fisher's permutation row, 0.037 and 0.060 respectively represent the differences in the FinTech coefficients between the two groups, and both are statistically significant at the 1% level. [] is %the empirical *p*-value of Fisher's Permutation test for the difference in coefficients between groups, which is obtained by the Bootstrap test, and the sampling times are set to 500. Other symbols are consistent with Table 6.

In contrast, high-tech companies already possess advanced information infrastructure, well-established compliance protocols, and standardized environmental disclosure practices. As a result, the potential for additional gains from FinTech adoption is comparatively limited. Moreover, high-tech firms' disclosure behaviors are predominantly shaped by internal strategic decisions, such as R&D scheduling and competitive positioning, rendering them less sensitive to external, broadly applied technological interventions [79]. This suggests that the effectiveness of FinTech in promoting EID is context-dependent, with firms that have more resource constraints and less mature disclosure practices benefiting most from its adoption.

6.2.2. Manufacturing and Non-Manufacturing Firms

High levels of emissions and energy use are typical features of manufacturing firms. They face stricter environmental regulations and public scrutiny, and their environmental disclosure practices are subject to multiple institutional pressures. In contrast, non-manufacturing enterprises span a wide range of industries, exhibit significant variations in environmental performance and disclosure motivations, and generally face a significant level of information asymmetry. To examine the industry heterogeneity of FinTech's impact, we use the methods of Bu et al. [80] to divide the sample into manufacturing and non-manufacturing groups.

The results in columns (3) and (4) of Table 12 indicate that FinTech significantly enhances environmental information disclosure among non-manufacturing enterprises, while its effect on manufacturing firms is negligible. The results of Fisher's permutation test also show that there are significant structural differences between different sample groups. This divergence is closely associated with sector-specific regulatory pressures and established disclosure practices. Environmental management in non-manufacturing firms is often not a top regulatory priority, resulting in a relatively weak disclosure foundation and limited voluntary reporting incentives. By improving supply chain transparency, introducing digital governance tools, and facilitating access to green financing, FinTech effectively encourages these firms to disclose environmental information and addresses capability constraints, yielding substantial marginal improvements. Addition-

ally, non-manufacturing firms may lack sophisticated internal reporting systems, making them more responsive to the efficiency gains and data verification mechanisms offered by FinTech technologies.

In contrast, manufacturing enterprises generally have mature, mandatory disclosure systems shaped by long-standing, stringent environmental regulations. Their disclosure practices are largely compliance-driven, and many have already achieved disclosure levels close to policy ceilings. Consequently, while FinTech can enhance reporting efficiency, data accuracy, and stakeholder credibility, it is unlikely to induce substantial incremental gains in disclosure levels. Moreover, the behavior of manufacturing firms is often guided by entrenched operational routines and institutionalized reporting processes, which may reduce their sensitivity to external technological interventions [81]. This suggests that the effectiveness of FinTech in promoting EID is contingent on industry context and existing regulatory maturity.

7. Conclusions

This paper further expands the research on the relationship between digital technologies and corporate environmental governance. We use the BERT large language model to construct an enterprise-level FinTech development index and discover that FinTech has the potential to greatly raise the company's EID level. In addition, mechanism analysis shows that FinTech increases firms' propensity and capacity to disclose information by fostering green innovation and mitigating information asymmetry. Furthermore, strict regional environmental regulations and internal corporate controls can further enhance the positive impact of FinTech. Heterogeneity analysis reveals that the effect of FinTech is stronger among non-high-tech and non-manufacturing firms, suggesting that it plays a crucial role in addressing disclosure shortcomings in traditional industries and responding to external oversight pressures.

Unlike existing studies that mainly focus on regional digitalization or digital finance development, this study emphasizes the governance consequences of actual enterprise-level FinTech adoption. By constructing a firm-level FinTech indicator based on BERT semantic recognition, this study provides more granular evidence on how digital technologies influence corporate environmental governance behavior. The core research findings are largely consistent with the relevant literature on digital finance promoting environmental information disclosure in terms of the influencing direction. For instance, Ren et al. [82] found based on the data of Chinese A-share listed companies from 2011 to 2022 that FinTech significantly promoted the disclosure of climate risks by enterprises. However, the conclusion differs somewhat from the studies focusing on bank FinTech; Zhang et al. [83] discovered based on the data of Chinese listed companies from 2014 to 2023 that bank FinTech was associated with lower levels of EID for enterprises. The mechanism lies in that bank FinTech alleviated the financial mismatch of enterprises, thereby reducing the incentives for enterprises to convey environmental responsibility through information disclosure. The reasons for this difference may mainly stem from the differences in research perspectives, measurement methods, and transmission mechanisms.

Drawing on the empirical findings, this study proposes the following policy implications: First, promote the application of FinTech in improving corporate environmental information governance. This paper finds that FinTech improves EID level by promoting internal green innovation and alleviating external information asymmetry. Based on this, it is suggested to guide financial institutions to build a platform for green innovation project identification and financing by using FinTech at the policy level, to provide precise financial support for enterprises' green R&D and clean technology upgrading. At the same time, promote the standardized application of FinTech in enterprise environmental information

verification and cross-department data sharing, and break the information barriers between regulatory authorities, financial institutions, and enterprises. Through the coordination of internal innovation empowerment and external transparency constraints, EID is provided with dual support of content supply and supervision and guarantees.

Second, strengthen the coordination between the external institutional environment and FinTech policies. The analysis of the moderating effect shows that strict environmental regulation can significantly enhance the promotion effect of FinTech on EID. Therefore, it is suggested that in the formulation and implementation of environmental regulations, enterprises should be explicitly encouraged to adopt trusted digital technology for compliance disclosure, and the effectiveness of environmental management carried out by enterprises using FinTech should be included in the green finance evaluation and environmental credit rating system, to give corresponding policy incentives. Through the organic combination of institutional framework and technical means, enterprises should be guided to change from passive compliance to active use of technical tools to improve environmental transparency and governance efficiency.

Third, improve the integration mechanism of FinTech with internal control and external supervision of enterprises. This paper finds that high-quality internal control can significantly strengthen the promotion effect of FinTech on EID. It is suggested that enterprises strengthen data governance and information system management in the internal control framework to ensure the standardization of the technology application process and the true traceability of information. At the same time, regulatory authorities can use regulatory technology to carry out real-time tracking, cross-verification, and risk warning of environmental information disclosed by enterprises, build a digital regulatory system of government-enterprise linkage, and effectively prevent opportunistic behaviors.

Fourth, implement differentiated FinTech support strategies. Further analysis reveals stronger FinTech-driven improvements in EID for non-high-tech and non-manufacturing firms. It is suggested that policy resources should be tilted to traditional industries, small and medium-sized enterprises, and other groups with weak disclosure ability, including providing training on the application of FinTech tools, encouraging cooperation with technology enterprises to develop lightweight scene-oriented environmental information management programs, and giving pilot subsidies to reduce the technology adoption threshold and transformation cost, and promoting the balanced improvement of the overall disclosure level.

Nevertheless, this study also has the following limitations, which provide directions for future research: First, based on observational panel data, we employ two-way fixed effects, IV, and lagged variables to mitigate endogeneity, yet omitted variable bias and reverse causality cannot be entirely excluded. Thus, our findings reflect statistical association rather than strict causality. Second, our sample covers only Chinese A-share listed firms, excluding unlisted ones. Given systematic differences in disclosure regimes and governance between the two groups, the generalizability of our conclusions should be confined to the listed-firm context. In addition, although we adopt the BERT model for semantic recognition to improve the accuracy of our FinTech indicator, measurement errors may persist due to the quality and availability of textual disclosure data. Third, this paper has verified two paths. However, the relative importance of these two paths in different enterprise characteristics and institutional environments still requires further research. Future studies can combine industry characteristics, enterprise life cycle, and institutional background to further identify the dominant conditions and differences in the effects of different mechanisms.

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