



Research article

Optimization mechanisms of corporate philanthropy for sustainable development: A two-stage network DEA approach

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Abstract: While corporate philanthropy is a core component of strategic Corporate Social Responsibility (CSR), its capacity to enhance corporate productivity and drive sustainable development remains contested. Utilizing a panel dataset of Chinese A-share listed firms from 2018 to 2022, this study investigated the impact of corporate philanthropy on total factor productivity (TFP). Panel regression analysis revealed a significant inverted U-shaped relationship between charitable donations and TFP, establishing the existence of an optimal threshold for CSR resource allocation. Beyond this critical point, excessive donations trigger a resource-crowding effect that suppresses productivity growth. To unpack the underlying mechanism, we applied a two-stage network Data Envelopment Analysis (DEA) model, decomposing the CSR process into an initial resource-allocation stage and a subsequent value-conversion stage. The evaluation demonstrated that second-stage efficiency is significantly lower than first-stage efficiency, identifying downstream value conversion as the primary bottleneck in CSR value creation. Furthermore, moderation analysis indicated that while second-stage efficiency is negatively associated with subsequent TFP, first-stage efficiency positively moderates this relationship. Additionally, operating in a pollution-intensive industry negatively moderates the impact of both stage-specific efficiencies on TFP. These findings advance the theoretical understanding of strategic CSR processes and provide actionable insights for firms seeking to optimize the balance between philanthropic investment, operational efficiency, and sustainable development.

Keywords: corporate philanthropy; corporate sustainable development; financing constraints; Corporate Social Responsibility (CSR); government subsidies

Mathematics Subject Classification: Primary 90C08; Secondary 91B03, 90B50

1. Introduction

As the highest form of corporate social responsibility [1], philanthropy is not only a symbol of social harmony but also a vital tool for promoting social equity and common prosperity. Corporate giving has become a major focus for both academics and society. According to the China Charity Development Report (2023), total corporate donations in China have grown steadily, consistently exceeding 100 billion yuan in recent years. This accounts for approximately 60% of all charitable donations nationwide, making businesses a cornerstone of the charitable sector. This rapid growth in corporate philanthropy plays a crucial role in reducing wealth inequality, maintaining social stability, and supporting development in impoverished regions. However, while the external social benefits of corporate giving are evident, a critical question remains: how does this massive outflow of resources impact the donor firms' own economic viability and long-term growth?

For businesses, the ultimate goal of strategic CSR is not merely altruism but achieving a dynamic synergy between societal contributions and their own operational growth. This naturally brings the focus to corporate sustainable development. Corporate sustainable development refers to a firm's ability to maintain long-term viability and sustained growth while creating economic value and value for stakeholders. From an economic perspective, this requires firms to continuously optimize resource allocation, promote technological progress, and improve operational efficiency. Within this context, total factor productivity (TFP) is widely used as a critical indicator of firm productivity and economic sustainability [2]. To fully grasp this process, it is essential to clarify the logical chain linking corporate philanthropy, CSR investment, TFP, and corporate sustainable development. In this paper, we argue that corporate philanthropy serves as a highly visible, strategic component of broader CSR investment. When managed effectively, philanthropic engagement allows firms to optimize their CSR resource allocation and strengthen stakeholder relations, which can theoretically enhance TFP. Ultimately, this sustained improvement in TFP acts as the foundational driver for achieving long-term corporate sustainable development.

However, this impact involves a complex trade-off between short-term resource consumption and long-term value creation. From the perspective of corporate finance and agency theory [3], philanthropy directly leads to outflows of cash and physical assets. In the short term, this reduces operational capacity and cash flow efficiency, potentially hurting profitability. Furthermore, if excessive donations exceed a firm's financial capacity or are driven by management's desire for personal reputation rather than shareholder interests, philanthropic activities may signal low resource allocation efficiency and a misuse of corporate resources. Conversely, stakeholder theory [4] suggests that philanthropy helps build a positive public image and deepens trust across ecosystems [5]. Donations can secure policy support, ease external resource constraints [6,7], and help firms gain critical resources for sustainable growth [8]. Similarly, signaling theory reveals that donations help firms establish a positive brand reputation [9,10], attract consumer support [11], and reduce information asymmetry, thereby boosting investor confidence.

Despite these theoretical insights, existing literature focuses predominantly on the direct, linear impact of donations on firm performance, often lacking a systematic deconstruction of the sustainable development process. To address this gap, this study proposes a unified analytical framework that combines econometric panel regression with a two-stage network Data Envelopment

Analysis (DEA) model. These two methods serve distinct yet highly complementary roles. The regression analysis is employed to establish the overarching causal relationship and identify specific nonlinear boundaries between corporate philanthropy and sustainable development (measured by TFP). In contrast, the two-stage network DEA model is utilized to open the “black box” of this causal chain by evaluating the internal, stage-by-stage operational efficiency of the CSR process. Because these methods serve different analytical purposes, they utilize different input and outcome indicators: regression captures the average net effect of philanthropy on productivity, whereas DEA measures the relative technical efficiency of transforming CSR resources. Together, they form a cohesive framework that answers both what the overarching impact is and how efficiently CSR resources are internally converted into sustainable productivity. Clarifying these underlying mechanisms provides practical guidance for firms seeking to navigate the balance between short-term costs and long-term value.

Guided by this unified framework, this paper makes three specific contributions to the literature. First, at the theoretical level, we clarify the transmission mechanism linking philanthropy, CSR, TFP, and sustainability. Moving beyond traditional linear assumptions, we confirm a significant inverted U-shaped relationship between corporate philanthropy and firm sustainability, identifying an optimal threshold for resource input. Second, at the methodological level, we innovate by applying a dual-method approach that decomposes the CSR “black box” into two distinct stages: an initial resource-allocation stage and a subsequent value-conversion stage. By using the network DEA model alongside our regression analysis, we identify that downstream value conversion acts as the primary bottleneck preventing CSR-related resources from translating into firm value and sustainable growth. Finally, at the institutional level, we build a nested framework linking micro-behavior with external industry contexts. Specifically, we systematically examine the heterogeneous moderating effects of operating in a pollution-intensive industry on CSR performance. These findings offer a scientific basis for firms aiming to achieve dynamic synergy between economic and social value, while providing decision-making references for regulators seeking to improve CSR governance.

The rest of this paper is structured as follows: Section 2 systematically reviews the existing literature on the relationship between corporate philanthropy and sustainable development. Section 3 elaborates on the relevant theoretical foundations and proposes the research hypotheses of this study. Section 4 introduces the research data and empirical methodology adopted in the paper. Section 5 presents the results of empirical tests, together with detailed regression analysis and two-stage network model estimation results. Finally, the last section summarizes the research conclusions, implications, and limitations of this study.

2. Literature review

2.1. Research on corporate philanthropy

Current research on corporate philanthropy primarily focuses on its impact on firm performance and the underlying motivations for such behavior. Some scholars argue that corporate philanthropy has a positive impact on business performance. [12] demonstrated that philanthropy can improve financial performance by helping firms build stronger government ties, gain social-political legitimacy, and secure positive reactions from stakeholders. Similarly, Seo et al. [13] found a strong positive correlation between the types of charity supported by large U.S. public firms and their

profitability. [6] confirmed that philanthropy significantly boosts earnings persistence. They argued that increased donations lead to more government subsidies, lower financing costs, higher innovation levels, and more stable customer relationships. These inputs, such as political, financial, innovative, and customer resources, collectively enhance earnings persistence.

Conversely, other scholars argue that philanthropy negatively affects performance. They contend that firms should not engage in philanthropy because it represents a pure expense that diverts valuable resources and distracts management [14]. It may also be used merely to enhance the personal reputation of managers [15]. Masulis and Reza [16] found that, while some firms donate frequently and in large amounts, there is no clear evidence that these expenditures positively affect corporate revenue, performance, or shareholder wealth. Shen et al. [17] observed that donations can distort managerial psychology, creating cognitive biases like over-optimism, which in turn leads to over-investment. Furthermore, major shareholders may use philanthropy to extract private benefits, which harms the interests of minority shareholders and hinders long-term development [18]. Finally, as litigation risk for listed companies rises, the instrumental value of philanthropy diminishes. Fu and Yuan [19] suggested that if major shareholders attempt to use donations to maintain their reputation after pledging their equity, it may be futile and ultimately result in a waste of corporate resources.

Existing research categorizes corporate donation motives into four types: altruistic, profit-driven, managerial self-interest, and political motives. Using an ensemble learning approach, Chen et al. [20] compared the predictive power of these multi-dimensional motives and found that internal governance is the primary driver of corporate philanthropy. Similarly, Xie et al. [7] examined the relationship between donation capacity, motives, and behavior. They found that for non-state-owned enterprises, donation behavior is driven more by strategic self-interest than by actual financial capacity.

As the key initiators of donation decisions, managers often gain private benefits such as social prestige or political capital. These actions simultaneously enhance their personal public welfare reputation and expand their social capital [18,21]. Essentially, corporate philanthropy is a form of CSR. Existing literature suggests that donation behavior often stems from complex strategic motives. On one hand, firms may use charity as a reputation management tool to distract the public from potential misconduct and improve organizational legitimacy [22]. On the other hand, philanthropy serves as a link to strengthen ties between firms and the government. Through strategic giving, firms establish stable interactions with government departments, reducing regulatory scrutiny while securing policy support. This duality highlights the instrumental nature of corporate philanthropy in fulfilling social responsibility, as well as the underlying logic of competing interest groups.

2.2. Research on corporate sustainable development

Academic research on corporate sustainable development mainly focuses on conceptual definitions, quantitative methods, and key determinants. The concept of corporate sustainability has received extensive attention. Muttakin et al. [23] defined it as a systematic business approach and strategy that considers the long-term social and environmental impacts of all economic activities on consumers, employees, owners, and shareholders. The concept of sustainability value has expanded corporate goals beyond simple economic or social maximization toward the maximization of sustainable development targets.

Jiang et al. [2] argued that the essence of driving corporate sustainability lies in enhancing total factor productivity (TFP). This shifts the development model from a focus on scale to a focus

on quality, ensuring that firms maintain long-term viability in highly competitive environments. In this view, the process of promoting TFP is synonymous with the process of advancing corporate sustainable development.

Regarding the determinants of corporate sustainable development, existing literature focuses on both internal innovation and external factors. Innovation is widely regarded as a key driver of sustainability. In the technology sector, Huang et al. [24] found that technical innovation support promotes financial sustainability in the new energy industry. Digital transformation also helps firms enhance R&D capabilities, improve internal controls, and optimize corporate governance. These mechanisms boost resource allocation efficiency, build core competitiveness, and drive sustainable growth [25]. Jie and Jiahui [26] showed that media attention promotes sustainability directly and indirectly by increasing green patent authorizations, which act as a mediator.

Beyond innovation, Li et al. [27] noted that optimized resource allocation is the endogenous engine of TFP growth, providing the bedrock for sustainability. Financial asset distribution is particularly critical, as it influences broader operational capabilities and plays an irreplaceable role in improving TFP [28]. Li and Li [29] pointed out that ESG engagement significantly improves productivity by conserving energy and streamlining resource use. Stakeholder pressure also encourages firms to reduce inefficient investment and increase capital utilization, thereby fostering sustainability [30]. Exploring external factors, Bagh et al. [31] demonstrated that distortions in capital and labor markets negatively impact firm value. However, high-quality institutions can mitigate these effects by improving market efficiencies. Finally, Huang et al. [32] found that trade credit significantly promotes sustainable growth in Chinese firms, especially for those with strong internal controls, suggesting that well-managed credit arrangements provide reliable financial scaffolding for long-term growth.

2.3. The nexus between corporate philanthropy and sustainable development

Although corporate philanthropy and sustainable development are inherently linked, the synthesis of these two research streams remains remarkably limited. Most existing studies isolate the two concepts: philanthropy research fixates on short-term financial returns and agency conflicts, while sustainability research prioritizes internal innovation and ESG metrics without thoroughly deconstructing the strategic value of philanthropic inputs.

A few pioneering studies have begun to bridge this gap. Wu and Zhang [33] identified a mutually reinforcing cycle where donations boost performance through brand value, which in turn fuels further strategic giving. Furthermore, Baumgartner [34] and Lu et al. [35] suggested that when philanthropy aligns with a firm's core competencies, it transcends traditional charity, minimizing systemic losses through optimized resource allocation and acting as a strategic pivot for long-term competitive advantage.

Despite these preliminary connections, closely related studies primarily assume a direct, linear relationship between philanthropy and firm outcomes and broadly treat the CSR value-creation process as a "black box". Our study addresses these critical gaps and differentiates itself from existing research by providing the following specific theoretical and methodological contributions: At the theoretical level, unlike prior studies that search for a simple positive or negative linear effect of donations on financial performance, this study systematically links corporate philanthropy directly to corporate sustainable development via the mechanism of TFP. We advance existing theory by

identifying an inverted U-shaped nonlinear relationship. Specifically, our findings demonstrate that while philanthropy initially optimizes resource allocation, excessive donations cross a critical threshold and trigger a phased value-transmission bottleneck, thereby clarifying the optimal boundary for CSR investments. At the methodological level, previous literature often utilizes singular empirical methods to test macro-level impacts, largely ignoring the internal efficiency of how philanthropic inputs are actually converted into sustainable outcomes. To address this, this study contributes a novel, unified analytical framework that pairs econometric regression analysis with a two-stage network DEA model. While the regression analysis robustly tests the overall directional impact and nonlinear boundaries, the network DEA opens the CSR “black box”. By separating the process into a resource-allocation stage and a value-conversion stage, we provide a micro-level measurement of transformation efficiency, precisely identifying where corporate resources become congested in the pursuit of sustainable development.

3. Theoretical analysis and research hypotheses

The impact of corporate philanthropy on sustainable development can be analyzed through the lenses of internal corporate environments and external institutional constraints. Internally, philanthropy helps firms ease financing constraints [36], facilitates resource acquisition, and gains employee support, which collectively encourage higher productivity [37]. Smith [38] also confirmed that strategic philanthropy improves production efficiency. Furthermore, philanthropy signals a firm's commitment to social responsibility. Social identity theory suggests that job seekers prefer firms with strong social performance (Zhang et al., 2024) [30], which helps firms optimize their human capital, drive R&D, reform organizational structures, and improve management efficiency [39]. Firms with a strong sense of social responsibility also attract investors, and this improved access to capital enhances total factor productivity (TFP) [40]. In the broader supply chain, a manufacturer's implementation of CSR is conducive to generating higher product quality, increased outsourcing volume, and enhanced profitability for all supply chain members [41]. As consumers' awareness of social responsibility continues to grow, their willingness to pay a premium for socially responsible products also increases, turning CSR into a strategic tool for profit generation [42].

However, donations also inherently consume corporate resources and increase operational costs [43]. This resource drain may limit the implementation of profitable projects, hinder long-term sustainability, and reduce resource allocation efficiency. Because donations directly deplete a firm's critical working capital [44], they can trigger a crowding-out effect. Gu and Peng [45] noted that when resources are limited, funds allocated to philanthropy crowd out the investments needed for core development and expansion. Specifically, excessive philanthropy may crowd out R&D expenditures, thereby weakening a firm's innovation capabilities [46]. Moreover, in firms with weak internal governance, philanthropy may serve as a mechanism for self-interested managers to abuse corporate assets for personal reputational gain [44].

Externally, corporate philanthropy helps firms build strong stakeholder ties and gain a competitive edge. The government is a key external stakeholder and a primary source of policy support. During regional industrial upgrades or high-quality development initiatives, firms often increase donations to align with local government goals. This alignment helps them secure policy support, subsidies, and lucrative government projects [47,48], ultimately leading to better access to

external financing [49]. By building this social reputation capital, philanthropy positively affects a firm's overall resource acquisition capabilities.

Nevertheless, given inherent resource constraints, corporate philanthropy cannot expand indefinitely without triggering diminishing marginal returns. Initially, moderate donations help build reputation, strengthen stakeholder networks, and boost market trust. These gains improve resource access and organizational efficiency, thereby enhancing TFP and supporting high-quality growth. However, once donation expenditures exceed the marginal returns in reputation and external resources, firms face severe resource allocation distortion. Significant resources are diverted to philanthropy, forcing detrimental cuts to core operations, R&D, and capital investment. This decline in allocation efficiency hinders long-term productivity growth. Consequently, resource misallocation and efficiency losses suppress TFP, ultimately harming the firm's sustainable development. Thus, the impact of philanthropy on TFP is not linear; rather, it follows a nonlinear pattern of being moderately beneficial but excessively harmful. Based on this logic, we propose the following hypothesis:

H1: There is an inverted U-shaped relationship between corporate philanthropy and firm TFP.

In recent years, corporations have focused increasingly on stakeholder engagement, and investment practices have placed greater emphasis on sustainability [50]. Based on the resource-based view (RBV), CSR investments, such as philanthropy and employee compensation, are strategic inputs for building intangible assets like reputation and stakeholder trust [51]. However, this value conversion is not a simple linear process; it is often hampered by conversion friction and execution lags. While existing studies suggest a positive link between CSR and firm value [52], they often overlook the system efficiency losses that occur between front-end resource allocation and back-end value realization. There are significant nonlinear conversion costs when translating reputation into actual financial performance [53].

From a two-stage network DEA perspective, corporate sustainability depends on the dynamic synergy between CSR resource allocation and strategic asset conversion. In the first stage, firms have high autonomy in turning inputs into intermediate variables like reputation and policy support. However, when attempting to convert these intermediate assets into tangible firm value and productivity (the second stage), a lack of core business responsiveness often causes severe transmission bottlenecks. Due to frictions in capital markets and the broader business environment, the unconstrained expansion of front-end resources often leads to both allocation surplus and value conversion gaps. Consequently, the marginal output of CSR investment decays significantly through these intermediate stages, preventing the system from reaching optimal efficiency.

Crucially, the first and second stages are not independent; they constitute a continuous, sequentially linked transformation process. First-stage efficiency reflects a firm's ability to convert initial CSR inputs (e.g., donations) into intermediate strategic resources (e.g., reputation, financing conditions, and government subsidies). Second-stage efficiency reflects the firm's ability to integrate and utilize these intermediate resources, transforming them into TFP and sustainable growth. Therefore, the effectiveness of second-stage value conversion is heavily dependent on the foundation laid in the first stage. When a firm exhibits high first-stage efficiency, it generates high-quality intermediate resources. These resources provide better conditions for subsequent value realization, making it easier to integrate CSR outcomes into core operations and technological innovation. Under such circumstances, improvements in second-stage efficiency are more likely to translate into enhanced productivity. Conversely, if first-stage efficiency is low, even a highly efficient second-stage process will be constrained by a lack of quality intermediate resources, limiting TFP

growth. Therefore, a complementary relationship exists: the higher the first-stage efficiency, the stronger the positive relationship between second-stage efficiency and firm TFP.

H2a: The efficiency of the second stage of CSR value conversion is significantly lower than that of the first stage, demonstrating a phased value-transmission bottleneck effect in CSR investment.

H2b: First-stage efficiency positively moderates the relationship between second-stage CSR value-transmission efficiency and firm TFP.

Finally, the efficiency of CSR value transmission is not determined entirely by internal capabilities; it is fundamentally constrained by the industry environment. Based on the institution-based view and contingency theory, the value conversion mechanism of CSR is dynamically shaped by industry competitive features and the macro-institutional environment. Different industries vary drastically in their social impacts, environmental risks, and stakeholder pressures.

Compared with non-polluting industries, pollution-intensive industries typically face stricter environmental regulations, higher environmental risks, and greater pressure to maintain basic social legitimacy. In these industries, CSR activities often serve a defensive purpose—meeting regulatory requirements and mitigating environmental crises—rather than an offensive, value-creating purpose. Consequently, the intermediate resources generated (such as CSR ratings and government tolerance) are exceedingly difficult to transmit directly into productive resources or technological progress. Because firms in pollution-intensive industries face intense public scrutiny and capital-market skepticism, their reputational resources and policy support are less readily converted into market recognition and long-term operating performance. Therefore, the negative externalities inherent to pollution-intensive industries suppress the entire CSR value-transmission chain.

H3: Pollution-intensive industry status negatively moderates the relationships between both stage-specific CSR conversion efficiencies (Stage 1 and Stage 2) and firm TFP.

4. Methodology

4.1. Sample selection and data sources

To examine the impact of corporate philanthropy on high-quality development, this study selects A-share listed companies in China from 2018 to 2022 as the initial sample. The sample is refined according to the following criteria: (1) excluding firms in the financial industry; (2) removing firms labeled as ST or *ST; and (3) discarding observations with missing values for key variables. Furthermore, to mitigate the potential influence of extreme outliers on the empirical regression results, all continuous variables are winsorized at the 1st and 99th percentiles. The final sample consists of 2381 firm-year observations. The data used in this study are sourced from the China Stock Market and Accounting Research (CSMAR) database.

4.2. Regression model

To investigate the inverted U-shaped relationship between corporate philanthropy and total factor productivity (TFP), we specify the following baseline regression model:

$$TFP_LP_{i,t} = \alpha_0 + \alpha_1 Donation_{i,t} + \alpha_2 Donation_Sqr_{i,t} + \sum Controls_{i,t} + \sum Ind + \sum Year + \varepsilon_{i,t} \quad (1)$$

Where i denotes the firm, and t denotes the year. $\beta_{i,t}$ represents the regression coefficients for each variable, and $\varepsilon_{i,t}$ represents the error term. $TFP_LP_{i,t}$ denotes the firm's total factor productivity, $Donation_{i,t}$ represents corporate philanthropy, $Donation_{i,t}^2$ represents the squared term of corporate philanthropy, and $Controls_{i,t}$ denotes a set of control variables. Additionally, this study includes industry and year fixed effects to control for the impact of potential industry-specific and time-invariant factors on total factor productivity.

4.2.1. Definition of variables

Dependent variable: Corporate sustainable development ($TFP_LP_{i,t}$). Total factor productivity (TFP) serves as a core indicator of resource utilization efficiency and technological progress. It is widely adopted in existing literature as a proxy for corporate sustainable development [2,54,55]. Various methods exist for measuring TFP, including the LP, OP, FE, GMM, and OLS approaches. Following Hu et al. [56] and Wang and Wang [57], this study adopts the Levinsohn-Petrin (LP) method to estimate TFP. By incorporating intermediate inputs as proxy variables, the LP method effectively mitigates the endogeneity problem in production function estimation, thereby reducing estimation bias and enhancing the accuracy and reliability of the TFP measure.

Independent variable: Corporate philanthropy ($Donation_{i,t}$). Following Li et al. [58], this study measures corporate philanthropy using the annual actual donation amount. The donation amount is scaled by a factor of 10 million to normalize the variable and improve the readability of the regression results.

Control variables: Drawing on related research by Zhao et al. [59], Li et al. [60], and Huang and Gao [61], this study incorporates the following control variables: Asset-liability ratio ($Lev_{i,t}$), return on assets ($ROA_{i,t}$), firm age ($Age_{i,t}$), operating income growth rate ($Growth_{i,t}$), Tobin's Q ($TobinQ$), operating net cash flow ($Cashflow_{i,t}$), top ten shareholder ownership ($Top10_{i,t}$), management expenses ($Mfee_{i,t}$), management shareholding ratio ($Mshare_{i,t}$), number of independent directors ($Indep_{i,t}$), board size ($Board$), CEO duality ($Dual_{i,t}$), and Big Four audit ($Big4_{i,t}$). These variables are included to control for firm-level financial conditions and corporate governance factors that may influence TFP.

Table 1. Variable definitions and measurements.

Variable category	Variable name	Symbol	Definition
Dependent variable	Total factor productivity	TFP_LP	TFP measured by the LP method
Independent variables	Corporate philanthropy	Donation	Amount of corporate donations/10,000,000
	Squared term of corporate philanthropy	Donation_Sqr	Square of the corporate donation amount
Control variables	Asset-liability ratio	Lev	Total liabilities/total assets
	Return on assets	ROA	Net profit/total assets
	Firm age	FirmAge	$\ln(\text{current year} - \text{year of incorporation} + 1)$
	Operating income growth rate	Growth	$\frac{\text{Operating Revenue_current year} - \text{Operating Revenue_previous year}}{\text{Operating Revenue_previous year} - 1}$
	Firm value	TobinQ	Tobin's Q value
	Operating Net cash flow	Cashflow	Net cash flow from operating activities/total assets
	Top Ten shareholder ownership	Top10	Shares held by top ten shareholders/total shares
	Management expenses	Mfee	Management expenses/operating revenue
	Management shareholding ratio	Mshare	Shares held by management/total shares
	Proportion of independent directors	Indep	Number of independent directors/total number of directors
	Board size	Board	$\ln(\text{number of directors on the board})$
	CEO duality	Dual	1 if the Chairman and General Manager are the same person; 0 otherwise
	Big Four audit	Big4	1 if the company is audited by the Big Four firms; 0 otherwise

4.3. Two-stage network DEA model

To further investigate the efficiency of corporate social responsibility (CSR) in promoting sustainable development, this study employs a two-stage network DEA model to analyze the efficiency of corporate sustainable development. Data envelopment analysis (DEA) is a widely used linear programming method for multi-input and multi-output systems. It does not require a prior specification of weights or the functional form of the production function, allowing efficiency scores

to be derived directly from model calculations. However, traditional DEA methods are often referred to as black-box evaluations, as they tend to overlook the internal structure or processes of decision-making units (DMUs) and fail to examine the linkage between inputs and outputs, thereby significantly reducing the accuracy of the evaluation. For instance, the inefficiency caused by the network-structured DMUs cannot be specified by the classic DEA models [62]. To address this, Kao and Hwang [63] introduced the relational network DEA model, which reflects the interrelationships between sub-stages by introducing constraints that equalize the weights of two-stage indicators. Network DEA models are applicable to the evaluation of DMUs composed of two or more sub-processes; by opening the black box, they enable an in-depth exploration of input-output linkages, yielding more meaningful efficiency estimates.

Assume there are n decision-making units (DMUs), with m inputs, k intermediate variables, s outputs, and i denoting the specific DMU. The input vector for the first stage is $X_i = (X_{i1}, X_{i2}, \dots, X_{im})$. The vector representing the output of the first stage and the input of the second stage is $Z_i = (Z_{i1}, Z_{i2}, \dots, Z_{ik})$, while the output vector for the second stage is $Y_i = (Y_{i1}, Y_{i2}, \dots, Y_{is})$. The weight vectors for the input variables, intermediate variables, and output variables are denoted as $V = (v_1, v_2, \dots, v_m)$, $W = (w_1, w_2, \dots, w_k)$, and $U = (u_1, u_2, \dots, u_s)$, respectively. The objective function and constraints are formulated as follows:

$$\begin{aligned} E_k &= \text{Max} U^T Y_k \\ \text{S.t. } V^T X_k &= 1 \\ U^T Z_i - V^T X_i &\leq 0 \\ W^T Z_i - V^T X_i &\leq 0 \\ U^T Y_i - W^T Z_i &\leq 0 \\ V &\geq \varepsilon e_m, \quad U \geq \varepsilon e_s, \quad W \geq \varepsilon e_k \end{aligned} \quad (2)$$

Let ε denote a non-Archimedean infinitesimal and $e^T = (1, 1, \dots, 1)$. Given the optimal solutions V^*, W^*, U^* , the overall efficiency is defined as $E_k = U^{*T} Y_k / V^{*T} X_k$. The efficiencies for the first and second stages are given by $E_k^1 = W^{*T} Z_k / V^{*T} X_k$ and $E_k^2 = U^{*T} Y_k / W^{*T} Z_k$, respectively, which satisfy the relationship $E_k = E_k^1 * E_k^2$.

This paper adopts per capita employee compensation (total compensation/number of employees) as the proxy variable for firms' internal social responsibility, and corporate donations (actual corporate donation amount) as the proxy variable for firms' external social responsibility, both of which are taken as the input variables in the first stage. In addition, we select corporate reputation (corporate reputation score calculated via factor analysis), financing constraint index (KZ index), corporate social responsibility score (the social dimension score of the Huazheng ESG rating index), and government subsidies (actual amount of government subsidies) as intermediate variables. The output variables of the second stage include firm value (total market value/total assets) and the Van Horne corporate sustainable growth index, which is calculated as: $\text{net profit margin} \times \text{retention ratio} \times (1 + \text{equity ratio}) / [1 / \text{total asset turnover} - \text{net profit margin} \times \text{retention ratio} \times (1 + \text{equity ratio})]$.

4.4. Moderating effect model

This paper incorporates the efficiency scores from the two-stage network DEA model into a panel regression model to further examine the relationship between stage-specific efficiency and firm TFP. Given the continuity of CSR resource transmission and the complementarity between the two

stages, the intermediate strategic resources formed in the first stage may provide the necessary foundation for second-stage value transmission. Therefore, this paper uses the interaction term between first-stage efficiency and second-stage efficiency (i.e., overall efficiency) to examine whether first-stage CSR resource-allocation efficiency strengthens the relationship between second-stage CSR value-transmission efficiency and firm TFP. The specific model is as follows:

$$TFP_LP_{i,t} = \beta_0 + \beta_1 E_{i,t-1}^1 + \beta_2 E_{i,t-1}^2 + \beta_3 E_{i,t-1}^1 * E_{i,t-1}^2 + \sum Controls_{i,t} + \sum Ind + \sum Year + \varepsilon_{i,t} \quad (3)$$

Where TFP_LP_{it} denotes the total factor productivity of firm i in period t ; $E_{i,t-1}^1$ and $E_{i,t-1}^2$ denote the first-stage CSR resource-allocation efficiency and second-stage CSR value-transmission efficiency of firm i in the previous period, respectively; the remaining variables are consistent with those in the previous regression model. If the coefficient of the interaction term, β_3 , is significantly positive, this indicates that first-stage efficiency positively moderates the relationship between second-stage efficiency and firm TFP. In other words, the higher the first-stage CSR resource-allocation efficiency, the stronger the marginal effect between second-stage value-transmission efficiency and firm productivity, thereby supporting H2b.

Furthermore, given that the environmental characteristics of a firm's industry may affect the value-transmission process of CSR resources, this paper incorporates pollution-intensive industry characteristics into the moderating effect model. Pollution-intensive industries typically face stricter environmental regulation, higher environmental governance costs, and greater pressure to maintain social legitimacy. These factors may weaken the transmission of CSR resource-allocation efficiency and value-transmission efficiency into firm productivity. This paper uses the pollution-intensive industry dummy variable $Pollution_i$ to measure the negative externality characteristics of the industry in which a firm operates. $Pollution_i$ takes a value of 1 when the firm belongs to a pollution-intensive industry and 0 otherwise. The specific model is as follows:

$$TFP_LP_{i,t} = \theta_0 + \theta_1 E_{i,t-1}^1 + \theta_2 E_{i,t-1}^2 + \theta_3 E_{i,t-1}^1 * Pollution_i + \theta_4 E_{i,t-1}^2 * Pollution_i + \sum Controls_{i,t} + \sum Ind + \sum Year + \varepsilon_{i,t} \quad (4)$$

In Model (4), θ_3 measures the moderating effect of pollution-intensive industry characteristics on the relationship between first-stage efficiency and firm TFP, while θ_4 measures their moderating effect on the relationship between second-stage efficiency and firm TFP. If the interaction terms are significantly negative, this indicates that pollution-intensive industry characteristics weaken the relationship between the corresponding stage efficiency and firm TFP, thereby supporting H3.

5. Empirical analysis

5.1. Descriptive statistics

Table 2. Descriptive statistics.

Variables	N	Mean	SD	Min	Median	Max
TFP LP	2381	9.192	1.004	6.445	9.121	11.169
Donation	2381	0.689	1.402	0.000	0.108	5.965
Donation_Sqr	2381	2.441	7.728	0.000	0.012	35.580
Lev	2381	0.484	0.172	0.054	0.485	0.903
ROA	2381	0.054	0.043	0.000	0.043	0.228
FirmAge	2381	3.129	0.230	2.197	3.135	3.584
Growth	2381	0.140	0.268	-0.589	0.105	1.797
Cashflow	2381	0.066	0.062	-0.152	0.061	0.247
TobinQ	2381	1.621	1.038	0.813	1.254	7.892
Top10	2381	0.576	0.148	0.231	0.576	0.906
Mfee	2381	0.056	0.041	0.007	0.048	0.376
Mshare	2381	0.056	0.117	0.000	0.001	0.672
Indep	2381	0.377	0.055	0.333	0.364	0.571
Board	2381	2.160	0.189	1.609	2.197	2.565
Dual	2381	0.195	0.397	0.000	0.000	1.000
Big4	2381	0.127	0.333	0.000	0.000	1.000

As shown in Table 2, the mean value of corporate total factor productivity (TFP) is 9.192, with a standard deviation of 1.004. This indicates significant heterogeneity in TFP across firms. Furthermore, over half of the enterprises fall below the mean, suggesting substantial room for improvement for most firms. The value of corporate donations ranges from a minimum of 0 to a maximum of 5.965. While more than half of the firms actively fulfill their social responsibilities, the high standard deviation indicates notable disparities in donation levels among different companies. All other control variables remain within reasonable ranges.

5.2. Analysis of regression results

Table 3 presents the baseline regression results. Column (1) shows that the linear term of corporate donation is positively associated with total factor productivity (TFP) at the 1% significance level, while the quadratic term is negative at the same level. This provides preliminary evidence of an inverted U-shaped relationship between corporate donation and TFP. Column (2) incorporates a series of control variables to account for other potential determinants of TFP. After controlling for these factors, the linear term remains significantly positive, and the quadratic term remains significantly negative at the 1% level. These results confirm that resource allocation is subject to a marginal optimal threshold. Corporate philanthropy promotes TFP only when it remains within an appropriate range; beyond this threshold, the

negative effects of excessive donation emerge, as the resulting resource crowding-out effect inhibits productivity growth.

To further verify the robustness of this relationship, we employ the *utest* command developed by Lind and Mehlum [64] to test the inverted U-shaped relationship. The regression results show that the inverted U-shaped relationship is significant at the 1% level in the model without control variables and remains significant at the 1% level after control variables are included. Meanwhile, the turning points all fall within the 95% confidence intervals calculated using the Fieller method, and the slope tests on both sides of the inverted U-shaped curve are significant, further confirming the existence of the inverted U-shaped relationship.

After controlling for other factors, the estimated turning point is 4.511, with a Fieller 95% confidence interval of [4.110; 5.116]. Thus, with 95% confidence, the optimal level of corporate donations that maximizes productivity is estimated to lie between RMB 41.10 million and RMB 51.16 million. The regression results indicate that corporate donations can promote total factor productivity and contribute positively to high-quality firm development only within an appropriate range. Once donations exceed this reasonable range, their negative effects begin to emerge, leading to a decline in total factor productivity and consequently hindering high-quality firm development.

Table 3. Result of regression analysis.

Variables	TFP_LP (1)	TFP_LP (2)
Donation	0.589*** (15.45)	0.378*** (13.67)
Donation_Sqr	-0.061*** (-9.36)	-0.042*** (-8.58)
Lev		2.161*** (21.78)
ROA		3.595*** (7.84)
FirmAge		-0.137** (-2.47)
Growth		0.075* (1.72)
Cashflow		-0.248 (-1.08)
TobinQ		-0.104*** (-6.14)
Top10		0.878*** (9.46)
Mfee		-8.986*** (-23.26)

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Variables	TFP_LP (1)	TFP_LP (2)
Mshare		-0.703*** (-6.80)
Indep		0.279 (1.01)
Board		0.246*** (2.94)
Dual		-0.074** (-2.31)
Big4		0.388*** (9.20)
cons	8.934*** (437.23)	7.768*** (24.48)
Industry FE	control	control
Year FE	control	control
N	2381	2381
adj. R2	0.42	0.71
T-statistic for the inverted U-shaped test	3.26(0.000)	3.62(0.000)
Turning point	4.844	4.511
95% confidence interval based on the Fieller method	[4.467;5.406]	[4.110; 5.116]
Left-side slope and t-statistic of the inverted U-shaped curve	0.589(15.447)	0.378(13.672)
Right-side slope and t-statistic of the inverted U-shaped curve	-0.136(-3.25)	-0.122(-3.615)

*Note: t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

5.3. Robustness tests

We conduct further robustness tests by re-estimating total factor productivity using the OP and GMM methods. As shown in columns (1) and (2) of Table 4, the primary coefficients of corporate donation are significantly positive at the 1% level, while the quadratic coefficients are significantly negative at the 1% level. These results are consistent with the baseline findings, confirming the robustness of our conclusions.

Table 4. Results of the robustness test.

Variables	TFP_OP (1)	TFP_GMM (2)
Donation	0.197*** (8.54)	0.563*** (16.31)
Donation_Sqr	-0.022*** (-5.27)	-0.064*** (-10.51)
Lev	1.431*** (16.81)	2.712*** (22.90)
ROA	2.901*** (7.86)	3.843*** (6.68)
FirmAge	-0.030 (-0.66)	-0.256*** (-3.89)
Growth	0.083** (2.26)	0.093* (1.67)
Cashflow	-0.744*** (-3.84)	0.342 (1.17)
TobinQ	-0.055*** (-4.15)	-0.164*** (-7.67)
Top10	0.517*** (6.81)	1.191*** (10.44)
Mfee	-7.822*** (-23.79)	-9.804*** (-20.24)
Mshare	-0.482*** (-5.58)	-1.123*** (-9.34)
Indep	-0.081 (-0.36)	0.956*** (2.88)
Board	-0.011 (-0.16)	0.551*** (5.35)
Dual	-0.034 (-1.26)	-0.092** (-2.38)
Big4	0.231*** (6.42)	0.516*** (10.09)
cons	5.636*** (21.65)	10.106*** (26.34)
Industry FE	control	control
Year FE	control	control
N	2315	2381
adj. R2	0.70	0.72

*Note: t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

5.4. Endogeneity test

Significant firm-level heterogeneity may lead to sample selection bias and endogeneity. Therefore, we employ propensity score matching (PSM) to mitigate these concerns. Specifically, we define firms that engage in donations (Donation_dum = 1) as the treatment group and those that do not (Donation_dum = 0) as the control group, using the previously identified control variables as covariates. We perform 1:1 nearest-neighbor matching with a caliper of 0.01 for robustness. Furthermore, considering that 1:1 matching may significantly reduce the sample size, we also conduct a 1:2 matching test. As shown in columns (1) and (2) of Table 5, the results are consistent with the baseline regression, confirming the robustness of our conclusions.

To address the potential endogeneity between corporate donations and total factor productivity, this paper employs an instrumental variable (IV) approach. Following Tang et al. (2024) [10], we use the average donations of other firms in the same year and industry, together with its squared term, as IV.

First, due to the existence of peer effects, firms' donation decisions are often influenced by the behavior of firms in the same region and industry. Therefore, the instrumental variables satisfy the relevance requirement. Second, the average donations of other firms in the same industry do not directly affect an individual firm's total factor productivity, thereby satisfying the exogeneity requirement.

According to the regression results reported in Columns (3)–(4) of Table 5, the KPF statistic is 46.242, which exceeds the 10% critical value of 7.03 proposed by Stock–Yogo, indicating that there is no weak-instrument problem. In addition, the KP_LM statistic is 82.703 ($p = 0.000$), indicating that the model is not underidentified. The results reported in Column (5) of Table 5 are consistent with those of the baseline regression, indicating that the conclusions of this study remain valid after controlling for endogeneity.

Table 5. Results of the endogeneity test.

Variables	1:1 Match(1) TFP_LP(1)	1:2 Match(2) TFP_LP(2)	IV method		TFP_LP(5)
IV			Donation	Donation_Sqr	
IV_Sqr			-1.046*** (-3.87)	-1.587 (-0.98)	
			-0.011 (-0.23)	-0.878*** (-2.88)	
Donation	0.406*** (4.13)	0.356*** (5.17)			0.441*** (3.53)
Donation_S	-0.046** (-2.69)	-0.041*** (-3.36)			-0.042** (-1.98)
Lev	2.104*** (10.02)	2.336*** (12.85)	1.076*** (5.79)	4.286*** (4.11)	2.089*** (19.00)
ROA	5.354*** (6.34)	6.291*** (8.03)	3.226*** (3.32)	14.874*** (2.72)	3.365*** (7.12)

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Variables	1:1 Match(1)	1:2 Match(2)	IV method		
	TFP_LP(1)	TFP_LP(2)	Donation	Donation_Sqr	TFP_LP(5)
FirmAge	-0.022 (-0.20)	-0.015 (-0.16)	-0.303** (-2.44)	-1.624** (-2.29)	-0.121** (-2.14)
Growth	-0.034 (-0.42)	0.020 (0.27)	-0.081 (-0.78)	-0.228 (-0.37)	0.079* (1.78)
Cashflow	-0.415 (-0.92)	-0.825** (-2.04)	0.845* (1.79)	3.739 (1.48)	-0.296 (-1.31)
TobinQ	-0.209*** (-5.45)	-0.193*** (-5.71)	0.010 (0.28)	0.096 (0.49)	-0.104*** (-6.12)
Top10	1.206*** (5.58)	0.802*** (4.53)	-0.039 (-0.18)	-0.507 (-0.41)	0.864*** (9.32)
Mfee	-8.417*** (-11.06)	-8.375*** (-13.06)	-1.573*** (-2.61)	-6.833** (-2.12)	-8.946*** (-22.63)
Mshare	-0.894** (-3.18)	-0.596*** (-2.59)	0.336* (1.92)	1.466 (1.55)	-0.722*** (-6.87)
Indep	-0.396 (-0.63)	-0.231 (-0.47)	2.201*** (3.45)	14.346*** (3.93)	0.088 (0.30)
Board	0.025 (0.11)	0.036 (0.21)	0.933*** (4.49)	5.762*** (4.83)	0.184** (2.03)
Dual	-0.079 (-1.04)	-0.122* (-1.93)	0.009 (0.13)	0.047 (0.13)	-0.074** (-2.31)
Big4	0.406*** (4.76)	0.435*** (6.06)	0.871*** (7.18)	4.695*** (6.47)	0.333*** (6.67)
cons	7.980*** (9.83)	7.958*** (12.99)	-0.022 (-0.03)	-1.953 (-0.39)	7.835*** (22.78)
Industry FE	control	control	control	control	control
Year FE	control	control	control	control	control
N	542	794	2324	2324	2324
R2					0.71
adj. R2	0.74	0.72			

*Note: t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

5.5. Analysis of the results of the two-stage network DEA approach

Given that a higher KZ index generally indicates more severe financing constraints, KZ is a negative indicator and is positively transformed before being incorporated into the network DEA model. This transformation ensures that a higher normalized KZ value corresponds to weaker financing constraints. Meanwhile, to eliminate differences in measurement scales across indicators, all indicators are further normalized to the interval [0.1, 1]. The lower bound of 0.1 is mainly set to

ensure that all inputs, outputs, and intermediate products in each stage of the network DEA model remain strictly positive, thereby avoiding interruptions in stage linkages, undefined efficiency ratios caused by zero values, and numerical instability during estimation. The transformation formula is as follows:

$$KZ_i^{rev} = \max(KZ) - KZ_i \quad (5)$$

$$X_i^{norm} = 0.1 + 0.9 \frac{X_i - \min(X)}{\max(X) - \min(X)} \quad (6)$$

Table 6. Descriptive statistics of the normalized DEA indicators.

Variables	Mean	SD	Min	Median	Max
Donation	0.114	0.060	0.100	0.101	1.000
Salary	0.190	0.073	0.100	0.170	1.000
KZ	0.525	0.150	0.100	0.508	1.000
Subsidy	0.112	0.037	0.100	0.104	1.000
S_Score	0.638	0.163	0.100	0.645	1.000
Reputation	0.750	0.240	0.100	0.800	1.000
SGR	0.313	0.125	0.100	0.283	1.000
TBQ	0.193	0.127	0.100	0.149	1.000

Table 6 shows the descriptive statistics of the normalized DEA indicators. Donation and salary exhibit relatively small variances, indicating limited variation across observations. Reputation has the largest variance, suggesting that reputation levels differ most substantially across samples. S-score and KZ follow, also showing considerable variation across observations, whereas subsidy has a relatively small variance. SGR and TBQ exhibit relatively large standard deviations, indicating substantial differences across samples. These findings suggest that different CSR inputs may be associated with considerable variation in outcomes.

Table 7 provides the result of the two-stage DEA approach. Based on the industry averages from 2018 to 2022, the overall sustainability efficiency (E_k) of China's A-share listed companies is generally low. It fluctuates between 0.186 and 0.211, though it shows a slight annual upward trend. A decomposition based on the multiplicative relationship of the two-stage network DEA reveals a significant structural imbalance. Across the 16 industries in our sample, the first-stage efficiency (E_k^1) for most sectors consistently remains high, ranging from 0.60 to 0.79. For instance, the manufacturing sector (Category C)—the largest group in our sample—maintained an E_k^1 between 0.730 and 0.758 over the five-year period. This suggests that Chinese listed firms possess a strong capacity to convert initial CSR inputs into intermediate strategic assets, such as corporate reputation, CSR ratings, and government subsidies. In contrast, with the exception of the health and social work sector (Category Q), the second-stage efficiency (E_k^2) for nearly all industries remains low, typically between 0.20 and 0.35. The E_k^2 for the manufacturing sector only hovered between 0.273 and 0.302. The empirical results indicate that the primary bottleneck for sustainable development efficiency in Chinese firms lies in the second-stage value conversion, rather than the initial stage of CSR resource allocation. While firms are adept at converting tangible inputs, such as employee compensation and corporate donations, into intermediate strategic assets, they face serious resource waste or misallocation when transforming those assets into final firm value and sustainability outcomes. This

structural imbalance of high allocation, low conversion is the fundamental cause of the generally low efficiency across the industry.

To test H2b, we examine the moderating-effect regression results reported in Column (1) of Table 11. The coefficient of lagged second-stage efficiency is significantly negative at the 5% level. This finding is mathematically consistent with the DEA results, confirming that the second stage constitutes the primary bottleneck in corporate sustainable development. However, the coefficient of the interaction term (which mathematically represents overall efficiency) is significantly positive at the 10% level, suggesting that higher first-stage efficiency mitigates the negative relationship between second-stage efficiency and TFP.

Based on these coefficients, the theoretical threshold at which the marginal effect of second-stage efficiency on TFP becomes zero is approximately 0.934 (calculated as $1.471/1.575$). Only when a firm's first-stage efficiency exceeds this 0.934 threshold does the marginal effect of second-stage efficiency on TFP become positive. In other words, second-stage value transmission is exceedingly difficult to improve independently; its contribution depends heavily on whether the firm has already developed exceptional capabilities to transmit initial CSR-related inputs into intermediate strategic resources. Therefore, the primary challenge facing firms is not merely insufficient CSR resource investment but rather establishing an effective link between upstream resource formation and downstream value conversion. Only firms that maintain highly synergistic efficiency across both stages can successfully translate CSR-related resources into tangible productivity improvements, thereby supporting Hypothesis H2b.

Table 7. Results of the two-stage DEA approach.

Industry code	Firm count	E_k	E_k^1	E_k^2	E_k	E_k^1	E_k^2	E_k	E_k^1	E_k^2	E_k	E_k^1	E_k^2	E_k	E_k^1	E_k^2
		2018			2019			2020			2021			2022		
A	2	0.177	0.507	0.384	0.174	0.495	0.408	0.144	0.476	0.333	0.146	0.506	0.316	0.136	0.595	0.232
B	18	0.160	0.678	0.238	0.143	0.657	0.220	0.143	0.674	0.212	0.176	0.669	0.263	0.262	0.617	0.414
C	288	0.207	0.758	0.277	0.204	0.758	0.273	0.209	0.730	0.290	0.224	0.750	0.302	0.224	0.743	0.301
D	27	0.170	0.663	0.264	0.159	0.651	0.252	0.155	0.628	0.258	0.160	0.670	0.242	0.197	0.646	0.306
E	22	0.167	0.697	0.240	0.177	0.676	0.258	0.156	0.592	0.262	0.170	0.640	0.265	0.184	0.627	0.291
F	32	0.200	0.753	0.271	0.197	0.743	0.282	0.162	0.715	0.233	0.168	0.730	0.234	0.175	0.644	0.274
G	38	0.177	0.590	0.315	0.168	0.575	0.307	0.151	0.571	0.280	0.165	0.610	0.279	0.189	0.688	0.276
H	1	0.135	0.771	0.176	0.167	0.679	0.246	0.142	0.802	0.177	0.129	0.914	0.141	0.157	0.658	0.239
I	15	0.180	0.789	0.231	0.211	0.794	0.268	0.236	0.777	0.300	0.219	0.791	0.278	0.218	0.749	0.293
K	36	0.208	0.676	0.317	0.206	0.671	0.310	0.172	0.638	0.274	0.153	0.675	0.229	0.155	0.637	0.246
L	6	0.174	0.760	0.233	0.153	0.710	0.218	0.148	0.716	0.206	0.231	0.746	0.325	0.179	0.725	0.250
M	4	0.204	0.797	0.254	0.180	0.784	0.229	0.164	0.755	0.216	0.230	0.799	0.290	0.204	0.735	0.276
N	4	0.179	0.654	0.283	0.169	0.657	0.265	0.186	0.720	0.264	0.203	0.736	0.272	0.192	0.744	0.257
Q	3	0.393	0.666	0.623	0.463	0.656	0.746	0.461	0.704	0.681	0.515	0.596	0.856	0.492	0.633	0.770
R	5	0.155	0.675	0.272	0.134	0.664	0.239	0.117	0.617	0.212	0.155	0.665	0.235	0.151	0.620	0.246
S	3	0.174	0.632	0.288	0.191	0.660	0.315	0.225	0.625	0.373	0.253	0.690	0.385	0.253	0.659	0.386
	MEAN	0.191	0.692	0.292	0.194	0.677	0.302	0.186	0.671	0.286	0.206	0.699	0.307	0.211	0.670	0.316

Therefore, the primary challenge facing firms is not merely insufficient CSR resource investment but rather how to establish an effective link between the formation of upstream CSR resources and downstream value transmission. Only firms that maintain relatively balanced efficiency across both stages are more likely to transmit CSR-related resources into productivity improvements.

This dynamic is further illustrated by industry-specific case analyses. The Q-category (health and social work sector) exhibits high efficiency across both stages. Its overall efficiency E_k rose from 0.393 in 2018 to 0.515 in 2021 and remained at 0.492 in 2022. The core driver is the high efficiency of the second-stage value conversion, with E_k^2 reaching 0.856 in 2021 and 0.770 in 2022. As sectors with strong public welfare and social service attributes, healthcare firms can efficiently translate corporate reputation and government subsidies into corporate social value and sustainability indices, demonstrating a robust capacity to monetize positive externalities.

Conversely, for B-category (mining) firms, overall efficiency E_k remained in the low range of 0.14–0.17 from 2018 to 2021 before improving to 0.262 in 2022. This chronically low level of overall efficiency heavily reflects the negative externalities associated with the mining industry. Mining firms generally face stricter environmental regulations, higher environmental governance costs, and intense legitimacy pressure from investors and communities. Under these defensive conditions, CSR-related inputs and intermediate assets are primarily utilized to mitigate environmental risks, satisfy regulatory requirements, and maintain basic organizational legitimacy. Consequently, reputation and government-related resources cannot be easily transformed into productivity-enhancing activities or long-term firm value.

Finally, to test Hypothesis H3, we examine the moderating-effect regression results reported in Column (2) of Table 11. Among firms in non-pollution-intensive industries, lagged first-stage efficiency is significantly and positively associated with current TFP at the 1% level, while the coefficient of lagged second-stage efficiency is negative but statistically insignificant. However, when introducing the pollution-intensive industry dummy, the interaction terms between pollution-intensive industry characteristics and the efficiencies of both stages are significantly negative. These results indicate that operating in a pollution-intensive industry significantly suppresses the capacity of stage-specific CSR efficiencies to enhance firm TFP. This constraint is particularly pronounced in the second-stage value-transmission process, as reflected by the larger negative coefficient of the second-stage interaction term. This rigorously confirms Hypothesis H3, demonstrating that negative industry externalities severely weaken the CSR value-transmission chain.

Table 8 presents the top 10 firms ranked by overall efficiency. Our analysis indicates that only a select few companies, such as Unigroup Guoxin (002049) and Tongrentang (000672), achieve true dual-stage optimization. By maintaining efficiency scores near the production frontier in both initial resource allocation and subsequent value transformation, these firms construct a robust CSR value chain. They efficiently convert CSR investments, such as corporate donations, into intermediate strategic assets like reputation capital and government subsidies. Through superior value-transformation mechanisms, they subsequently drive a synergistic increase in both financial performance and sustainable development capacity. Consequently, these firms achieve a significant lead in overall efficiency, effectively bridging the gap between CSR fulfillment and high-quality economic development.

Table 8. Top 10 firms and years ranked by overall efficiency.

Year	Id	E_k	E_k^1	E_k^2	Industrial codes
2018	000672	0.642	0.709	0.905	C30
2022	002460	0.637	1.000	0.637	C32
2018	000055	0.630	0.786	0.802	C33
2019	002182	0.627	0.627	1.000	C32
2020	002507	0.624	0.756	0.826	C14
2022	002497	0.623	0.917	0.680	C26
2020	600763	0.617	0.690	0.895	Q83
2021	002049	0.617	0.617	1.000	C39
2021	600763	0.617	0.654	0.943	Q83
2021	600500	0.617	0.787	0.783	C26

Table 9 highlights the top 10 firm-year observations ranked by first-stage efficiency. Taking Ganfeng Lithium (002460) in 2018 and GAC Group (601238) in 2019 as examples, both firms achieved the efficiency frontier (1.000) in their initial CSR resource allocation. However, their second-stage value-conversion efficiencies remained severely low at 0.260 and 0.164, respectively, leading to suboptimal overall performance. This stark contrast illustrates that the impact of CSR investment on corporate sustainable development is neither an independent nor a linear process. A high level of first-stage efficiency only indicates that a firm can effectively allocate inputs to generate intermediate resources; it does not guarantee that these resources will be successfully translated into sustainable productivity. Ultimately, only through an efficient second-stage conversion mechanism can a firm fully translate CSR investments into operating performance, social benefits, and long-term developmental capabilities.

Table 9. Top 10 firms and years ranked by first-stage efficiency.

Year	Id	E_k	E_k^1	E_k^2	Industrial codes
2018	002460	0.260	1.000	0.260	C32
2019	601238	0.164	1.000	0.164	C36
2020	000650	0.193	1.000	0.193	C27
2020	002415	0.370	1.000	0.370	C39
2020	600585	0.306	1.000	0.306	C30
2021	601636	0.321	1.000	0.321	C30
2022	002460	0.637	1.000	0.637	C32
2019	002572	0.247	0.999	0.248	C21
2019	000895	0.289	0.998	0.289	C13
2018	002572	0.232	0.992	0.234	C21

Table 10 reports the top 10 firm-year observations ranked by second-stage efficiency. Firms leading in this stage, such as Unigroup Guoxin (002049) from 2020 to 2021 and Tongce Medical (600763) across multiple years, consistently reached or approached the efficiency frontier (1.000) in the second stage while simultaneously maintaining high first-stage input efficiency. These firms demonstrate exceptional resource integration capabilities, effectively converting accumulated

reputation and policy support into tangible firm value. This dynamic alignment of high allocation, high conversion, and high output ensures their competitive advantage in transforming CSR fulfillment into sustainable performance.

Conversely, Lishang Guochao (600738) achieved second-stage frontier efficiency in 2019, but its overall performance was severely constrained by its lagging first-stage resource-allocation efficiency. Lacking sufficient intermediate strategic assets, the firm could not effectively internalize its CSR efforts into core competitive advantages, resulting in a “low-input, low-output” dilemma. This stage-specific disruption further proves that even with high technical efficiency in downstream value conversion, a lack of upstream strategic resources prevents the realization of overall sustainability.

Table 10. Top 10 firms and years ranked by second-stage efficiency.

Year	Id	E_k	E_k^1	E_k^2	Industrial codes
2018	600763	0.582	0.582	1.000	Q83
2019	002182	0.627	0.627	1.000	C32
2020	002049	0.611	0.611	1.000	C39
2021	002049	0.617	0.617	1.000	C39
2019	600738	0.314	0.314	1.000	F52
2019	600763	0.603	0.622	0.970	Q83
2021	600763	0.617	0.654	0.943	Q83
2022	600763	0.616	0.663	0.930	Q83
2022	002049	0.610	0.672	0.908	C39
2018	000672	0.642	0.709	0.905	C30

Table 11. Moderating effect model.

	(1) TFP_LP	(2) TFP_LP
E_{t-1}^1	0.161 (0.56)	0.816*** (4.56)
E_{t-1}^2	-1.471** (-2.48)	-0.061 (-0.32)
$E_{t-1}^1 * E_{t-1}^2$	1.575* (1.81)	
$E_{t-1}^1 * Pollution_i$		-0.643** (-2.07)
$E_{t-1}^2 * Pollution_i$		-1.269*** (-4.26)
Lev	2.515*** (20.70)	2.536*** (20.88)
ROA	4.426*** (7.46)	4.694*** (7.93)

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	(1) TFP_LP	(2) TFP_LP
FirmAge	-0.200*** (-3.01)	-0.203*** (-3.08)
Growth	0.023 (0.46)	0.022 (0.45)
Cashflow	0.016 (0.06)	0.028 (0.10)
TobinQ	-0.075*** (-3.71)	-0.089*** (-4.38)
Top10	0.862*** (7.45)	0.805*** (6.97)
Mfee	-9.290*** (-20.19)	-9.254*** (-20.02)
Mshare	-0.699*** (-5.76)	-0.668*** (-5.51)
Indep	0.461 (1.50)	0.425 (1.38)
Board	0.334*** (3.44)	0.339*** (3.47)
Dual	-0.061 (-1.60)	-0.050 (-1.30)
Big4	0.507*** (10.00)	0.507*** (10.09)
Cons	7.628*** (17.47)	7.293*** (18.69)
Industry FE	control	control
Year FE	control	control
N	1903	1903
adj. R2	0.68	0.68

*Note: t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

5.6. Sensitivity analysis

The multiplicative model proposed by Kao and Hwang [63] effectively identifies the source of overall inefficiency, pinpointing whether the first or second stage contributes to low performance. However, this efficiency decomposition merely indicates the relative inefficiency of a given stage. It cannot determine whether a firm's stage-specific efficiency would shift from efficient to inefficient following a marginal change in a specific input variable. Furthermore, it does not explain the robustness of our finding that the CSR resource allocation stage exhibits superior efficiency compared to the value conversion stage; specifically, it fails to quantify the range of data perturbations within which this conclusion remains valid.

To address this, we refer to the stability radius (τ) for DEA efficiency proposed by Neralić and Wendell [65]. This metric measures the ratio by which an input-output vector must change to alter the efficiency classification of a decision-making unit (DMU), excluding itself from the reference set. For efficient DMUs ($\theta = 1$), τ^* represents the maximum allowable proportional increase in inputs while maintaining efficiency. For inefficient DMUs ($\theta < 1$), τ^* denotes the minimum proportional reduction in inputs required to reach the efficiency frontier. A value of τ^* equal to infinity indicates that the DMU's input-output combination is non-substitutable within the reference set. In such cases, the DMU cannot be enveloped by others, even with arbitrarily large input increases. We choose to calculate the stability radius using the independent-stage CCR model rather than the Kao and Hwang [63] two-stage network model. In the two-stage network DEA model, the first-stage efficiency E_1 measures the conversion capacity from inputs (X) to intermediate products (Z). The second-stage efficiency E_2 measures the conversion from intermediate products (Z) to final outputs (Y). Technically, these two conversion processes correspond to the production technologies of Independent Stage 1 CCR and Independent Stage 2 CCR, respectively. Therefore, the stability of stage efficiency should be evaluated within the corresponding stage-specific production possibility sets. We apply the independent CCR framework to calculate τ^* to ensure meaningful robustness tests at the stage level.

Table 12. Independent first-stage stability radius (τ) for DEA efficiency.

Year	id	τ^*_{-1}	E_k	E_k^1	E_k^2
2018	000417	inf	0.163	0.838	0.195
2018	000652	inf	0.198	0.862	0.229
2018	000895	inf	0.488	0.893	0.547
2018	002078	inf	0.323	0.938	0.344
2018	002083	inf	0.237	0.826	0.287
2018	002091	inf	0.278	0.905	0.307
2018	002460	inf	0.260	1.000	0.260
2018	002475	inf	0.336	0.841	0.399
2018	002572	inf	0.232	0.992	0.234
2018	600028	inf	0.091	0.949	0.096
2018	600180	inf	0.194	0.855	0.227
2018	600585	inf	0.369	0.971	0.380
2018	601179	inf	0.126	0.834	0.151
2019	000100	inf	0.148	0.967	0.153
2019	000623	inf	0.170	0.908	0.187
2019	000652	inf	0.158	0.908	0.174
2019	000672	inf	0.581	0.943	0.616
2019	000830	inf	0.213	0.889	0.239
2019	000895	inf	0.289	0.998	0.289
2019	002091	inf	0.251	0.888	0.283

*Note: τ^*_{-1} represents the sub-sample for the stability radius (τ^*) portion in the independent first stage.

In the social responsibility resource allocation stage, 54 DMUs exhibit $\tau^* = \infty$, while the remaining DMUs have $\tau^* = 0$. These 54 DMUs all achieve an independent first-stage efficiency of 1.0, positioning them on the stage-specific efficiency frontier. The $\tau^* = \infty$ value indicates that when these DMUs are excluded, no convex combination of other DMUs can achieve intermediate product outputs exceeding those of these DMUs while maintaining lower social responsibility inputs. However, within the K&H framework, the mean first-stage efficiency for these firms is 0.907, significantly higher than the full-sample mean of 0.714. Notably, the average overall efficiency of these 54 frontier-defining firms is only 0.246, which is marginally higher than the full-sample mean of 0.200, with only one firm ranking in the top ten for overall efficiency. Table 12 shows the independent first-stage stability radius (τ) for DEA efficiency. Taking firm ID 600028 (2018) as an example, in the independent Stage 1 CCR model, the firm achieves a perfect efficiency score of 1.0 with $\tau^* = \infty$, establishing an extreme and irreplaceable position in its donation-compensation strategy. However, under the K&H two-stage network model, its stage 1 efficiency is 0.949, while its stage 2 efficiency is only 0.096, resulting in an overall efficiency of 0.091, which is far below the sample average. This firm demonstrates that high efficiency in input strategy cannot compensate for a severe deficit in stage 2 investment conversion capacity; in other words, donating well does not equate to utilizing well. Regarding time trends, the number of DMUs with $\tau^* = \infty$ in the first stage decreased from 13 in 2018 to 3 in 2022, reflecting a gradual convergence in corporate donation-compensation input combinations.

Table 13. Independent second-stage stability radius (τ) for DEA efficiency.

Year	id	τ^*_2	E_k	E_k^1	E_k^2
2018	000014	inf	0.301	0.394	0.766
2018	000025	inf	0.360	0.540	0.667
2018	000055	inf	0.630	0.786	0.802
2018	000672	inf	0.642	0.709	0.905
2018	002451	inf	0.285	0.328	0.869
2018	600763	inf	0.582	0.582	1.000
2019	002016	inf	0.546	0.694	0.787
2019	002182	inf	0.627	0.627	1.000
2019	600683	inf	0.244	0.570	0.427
2019	600738	inf	0.314	0.314	1.000
2019	600763	inf	0.603	0.622	0.970
2020	000025	inf	0.314	0.682	0.460
2020	002049	inf	0.611	0.611	1.000
2020	002352	inf	0.209	0.421	0.497
2020	002451	inf	0.225	0.393	0.573
2021	002049	inf	0.617	0.617	1.000
2021	600141	inf	0.401	0.565	0.710
2021	600500	inf	0.617	0.787	0.783
2022	002049	inf	0.610	0.672	0.908
2022	600763	inf	0.616	0.663	0.930

*Note: τ^*_2 represents the sample for the stability radius (τ^*) portion in the independent second stage.

Table 13 presents the independent second-stage stability radius (τ) for DEA efficiency. In the value conversion stage, only 20 DMUs exhibit $\tau^* = \infty$, while τ^* values for the remaining DMUs are all 0. All of these units are also efficient in the independent stage 2 model. In sharp contrast to stage 1, these 20 frontier-defining units achieve an average overall efficiency of 0.468 under the K&H network model, which is significantly higher than the full-sample mean of 0.200. Among the top 10 DMUs with the highest overall efficiency, half are also independent stage 2 efficient units. This positive correlation indicates that the value conversion stage plays an irreplaceable role in the two-stage network model. It serves as the key pathway for firms to achieve high overall two-stage efficiency. Specifically, firm ID 000672 (2018) ranked as the full-sample optimum with an overall efficiency of 0.642, a K&H stage 2 efficiency of 0.905, and $\tau^* = \infty$. Firm ID 002049 achieved a K&H stage 2 efficiency of 1.0 multiple times during the sample period. These firms represent best practices in the efficiency of CSR input conversion in China. Their value conversion paths are difficult for other firms to replicate through simple combinatorial learning. Unlike the uniqueness but inefficiency observed in stage 1, the uniqueness of stage 2 stems from a superior capacity to convert intermediate resources—such as reputation capital, CSR scores, and government subsidies—into sustainable growth and market value. This capacity constitutes a genuine and enduring competitive advantage. Regarding time trends, the number of DMUs with $\tau^* = \infty$ in stage 2 decreased from 6 in 2018 to 2 in 2022. This suggests that as capital markets deepen their understanding of the value of charitable donations, the number of frontier-defining individuals is gradually decreasing. This indicates that corporate investment conversion paths are also converging, which is a positive signal for the overall improvement of industry efficiency.

Comparing the τ^* distributions across the two stages reveals that no DMU exhibits $\tau^* = \infty$ in both stages simultaneously. Firms cannot reach the efficient frontier of the independent CCR model in both stages, reflecting the distinct characteristics of CSR performance. Firms proficient in acquiring intermediate resources through CSR are often less capable of converting them into sustainable development, and vice versa. Furthermore, the mean overall efficiency of DMUs with $\tau^* = \infty$ in the second stage is 0.468, far exceeding the 0.246 observed for their counterparts in the first stage. While 25% of the former rank in the top ten of the full sample, only 1.9% of the latter do so. This indicates that the second stage—value conversion—is the core determinant of overall efficiency. The uniqueness of CSR resource allocation cannot be effectively translated into a competitive advantage across the entire chain. Finally, the number of DMUs with $\tau^* = \infty$ has declined annually in both stages. This suggests a trend toward strategic convergence in CSR fulfillment. Market mechanisms have eliminated extremely inefficient behavioral patterns, as both CSR investment and value conversion paths increasingly align with best practices.

6. Conclusions and implications

6.1. Conclusions

This study investigates the relationship between corporate philanthropy and sustainable development efficiency by integrating econometric regression analysis with a two-stage network DEA model. Our empirical results reveal a significant inverted U-shaped relationship between corporate donations and total factor productivity (TFP), establishing the existence of an optimal threshold in corporate resource allocation. While moderate philanthropic engagement acts as a

strategic asset facilitating sustainable development, excessive donations beyond this threshold trigger a resource-crowding effect that hampers productivity growth.

Furthermore, by employing the two-stage network DEA model to deconstruct the CSR value-creation mechanism, we identify the operational pathways through which philanthropy drives sustainability. The results indicate that the primary bottleneck for sustainable development in Chinese firms lies in the second-stage value conversion, rather than the initial stage of CSR resource allocation. While firms are adept at converting tangible inputs, such as employee compensation and corporate donations, into intermediate strategic assets, they face severe resource waste or misallocation when attempting to translate those assets into final firm value and sustainability outcomes. This structural imbalance of high allocation and low conversion is the fundamental cause of the generally low sustainability efficiency across the industry. In contrast, leading firms demonstrate a dual synergy between resource allocation and value conversion, effectively transforming philanthropic outlays into enduring competitive advantages and innovation momentum.

Our moderating effect analysis further highlights the critical role of inter-stage interactions and industry externalities. The regression results indicate that the effects of the two stages on firm productivity are deeply interdependent. Although the independent coefficient of second-stage efficiency is significantly negative (confirming the bottleneck), the positive interaction term between the two stages reveals a conditional complementary relationship. Specifically, when firms possess strong upstream capabilities to effectively convert CSR inputs into intermediate strategic resources, the downstream value-conversion process exerts a significantly more positive effect on firm productivity. Effective CSR value creation thus requires holistic coordination across both stages, rather than isolated improvements in a single stage. Additionally, our analysis shows that pollution-intensive industry characteristics significantly suppress the relationship between stage-specific CSR efficiency and firm TFP. Environmental regulatory pressure, high governance costs, and organizational legitimacy constraints heavily dilute the positive productivity effects of CSR. Consequently, firms in pollution-intensive industries not only face more pronounced downstream conversion constraints but also struggle to translate CSR efficiency improvements into tangible productivity gains. Ultimately, these findings confirm that philanthropy is not merely a social obligation but a strategic lever requiring precise calibration to balance social responsibility with operational efficiency.

To fully realize the dividends of donation-driven sustainable development, firms must shift their donation models from ad hoc, extensive philanthropy to strategic value co-creation. Rather than engaging in unconstrained spending, firms should utilize donations as a strategic tool to deepen supply-chain relationships and accumulate reputational assets. Companies must implement strategic calibration based on their specific efficiency profiles. Firms trapped in a high allocation and low conversion mismatch should optimize their donation targets, embedding philanthropic efforts directly into their core business and technological innovation to break the downstream bottleneck. Conversely, firms with high conversion efficiency should scale their human capital investments and stakeholder governance, using donations as a bond to solidify their sustainable development foundation. For firms in pollution-intensive sectors, CSR investments must be tightly integrated with environmental risk management, technological upgrading, and production efficiency improvements to overcome inherent industry penalties.

6.2. Limitations and future research

This study has several limitations that offer promising directions for future research. First, this paper does not systematically examine how overarching institutional factors, such as government policies, environmental regulations, and the macroeconomic environment, affect the CSR value-conversion process. The pollution-intensive industry dummy serves as a broad proxy, but it cannot fully capture nuanced differences in regional regulatory intensity, institutional quality, green-finance development, or macroeconomic policy shifts. Future research should incorporate these macro-level variables to evaluate how external shocks and institutional environments shape CSR resource-conversion efficiency.

Second, the two-stage network DEA model measures relative efficiency within the sample; thus, the efficiency scores do not necessarily represent absolute levels of CSR investment or value creation. Furthermore, while this study utilizes one-period-lagged efficiency scores to mitigate endogeneity, the moderating-effect regressions primarily capture conditional associations rather than definitive causal relationships. Future studies could employ system GMM paired with exogenous quasi-natural experiments to establish more robust causal evidence.

Finally, future research could disaggregate philanthropic activities by type (e.g., environmental conservation, educational funding, disaster relief, and local community investment) to examine their differential impacts on two-stage CSR value conversion. This granular approach would provide deeper insights into how the specific nature and targets of philanthropic activities, as well as their strategic alignment with core corporate operations, dictate corporate sustainable development outcomes.

Author contributions

All authors reviewed and approved the final version of the manuscript and accept responsibility for its content. Minghui Kang: Original draft writing, model calculation, data collection. Xubin Liu: Literature retrieval, empirical analysis, figure plotting; Jinghua Tan: Research design, framework construction, manuscript revision and finalization, project administration; Tao Wang: Conceptual discussion, result verification, proofreading. All authors have read and agreed to the final version of the manuscript.

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Use of Generative-AI tools declaration

No generative artificial intelligence tools (such as large language models, AI image generators, etc.) were used for writing, data analysis, figure generation or manuscript revision throughout the preparation of this paper. All content of this manuscript was independently completed by the authors.

Conflict of interest

The authors declare that there are no conflicts of interest that could affect the objectivity of this research. There are no commercial, financial or other relationships that may cause potential bias.

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