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Maximizing Environmental Returns under Capital Constraints: A Sectoral Optimization Model Using P-Graph

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Green investment is increasingly regarded as a critical driver of corporate environmental performance. Yet, decision-makers face a fundamental challenge: how to allocate limited green capital across diverse industrial sectors to achieve the most significant environmental impact. Existing approaches often lack normative guidance, providing limited support for strategic resource allocation. This paper develops a sectoral optimization framework using the P-Graph methodology to guide ESG investment allocation under capital constraints prescriptively. Using panel data from Chinese listed firms from 2011 to 2023, this study empirically estimates the marginal environmental returns of green investment across capital-, technology-, and labor-intensive sectors. These coefficients are embedded into a P-Graph model to determine the optimal allocation of green investment budgets. Results show that capital- and technology-intensive sectors deliver significantly higher environmental returns, whereas labor-intensive sectors contribute little or even negative returns. Budget simulations reveal threshold effects in investment efficiency, underscoring the need for strategic capital deployment. By integrating econometric analysis with network-based optimization, this study offers a prescriptive decision-support tool for ESG-driven investment planning in resource-constrained environments.

1. Introduction

In recent years, Environmental, Social, and Governance (ESG) considerations have gained traction in both financial markets and corporate strategic agendas. Institutional investors now routinely integrate ESG metrics into their capital allocation frameworks, particularly as environmental concerns rise amid global efforts to decarbonize (Laokulrach, 2025). Among ESG dimensions, the environmental (E) pillar has attracted heightened scrutiny, especially in China, where the national "dual carbon" strategy, peaking emissions by 2030 and achieving neutrality by 2060, has redefined industrial investment priorities and created a unique policy-driven context for ESG research (Xue et al., 2024). The Chinese A-share market also provides high-quality disclosure data and a broad cross-section of firms, making it a valuable setting for examining capital allocation under sustainability transitions. Green investment, broadly defined as firm-level capital expenditures aimed at reducing environmental externalities, is increasingly positioned as a core mechanism for corporate sustainability transitions (Khalid et al., 2025). However, its effectiveness and allocative efficiency remain contested. Resource constraints, whether in the form of fiscal tightening, policy ambiguity, or capital market imperfections, mean that firms and regulators must determine how to deploy limited green capital to generate maximum environmental impact.
While prior studies have explored the relationship between green investment and firm-level environmental outcomes through panel regressions and quasi-experimental designs (Li et al., 2024), these approaches are largely retrospective and descriptive. They provide evidence of average treatment effects but fall short of offering prescriptive guidance on how capital should be optimally distributed. Moreover, little research has integrated econometric evidence with optimization frameworks to produce actionable allocation strategies for ESG

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investment. The lack of a normative decision-support framework represents a significant gap in ESG investment research.

To address this, this research proposes an integrated empirical optimization approach. The study first estimates the marginal environmental return of green investment across firms using panel data of Chinese A-share listed companies from 2011 to 2023. These estimated coefficients are then incorporated into a Process Graph (P-Graph) model, an advanced combinatorial optimization technique developed initially for process network synthesis (Lim et al., 2025). While the P-graph has been successfully extended to applications such as food-energy-water nexus systems and renewable energy planning (Tan et al., 2024), its application in ESG capital allocation remains underexplored.

This study pioneers the use of the P-graph for optimizing environmental investment. By integrating econometric estimates with process-based decision modeling, it identifies the most efficient portfolio of green investments under capital constraints. The results offer both theoretical advancements, by linking environmental finance with operations research, and practical insights for ESG investors and policymakers in emerging markets undergoing structural green transitions. The remainder of the paper is organized as follows: Section 2 details the empirical strategy and model formulation; Section 3 introduces the empirical analysis and optimization Results; Section 4 presents the discussions and concludes.

2. Methodology

2.1 Research Design

This study adopts a two-stage analytical framework to address the core research question: how to optimally allocate limited green investment across industrial sectors to maximize environmental performance. The framework integrates fixed-effects regression estimation with combinatorial optimization using the P-graph methodology. In the first stage, firm-level environmental return on investment (EROI) is estimated via panel regressions, following methods established in prior ESG investment literature (Xue et al., 2024). Regression models are implemented using Stata 18, with firm and year fixed effects and clustered standard errors at the firm level to ensure robustness. These sector-specific estimates are then embedded into the P-graph model, which identifies the globally optimal capital allocation under budget constraints (Lim et al., 2025). Optimization is conducted in P-Graph Studio v5.2 using the Accelerated Branch-and-Bound (ABB) and Maximum Structure Generation (MSG) algorithms under default solver settings. As illustrated in Figure 1, the econometric module focuses on empirical diagnosis and causal inference, providing data-driven estimates that quantify EROI across sectors. The optimization module serves as a prescriptive decision-support system, mapping feasible capital allocation schemes and identifying the most effective investment combination. This dual structure bridges empirical estimation with strategic ESG resource planning, enabling performance-maximizing decisions under financial limitations. By combining regression-based insights with structural optimization, the framework advances sustainable finance research by operationalizing ESG capital allocation within a normative decision-support paradigm.

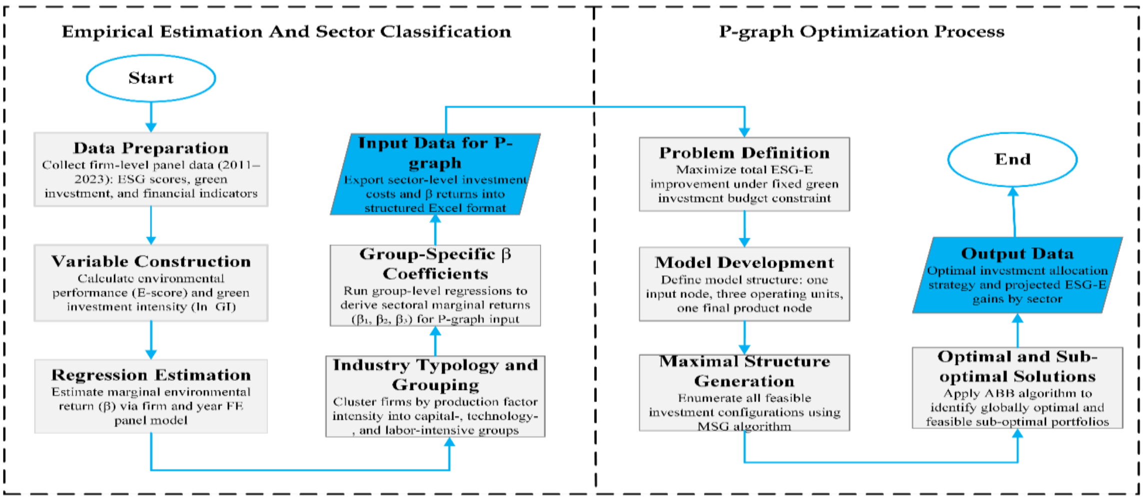

Figure 1: Research Framework: Econometric Estimation and Optimization Integration

2.2 Data Sources and Variable Definitions

This study constructs an unbalanced panel dataset of Chinese A-share listed firms spanning the period from 2011 to 2023, comprising 42,046 firm-year observations across heterogeneous industries and ownership types. Financial and corporate characteristics are sourced from the CSMAR database, while ESG scores are obtained from the Huazheng ESG Ratings database. Observations with missing ESG scores are excluded, while firm-years with zero green investment are retained if other variables are complete. All continuous variables are winsorized at the 1st and 99th percentiles to mitigate the impact of outliers. Industry- and year-fixed effects are incorporated in all regressions to control for structural and temporal heterogeneity (Donghui et al., 2025). The key outcome variable is the firm-level Environmental Score (E-Score), a composite index (0–100) reflecting compliance, emissions, waste management, and environmental disclosure quality. The primary explanatory variable, Green Investment (GI), is defined as annual capital expenditures specifically earmarked for environmental technologies and pollution-control projects, identified from corporate annual reports using an NLP-assisted keyword-matching algorithm. GI values are log-transformed for elasticity-based interpretation. Control variables include firm size, profitability, leverage, age, and state ownership status, accounting for firm capacity, life cycle, and policy heterogeneity. Table 1 summarizes all variables and measurements.

Table 1: Variable Classification and Description

Type	Variable	Definition/Measurement
Dependent	E-Score	Environmental score (Huazheng): proxy for firm-level environmental performance; range: 0–100
Independent	GI	Green investment (ln of annual capital expenditures on environmental projects, in M RMB)
Control Variable	Size	Firm size (log of total assets)
	ROA	Profitability (return on assets, %)
	Lev	Financial leverage (total liabilities / total assets)
	Age	Firm age (years since listing)
	SOE	Ownership type (1 = state-owned enterprise; 0 = otherwise)

2.3 Econometric Specification

To generate input parameters for optimization, we first estimate the sector-specific marginal environmental return (β) of green investment using fixed-effects panel regression. The model is specified as follows:

$$E\_Score_{i,t} = \alpha + \beta GI_{i,t} + Control_{i,t} + Id + Year + \epsilon_{i,t} \tag{1}$$

where $E\_Score_{i,t}$ refers to the environmental (E) score of firm i in year t, serving as the dependent variable. $GI_{i,t}$ Is the log-transformed green investment expenditure, allowing for elasticity-based interpretation of β as the percentage change in E-Score per 1 % increase in GI. The control vector $Control_{i,t}$ Includes firm size, ROA, leverage, age, and ownership type. Fixed effects Id and Year absorb time-invariant firm traits and common temporal influences. Standard errors are clustered at the firm level to account for within-firm autocorrelation. To capture structural heterogeneity, this research categorizes firms into capital-, technology-, and labor-intensive sectors based on the intensity of their production factors. Separate regressions yield sector-specific β coefficients, which are embedded into the P-graph model to support capital allocation decisions.

2.4 P-graph Optimization Model

This research employs a P-graph-based optimization model to determine the optimal allocation of limited green capital across various industrial sectors. Each sector, capital-intensive, technology-intensive, and labor-intensive, is modelled as an operating unit that consumes green capital and generates environmental output based on its estimated marginal return β. The optimization objective is:

$$\text{Maximize} \quad ESG\_E\_Total = \sum_{i=1}^{3} \beta_i \times x_i \quad , \quad \text{Subject to} \quad \sum_{i=1}^{3} x_i \leq B,\ x_i \geq 0 \ \ for\ all\ i \in \{1,2,3\} \tag{2}$$

Where x_i denotes the amount of green investment allocated to sector i, β_i represents the estimated marginal return of that sector, and B is the total available green investment budget. The model is implemented in P-Graph Studio v5.2 and then identifies the globally optimal allocation strategy. Compared to conventional linear or integer programming, the P-graph supports combinatorial completeness, enabling the exhaustive screening of portfolios and the maximization of performance. It accommodates both discrete and continuous allocation schemes, ensuring that the selected investment configuration is globally optimal under empirical returns and resource constraints.

3. Empirical Analysis and Optimization Results

3.1 Main Regression Results: Green Investment and Environmental Performance

The empirical analysis begins by estimating the effect of corporate green investment on firm-level environmental performance. Column (1) of Table 2 reports the baseline fixed-effects regression, showing that green investment (GI) has a positive and statistically significant impact on ESG-E scores ($\beta = 0.101$, $p < 0.05$). Interpreted in elasticity terms, a 1 % increase in green investment intensity corresponds to a 0.101 % improvement in the environmental score, reinforcing the efficiency-enhancing role of targeted green spending. Robustness checks using logit and quantile regressions (Columns 2–5) confirm the consistency of this effect. Notably, the impact is more substantial among firms with initially lower ESG-E scores, suggesting that marginal gains are most significant where baseline environmental performance is weaker. These results establish the reliability of green investment as a performance-enhancing strategy across firm types and performance levels.

Table 2: Main Regression and Robustness Check Results

	Main regression	Logit Regression	Quantile Regression		
			(1) 25 %	(2) 50 %	(3) 75 %
Variables	(1) Huazhegn_E	(2) E_dummy	(3) Huazhegn_E	(4) Huazhegn_E	(5) Huazhegn_E
GI	0.101^{**}	0.087^{***}	0.401^{***}	0.363^{***}	0.241^{***}
	(0.046)	(0.014)	(0.034)	(0.033)	(0.041)
Control variables	Yes	Yes	Yes	Yes	Yes
Constant	38.272^{***}	-4.862^{***}	32.999^{***}	33.486^{***}	32.716^{***}
	(3.787)	(0.457)	(0.961)	(0.927)	(1.170)
Year	Yes	Yes	Yes	Yes	Yes
Id	Yes	Yes	Yes	Yes	Yes
Observations	40563	41176	40563	40563	40563

Standard errors in parentheses* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.2 Sectoral Heterogeneity: Differential Returns Across Industries

To capture structural heterogeneity in environmental returns on green investment, this study segments firms into capital-intensive, labor-intensive, and technology-intensive groups. The classification is based on Ward's hierarchical clustering using two indicators—fixed asset intensity and the R&D-to-labor ratio—across 67 CSRC two-digit sectors. Capital-intensive industries emphasize infrastructure and physical assets (e.g., metal smelting, power generation), labor-intensive sectors rely on manual labor and scale (e.g., food processing, retail), while technology-intensive sectors feature high R&D (Research and Development) dependence and innovation input (e.g., electronics manufacturing, software services). This typology enables a structurally grounded evaluation of green investment impacts across differentiated industrial contexts. Table 3 presents the group-level regression coefficients (β_1), which represent the sector-specific elasticity of the E-score concerning green investment. The results reveal sharp differences in marginal effectiveness. Both capital- and technology-intensive sectors exhibit large, statistically significant positive returns ($p < 0.01$), indicating a substantial environmental payoff per unit of green capital. In contrast, the labor-intensive group exhibits a negative and statistically insignificant β, suggesting poor alignment between green investment and environmental outcomes in those sectors.

Table 3: Group-Level Environmental Returns and Normalized Investment Costs

Industry Type	β_1 (Environmental Return)	Mean Investment (M RMB)	Normalized Cost (c_i)
Capital-Intensive	3.518***	8.65	1
Labor-Intensive	–0.359	4.113	0.475
Technology-Intensive	3.139***	3.453	0.399

3.3 P-Graph Optimization: Sector Selection under Capital Constraints

Building on the sector-specific β coefficients obtained from fixed-effects regression, this study implements a P-graph optimization model to derive the most efficient allocation of green investment under predefined capital constraints. Each industry group—capital-intensive, technology-intensive, and labor-intensive—is modeled as an independent decision unit, characterized by its estimated marginal environmental return (β) and normalized investment cost, calibrated against sector-level green investment averages. The mathematical formulation and optimization objective are detailed in Section 2.4. Utilizing the Maximal Structure Generation (MSG) and

Accelerated Branch-and-Bound (ABB) algorithms within the P-graph Studio environment, all feasible investment allocation structures are exhaustively enumerated, and the globally optimal portfolio is identified. Figure 2 illustrates the resulting process network. Capital flows from the Green_Investment_Budget node to sector-specific operations, where each unit converts input investment into ESG-E gains weighted by its β coefficient (e.g., 3.139 × Tech_Investment). These outputs are then aggregated to form ESG_E_Total. Notably, the labor-intensive sector receives zero allocation in the optimal portfolio, reflecting its negative or non-significant marginal returns and confirming the prioritization of sectors with demonstrably higher efficiency. This graphical representation enhances interpretability by visually encoding the efficiency-based prioritization logic embedded in the optimization algorithm.

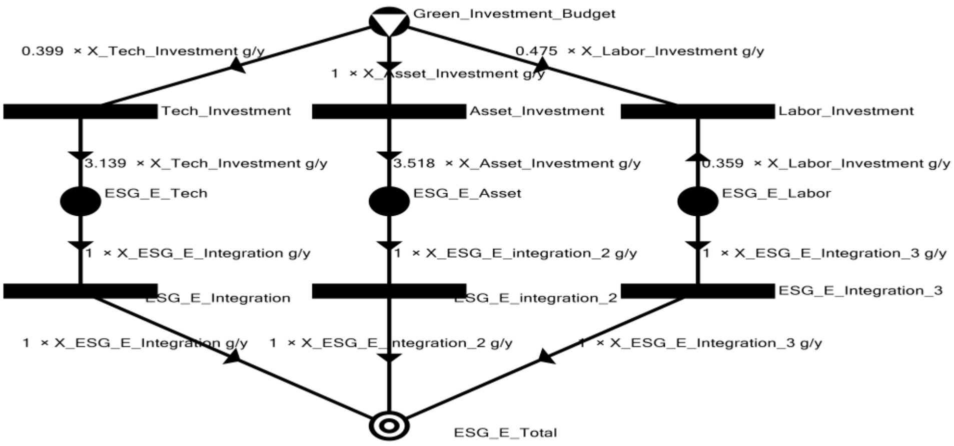

Figure 2: P-Graph-Based Optimization Structure for Sectoral Green Investment Allocation.

3.4 Optimization Results: Efficient Allocation Strategy

Using the Accelerated Branch and Bound (ABB) algorithm within the P-Graph framework, we identified three feasible investment structures under a fixed RMB 10 M green investment budget. As shown in Table 4, the optimal configuration (Structure 1) directs the full budget to technology-intensive investments, resulting in the highest ESG_E score of 78.67 and signaling the superior marginal environmental returns of innovation-driven sectors. Despite incurring a higher systemic cost (RMB 7.867 M), this structure reflects a more efficient conversion of capital into environmental benefit. In comparison, the suboptimal Structure 2 channels the same budget into asset-intensive sectors, achieving a lower ESG_E score of 35.18 at a reduced cost (RMB 3.518 M), indicating less effective ESG leverage. Consistent with the regression results in Section 3.2, labor-intensive sectors are fully excluded from the optimal allocation due to their negative or insignificant marginal returns, confirming their limited absorptive capacity for technology-driven upgrades. These findings demonstrate that effective ESG outcomes hinge not only on investment magnitude but also on sectoral alignment and structural configuration, with technology-intensive pathways offering the most impactful strategy for maximizing ESG performance under budget constraints.

Table 4: Optimal and Suboptimal Investment Structures Derived from P-Graph Optimization

Solution Structure	Budget (M RMB)	E_Score	Asset Investment	Labor Investment	Tech Investment	Cost (M RMB)
Structure 1 (Optimal)	10	78.67	—	—	2.506	7.867
Structure 2 (Suboptimal)	10	35.18	10	—	—	3.518
Structure 3 (Inactive)	0	0	—	—		

3.5 Suboptimal Configuration and Alternative Investment Paths

While Structure 1 achieves the highest environmental performance score (78.67) by channeling all resources into technology-intensive investments, Structure 2 emerges as a cost-efficient suboptimal alternative, reaching a lower environmental score of 35.18 with a substantially reduced investment cost (RMB 3.518 M). This configuration allocates the entire budget to asset-based improvements, bypassing labor and technology pathways and instead favoring direct physical capital upgrades. Such an investment structure reflects the operational logic of capital-intensive industries, including electric power production, metal smelting, and bulk chemical manufacturing, where fixed-asset retrofitting remains the primary channel for environmental performance improvement due to limited responsiveness in R&D. In contrast, technology-intensive sectors, such as electronics manufacturing, precision instrumentation, and digital services, derive more substantial environmental returns from innovation-driven initiatives. Although Structure 2 underperforms in terms of aggregate environmental impact, it remains a viable option for industries constrained by rigid capital structures, shorter investment horizons, or limited innovation absorptive capacity. The P-Graph framework's ability to enumerate globally optimal and feasible sub-optimal configurations provides decision-makers with flexibility to trade off environmental gains against financial and operational constraints, enhancing its practical relevance for policy-oriented ESG capital planning. Structure 2 thus provides a context-sensitive reference point that accommodates sectoral constraints while preserving positive environmental returns within budgetary limits.

4. Discussion and Conclusion

The optimization results derived from the ABB-embedded P-Graph framework offer critical insight into how sectoral heterogeneity affects the efficiency of green investment under fixed budget constraints. As confirmed in Table 4, the optimal structure allocates the whole RMB 10 M budget to technology-intensive sectors, generating an ESG_E score of 78.67, more than twice the return of the suboptimal, asset-intensive configuration (35.18). This divergence underscores that environmental impact is not linearly correlated with investment magnitude but is structurally dependent on sector-specific marginal productivity. Notably, labor-intensive sectors are entirely excluded from efficient configurations, reflecting systemic inefficiencies and limited absorptive capacity for technology-driven environmental upgrades in these industries. These findings validate our econometric estimation of industry-specific elasticities and highlight the value of process network synthesis for formulating resource-constrained ESG investment strategies.

Relative to conventional ESG studies that focus on descriptive impact evaluations, this study advances the literature by integrating a normative optimization framework into sector-level investment modeling. This methodological innovation links regression-based elasticity estimates with prescriptive allocation decisions, offering a decomposable decision-support structure that formalizes the relationship between ESG returns and allocation logic. In the context of China's "dual-carbon" strategy, the results provide timely guidance for policymakers and investors on prioritizing green funds toward innovation-driven sectors with the highest environmental returns. However, the study also acknowledges several limitations, including the static nature of budget constraints, the exclusion of social and governance criteria, and the lack of intertemporal dynamics. Future research may extend this work by introducing multi-objective functions, just transition trade-offs, and probabilistic risk adjustments. Ultimately, our framework offers a scalable solution for ESG-aligned capital planning, bridging the gap between econometric diagnosis and actionable allocation strategies while enabling alignment between ecological impact and institutional constraints.

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References

Laokulrach M., 2025, ESG Integration in Investment Analysis. Environmental, Social, and Governance (ESG) Investment and Reporting. Springer Nature, Cham, Switzerland.

Xue J., Poon J., Yang Y., Ji Q., 2024, Effect of green industrial policy on China's outward renewable energy investment. Energy Economics, 138, 107830.

Khalid F., Su C.Y., Weiwei K., Voinea C.L., Srivastava M., 2025, Financial mechanism for sustainability: the case of China’s green financial system and corporate green investment. China Finance Review International, 15, 93-116.

Li X., Li M., Zeng H., 2024, Environmental judicial reform and corporate investment behavior — Based on a quasi-natural experiment of environmental courts. Journal of Environmental Management, 365, 121640.

Lim S.Y., Chemmangttuvalappil N.G., Tapia J.F.D., Khoiroh I., Chai P.V., Ng L.Y, 2025, Optimal chemical reaction pathway for palm process residue recovery using Process Graph (P-graph) framework. Computers & Chemical Engineering, 194, 109000.

Tan A.S.T., Uthayakumar H., Yeo L.S., Kong K.G.H., Lo S.L.Y., Andiappan V., Loy A.C.M., Teng S.Y. , How, B. S., 2024, Shapley-Shubik Agents Within Superstructure-Based Recycling Model: Circular Economy Approaches for Fish Waste Eco-Industrial Park. Process Integration and Optimization for Sustainability, 8, 487-501.

Donghui Z., Yusoff W.S., Salleh M.F.M., Lin N.S., Jamil A.H., Abd R.M.J., Shaari M.S., 2025, The impact of ESG and the institutional environment on investment efficiency in China through the mediators of agency costs and financial constraints. Social Sciences & Humanities Open, 11, 101323.