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Supply chain integrated merger and acquisitions (M&As) and firm energy performance

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A R T I C L E I N F O

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A B S T R A C T

This paper examines the impact of upstream merger and acquisition (M&A) activities driven by supply chain integration motives on firm energy performance. By developing a microlevel theoretical framework, we examine the intricate relationship between firms' upstream M&A strategies geared toward supply chain integration and their energy efficiency. We examine the impact of upstream M&A activities on energy performance using data from Chinese listed companies from 2007 to 2021. Our findings reveal that upstream M&A initiatives can enhance firms' energy efficiency, although there are discernible variations in the effects observed for M&A activities targeted downstream or within the same industry. By examining mechanisms, we elucidate the pivotal roles of input substitution effects and productivity enhancements through which upstream M&As boost energy performance. Furthermore, our analysis underscores the catalyzing impact of M&A activities in fostering collaborative innovation in green technologies among firms and suppliers, thus improving productivity and energy efficiency. We provide new microlevel evidence of the relationship between M&A transactions and corporate energy efficiency from upstream and downstream perspectives.

1. Introduction

Under the Paris Agreement, each signatory country must propose Nationally Determined Contributions (NDCs), i. e., National Targets and Plans for Reducing Greenhouse Gas (GHG) emissions. Developing countries, including China, are facing serious resource and environmental problems due to rapid industrialization (Fan et al., 2021; Zhang et al., 2021); thus, they are developing emission-reduction strategies based on agreement commitments and development needs. As the world's largest energy consumer and carbon emitter, China proposed the following green development goals at the 75th United Nations General Assembly in September 2020: reaching peak carbon by 2030 and achieving carbon neutrality by 2060. Along with the Chinese government's carbon emission plan advancing nationwide, enterprises, especially in the more industrialized provinces, are facing increasingly stringent production emission requirements, and low-carbon and green production is gradually becoming one of the most important goals for their development.

Self-developed energy-saving technologies and optimized production input structures are crucial for improving corporate energy efficiency (Long et al., 2017; Shapiro and Walker, 2018). However, due to the time costs of these methods and the difficulty in reducing emissions in the short term, many enterprises have adopted low-carbon mergers and acquisitions (M&As) (Li and Lu, 2023; Lu et al., 2024). Companies acquire green technologies or management experience through M&As and use them to improve energy performance (Altunbaş et al., 2023; Liang et al., 2022; Yang and Chi, 2023; Zhang et al., 2023). However, little research exists on the relationship between M&As and corporate energy performance from the production chain perspective.

Complex production chains in manufacturing have developed due to global industrialization, and the multistage characteristics of production have become increasingly prominent, resulting in an international production division of labor in a vast network of global value chains (GVCs) (Baldwin, 2012). From the microperspective of individual enterprises, production activities are closely related to the industry chain's upstream suppliers and downstream customers. Under the framework of globalized production, enterprises commonly engage in M&As in response to production chain integration or supply chain layout (Hu et al., 2023). However, no study has analyzed the impact of M&A behaviors on enterprises' energy performance from the industrial chain's upstream and downstream perspectives. Up-

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stream suppliers are particularly vital in this context because they play a key role in enterprises' production input.

This article fills this research gap. First, we construct a theoretical model to analyze how firms' upstream M&A activities affect their energy efficiency. Our theoretical model predicts that M&A activities based on upstream supply chain integration increase integrated intermediate inputs and productivity growth, triggering input substitution and productivity effects favoring energy performance. Second, from the production chain perspective, we empirically examine the relationship between M&A activities and corporate energy performance. Finally, we test how upstream M&As affect energy performance, establishing a systematic analytical framework for analyzing upstream M&A behavior and firm energy performance.

The remainder of this article is organized as follows. Section 2 reviews the literature on the economic consequences of M&As and the influences on firms' environmental performance. Section 3 introduces the theoretical model. Section 4 demonstrates the empirical methodology and describes the variable definitions and data treatment. Section 5 reports the empirical results. Section 6 concludes.

2. Literature review

We reviewed the literature related to the three main aspects of our research. The first is on the relationship between M&As and corporate green development. Studies on the impact of M&As on corporate performance mainly focus on financial aspects, with only a few analyzing the relationship between M&As and corporate green development. For example, in terms of sustainable development, Mihaiu et al. (2021) and Caiazza et al. (2021) confirmed the positive effects of M&As on a company's sustainable performance (ESG scores). Some studies combine M&A activities with technological innovation in green development, one of the most direct ways to acquire technology (Liang et al., 2022; Yang and Chi, 2023; Zhang et al., 2023). Other studies focus on the motive behind M&A activities, such as selecting acquisition targets, where companies with excellent environmental performance are more likely to become acquisition targets (Berchicci et al., 2012; Bose et al., 2021; Eng and Fikru, 2020) or using the target company's ESG score as a screening criterion for assessing carbon risk in M&As (Barros et al., 2022; Gomes, 2019). However, these studies did not explicitly verify the impact of M&As on emissions. Altunbaş et al. (2023) conducted research using multinational corporate samples. They found that M&As only affect a company's carbon intensity in the short term, with no significant impact in the medium to long term. Li and Lu (2023) and Lu et al. (2024) analyzed the impact of M&A decisions on energy companies' carbon emissions, focusing on the low-carbon nature of M&A activities. Unfortunately, to date, no research has investigated the environmental effects of M&A activities from the perspective of integration strategies.

The second literature stream is related to production or supply chains. GSCs have been the focus of attention of the international business and policy community over past decades (Alfaro and Chor, 2023). Porter's (1985) value chain theory emphasizes the importance of supply chain linkages for firm production. With the assistance of communication technologies and free trade policies, firms have achieved multistage production on a global scale and extensive transnational sourcing of intermediate goods, which researchers summarize as GVCs (Gereffi and Kaplinsky, 2001). Antràs and Chor (2022) observed that GVCs can be configured in two ways: the "Spider" structure where multiple components converge in a single export assembly plant, and the "Snake" structure of the serial production model. According to the Snake structure's serial production view, analyzing an industry's upstream and downstream position in the production chain is possible. Fally (2011) and Antràs et al. (2012) first did this in decomposing and measuring GVCs. The popularity of GVCs allowed firms that do not otherwise trade across borders to participate in sequential production chains and link up with upstream and downstream firms through purchasing and selling relationships. The prevalence of GVCs has enabled purely domestic enterprises to participate in sequential production chains, establishing connections with upstream and downstream manufacturers through procurement and sales relationships.

Finally, there is research on the association between M&As and supply chains or production chain linkages. Cho (2014) argued for the operational synergies of M&As from a production chain perspective. Kim and Jin (2017) found a higher likelihood of M&As between companies with business connections in the production chain. Similarly, Chae et al. (2022) investigated the association between structural equivalence between acquiring and target companies and M&A performance using the proportion of shared suppliers and customers among affiliated companies to measure equivalence. In one of the few studies targeting this area, Bernile and Lyandres (2019) examined how M&A activities with competitors, suppliers, or customers affect a firm's operational efficiency. Overall, these studies conclude that enhancing supply chain operational efficiency is a primary M&A motivation. Companies commonly target firms along their supply chains during M&A activities (Hu et al., 2023) .

In summary, research has begun to focus on issues related to production chain relationships or green development in M&A activities. With the deepening of GVCs, specialization in the division of labor has become inevitable, and building reasonable production chain relationships will become an important task in corporate decision-making. The GVC literature provides a rich research foundation for deconstructing corporate production chain relationships. However, our literature review shows that most studies are concentrated in several independent fields mentioned in this paper. There is a lack of literature that analyzes the impact of M&A activities on corporate energy performance from a supply chain perspective, creating a research gap among the three topics of M&A, supply chain, and energy performance. Our research aims to bridge these gaps.

3. Theoretical model

3.1. Basic setup

This section explains how supply chain integrated M&A decisions affect firms' energy performance by constructing a simple theoretical model. The model has two keys. First, different sources of intermediate inputs impact the output differently. A firm can obtain intermediate inputs by outsourcing or from internal suppliers. In contrast, a firm's M&A activities related to supply chain integration will determine whether it can receive inputs internally and at what price. Second, M&As may lead to production-related technology absorption or joint innovation that contributes to productivity gains. Our approach is similar to Sousa et al.'s (2015) focus on the issue of input sourcing. Drawing on a monopolistic competition framework, the model assumes a fixed number of firms, each producing a single variety of products ω. These products can be sold as intermediate inputs or for final consumption, with firms sharing identical factor endowments and input preferences. Firms exhibit heterogeneity in productivity φ_i, with exogenous technological innovations improving productivity levels. Production involves three factors: labor l, intermediate inputs M, and environmental services z. Assuming that one unit of environmental service generates one unit of emission simplifies our analysis. The production function takes the Cobb–Douglas form, allowing for factor substitution, which implies that pollution emissions can be reduced by employing more labor or using more intermediate input while holding the output constant. We refrain from modeling consumer behavior in detail to concentrate on the partial equilibrium characteristics of the production side. Hence, the output can be expressed as follows.

$$q_i = \varphi_i z_i^{\alpha} M_i^{\beta} l_i^{1-\alpha-\beta} \tag{1}$$

Where, q_i represents the total output of the firm i, φ_i, and denotes the exogenously given productivity at the firm level, $0<\alpha<1$, $0<\beta<1$ and $0<1-\alpha-\beta<1$, in terms of the input elements. We express product demand as comprising fixed f and marginal components $bm(\omega)$, where f and b are constants. $m(\omega)$ denotes the number of inputs required by the firm to produce variety ω. Fixed product demand ensures that the firm's output remains constant, as expressed by the following equation.

$$q_i = f + bm_i(\omega) = \varphi_i z_i^{\alpha} M_i^{\beta} l_i^{1-\alpha-\beta} \tag{2}$$

For intermediate inputs M_i, we consider that firms can utilize two distinct sources of inputs: inputs $m_i^s(\omega)$ from outsourced procurement and internally sourced inputs $m_i^I(\omega)$ obtained from integrated affiliates. The aggregate intermediate inputs are represented as follows.

$$M_i = \left[\int_{\omega\in\Omega_S} m_i^s(\omega)^{\sigma-1/\sigma} d\omega + \theta_i \int_{\omega\in\Omega_I} m_i^I(\omega)^{\sigma-1/\sigma} d\omega\right]^{\sigma/\sigma-1} \tag{3}$$

Where, the composition M_i determines the intensity of demand for externally outsourced inputs $m_i^s(\omega)$ and internally sourced inputs $m_i^I(\omega)$, representing the constant elasticity of substitution between the outsourced and internalized inputs. A higher value of σ implies greater substitutability between the intermediate inputs. θ_i denotes the upstream supply chain integration decisions based on productivity. When a firm lacks M&A activities related to supply chain integration, i.e. $\theta_i=0$, it relies solely on outsourced intermediate. However, when a firm integrates upstream supply chains through M&As ($\theta_i=1$), it gains access to internalized inputs.

3.2. Cost minimization problem

Given the demand level $\bar{m}_i$ for production, we analyze the cost minimization problem as follows.

$$\begin{aligned} &\min_{z,M,l} PM_i + p_z z + wl \\ &s.t.\ \ bm_i(\omega) = \varphi_i z_i^{\alpha} M_i^{\beta} l_i^{1-\alpha-\beta} - f \end{aligned} \tag{4}$$

Where, P denotes the composite price index faced by the intermediate input factors M, p_z denotes the price of environmental services, and w denotes the wage rate for hiring labor. In our setup, prices associated with production factors p_z are exogenously given and w remains fixed. The only exception is that M&A decisions related to supply chain integration can affect the intermediate inputs' composite price index because the firm has greater bargaining power to negotiate lower purchase prices if it obtains intermediate inputs from an integrated internal supplier. We will discuss this issue in subsequent sections. Utilizing the first-order conditions, we can derive the production costs under the given demand level $\bar{m}_i$ as follows.

$$\bar{C}_i(\bar{m}_i) = \frac{1}{\gamma\varphi_i}\left(f + b\bar{m}_i\right) p_z^{\alpha} P^{\beta} w^{1-\alpha-\beta} \tag{5}$$

Where, $\gamma = \alpha^{\alpha}\beta^{\beta}(1-\alpha-\beta)^{1-\alpha-\beta}$.

3.3. Demand for different factors

We next utilize Shepard's lemma to derive the demand level for environmental services z.

$$\frac{\partial \bar{C}_i(\bar{m}_i)}{\partial p_z} = z = \frac{\alpha}{\gamma\varphi_i}\left(f + b\bar{m}_i\right) p_z^{\alpha-1} P^{\beta} w^{1-\alpha-\beta} \tag{6}$$

Given the duality between cost minimization and output maximization, we impose the constraint of production costs to solve the maximization problem, yielding the constant elasticity demand functions for each input factor ω as follows.

$$m_i^s(\omega) = \left[\frac{p^S(\omega)}{P}\right]^{-\sigma} \frac{E}{P} \quad \text{and} \quad m_i^I(\omega) = \left[\frac{p^I(\omega)}{P}\right]^{-\sigma} \frac{E}{P} \tag{7}$$

Where, $E = \beta\bar{C}_i(\bar{m}_i)$ denotes the expenditure level of the firm for each variety of intermediate inputs, while $p^S(\omega)$ and $p^I(\omega)$ denote the prices of externally outsourced and internally sourced intermediate inputs, respectively. We set the benchmark price for purchasing intermediate goods from the market as $p(\omega)$. When the firm does not engage in M&As related to supply chain integration, its outsourcing procurement price equals the market benchmark price, i.e., $p^S(\omega)=p(\omega)$. After the M&A, the firm can obtain inputs from internal suppliers at prices more favorable than$p$ (ω), a relationship represented by $p^I(\omega) = (1/\lambda_i)p(\omega)$, where $\lambda_i \geq 1$ denotes the firm's level of integration. If the firm lacks a relevant supply chain integration through an M&A, $\lambda_i=1$, the prices for outsourced and internally sourced intermediate inputs are identical. As the firm has no affiliated internal suppliers, it can only engage in outsourcing. As the frequency of M&As for supply chain integration increases, the firm's level of integration λ_i also rises. In our setting, this implies that firms with higher levels of integration can secure more favorable prices for internally sourced intermediate inputs. In this case, the composite price index P of intermediate inputs M can be expressed as follows.

$$P = \left[\int_{\omega\in\Omega_S} p^S(\omega)^{1-\sigma} d\omega + \theta_i \int_{\omega\in\Omega_I} p^I(\omega)^{1-\sigma}\right]^{\frac{1}{1-\sigma}} \tag{8}$$

3.4. Mechanism

Like Huang et al. (2022) and Fan et al. (2021), we define the energy performance of firm i as (q_i/z_i), i.e., the output level corresponding to each unit of environmental service input. By combining Equations (2) and (6), we can derive as follows.

$$\left(\frac{q_i}{z_i}\right) = \frac{\gamma\varphi_i}{\alpha} p_z^{1-\alpha}\left(\frac{1}{P}\right)^{\beta}\left(\frac{1}{w}\right)^{1-\alpha-\beta} \tag{9}$$

The primary factors associated with M&As for supply chain integration are the prices of intermediate inputs P and the firm's productivity level φ_i, corresponding to two potential mechanisms: input substitution and productivity enhancement effects.

The first scenario is the input substitution effect. M&As increase the firm's level of integration, allowing it to obtain lower internalized input prices. Let n_i^{MA} denote the number of M&As related to supply chain integration for firm i. According to the above analysis, we have $\partial\lambda_i/\partial n_i^{MA} > 0$ and $\partial p^I(\omega)/\partial\lambda_i < 0$. Combining Equation (8), we have $\partial P/\partial p^I(\omega) > 0$. Consequently, according to Equation (9), we have $\partial(q_i/z_i)/\partial P < 0$. The final relationship between the energy performance and the number of M&As can be expressed as follows.

$$\frac{\partial(q_i/z_i)}{\partial n_i^{MA}} = \underset{(-)}{\frac{\partial(q_i/z_i)}{\partial P}} \times \underset{(+)}{\frac{\partial P}{\partial p^I(\omega)}} \times \underset{(-)}{\frac{\partial p^I(\omega)}{\partial \lambda_i}} \times \underset{(+)}{\frac{\partial \lambda_i}{\partial n_i^{MA}}} > 0 \tag{10}$$

Hypothesis 1: M&As aimed at upstream supply chain integration enhance a firm's energy performance. The more the number of effective integration M&As, the greater the improvement.

Hypothesis 2: Supply chain integration M&As create a substitution effect between internally sourced and externally outsourced inputs, enhancing a firm's energy performance by reducing the composite price index of inputs.

While theoretical derivations suggest that the decrease in the input price index improves energy performance, from a production perspective, the decline in input prices results in substituting internally sourced inputs for externally outsourced inputs. We refer to this mechanism as the input substitution effect.

The second scenario is the productivity enhancement effect. Many studies suggest M&A improve firm productivity by absorbing target technologies, management experiences, and other factors. Under this premise, improved productivity enhances a company's energy performance. This relationship can be represented as follows.

$$\frac{\partial(q_i/z_i)}{\partial n_i^{MA}} = \underset{(+)}{\frac{\partial(q_i/z_i)}{\partial \varphi_i}} \times \underset{(+)}{\frac{\partial \varphi_i}{\partial n_i^{MA}}} > 0 \tag{11}$$

Hypothesis 3: A firm's supply chain integration through M&A transactions enhances its energy performance by increasing productivity.

We also examine whether a firm's supply chain integration M&As can lead to related technological innovations. Theoretically, technological innovation is part of a firm's productivity. The literature suggests that M&A transactions positively impact green technological innovation (Liang et al., 2022; Yang and Chi, 2023; Zhang et al., 2023), considered highly correlated with firm energy performance and pollution emissions (Long et al., 2017; Shapiro and Walker, 2018). Therefore, we believe that supply chain integration M&As have a strong technological-seeking motive that can collaborate on green technological innovations with target firms to improve the acquirer's energy performance. We consider green technological innovation as a supplementary validation of the productivity effect.

Hypothesis 4: A firm's supply chain integration M&As enhance the level of green technological innovation, thereby improving energy performance.

4. Research design

4.1. Model specification

Based on the CSMAR database of listed companies in China, we establish panel data at the firm level that matches M&A activities. Fixed effects are used in the benchmark. The following equation evaluates the "intensity" of firm carbon emissions rather than total emissions.

$$\mathrm{EPerform}_{it} = \alpha_0 + \beta_1 \mathrm{MAUP}_{it} + \beta_2 \mathrm{MADOWN}_{it} + \beta_3 \mathrm{MASAME}_{it} + \beta' Z_{it} + \{\mathrm{FE}\} + \upsilon_{it} \tag{12}$$

Where, $\mathrm{EPerform}_{it}$ denotes the energy performance of the listed company i at time t; MAUP_{it} denotes the upstream M&As variable of the company motivated by supply chain integration, which counts the cumulative number of upstream M&As by the company. For comparison, we also control MADOWN_{it} and MASAME_{it}, representing the cumulative number of downstream and intraindustry M&As identified by industry-level upstream data. These three variables are observations of different types of M&As compared by the acquirers and targets. Our study examines the estimation coefficient β_1 of variable MAUP_{it}. Z_{it} denotes possible control variables, $\{\mathrm{FE}\}_{it}$ is the set of fixed effects, and υ_{it} denotes the disturbance term.

4.2. Variable definition and identification

The dependent variable $\mathrm{EPerform}_{it}$ represents energy performance. However, calculating carbon emissions individually for each company based on available data on Chinese listed companies is not possible (Shen et al., 2020). Thus, our method follows the approach of Wang et al. (2023), which uses industry-level energy consumption information as a basis and applies weights per the characteristics of the enterprise scale. As larger industrial enterprises generally consume more energy inputs (Guo et al., 2019), operating costs are used as a proxy for company scale. Firm carbon emissions $\mathrm{CEmission}_{it}$ are calculated as follows.

$$\mathrm{CEmission}_{it} = \frac{\mathrm{OPcost}_{it}}{\mathrm{OPcost}_{st}^{industry}} \mathrm{CEmission}_{st}^{industry} \tag{13}$$

Where, OPcost_{it} denotes firm-level operating costs. $\mathrm{OPcost}_{st}^{industry}$ denotes the overall scale of the industry s in which the firm operates. $\mathrm{CEmission}_{st}^{industry}$ is the total industrial carbon emissions calculated based on the *China Statistical Yearbook, China Energy Statistical Yearbook*, and the IPCC National Greenhouse Gas Inventory Guidelines. Following Equation (9), and considering the introduction of output factors, we use firm sales revenue $\mathrm{Revenue}_{it}$ as a proxy and define the final energy performance indicator formula as follows.

$$\mathrm{EPerform}_{it} = \frac{\mathrm{Revenue}_{it}}{\mathrm{CEmission}_{it}} \tag{14}$$

The core explanatory variable is MAUP_{it}. Because firms procure intermediate inputs from upstream suppliers for production, our interest is in the M&As aiming at upstream targets for supply chain integration. We measure the upstream and downstream positions of the acquirer and target in the industry chain on the basis of the industry-level upstreamness index proposed by Fally (2011) and Antràs et al. (2012). Adopting a sequential production perspective, this method analyzes a country's industries' upstream and downstream positions in the production chain. By decomposing the destination of intermediate goods exports using the IO table, we derive the weighted distance of the sector's output relative to the final consumers—the upstreamness index. The larger the index, the more the sector leans toward the upstream. Antràs (2020) suggested that world input–output analysis indicators can be effectively applied at the firm level, thus opening the door for empirical analysis of firms' participation in GVCs at the firm level. We use the US 2017 Input–Output (USIO) Table to calculate industry-level upstreamness. This is because the M&A information compiled by Thomson SDC uses the SIC industry classification standard, which can be easily combined with the industry classification in the USIO, and provides more detailed industry classifications than the World Input – Output Table (WIOD) or the China Input – Output (CHIO) Table.

Conceptually, upstreamness U_s is a weighted average of the number of production stages required for an industry's output to reach its final demand, treating the industry as the input end. In an economy with $N \geq 1$ industries, the total output Y_s of industry s can be decomposed into final product output F_s and the intermediate input Z_s flowing to other sectors. Further decomposition based on the industry r it flows into, we can obtain the following.

$$Y_s = F_s + Z_s = F_s + \sum_{s=1}^{N} d_{sr} Y_r \tag{15}$$

Where, d_{sr} denotes the direct input coefficient from industry s to r, indicating the input value of industry s required to produce one unit of output in industry r. Expanding the intermediate input portion in sequence, we obtain the following.

$$Y_s = F_s + \sum_{s=1}^{N} d_{sr} F_r + \sum_{r=1}^{N}\sum_{k=1}^{N} d_{sk} d_{kr} F_r + \sum_{r=1}^{N}\sum_{k=1}^{N}\sum_{l=1}^{N} d_{sl} d_{lk} d_{kr} F_r + \cdots \tag{16}$$

Assuming that products are produced sequentially, with each production stage having a distance of 1, the industry-level upstreamness index can be expressed as follows.

$$\begin{aligned} U_s = {} & 1 \times F_s/Y_s + 2 \times \sum_{s=1}^{N} d_{sr} F_r / Y_s \\ & + 3 \times \sum_{r=1}^{N}\sum_{k=1}^{N} d_{sk} d_{kr} F_r / Y_s + 4 \times \sum_{r=1}^{N}\sum_{k=1}^{N}\sum_{l=1}^{N} d_{sl} d_{lk} d_{kr} F_r / Y_s + \cdots \end{aligned} \tag{17}$$

Antràs et al. (2012) indicated that the numerator in Equation (17) can be expressed sequentially as the elements of the $N \times 1$ matrix $[\mathrm{I} - \boldsymbol{D}]^{-2} F$, where $\boldsymbol{D}$ is a $N \times N$ matrix with elements d_{sr}. We calculate industry-level upstreamness indices based on the USIO table. We observe the upstreamness of acquirers ($\mathrm{Upstreamness}_{it}^{acquiror}$) and targets ($\mathrm{Upstreamness}_{imt}^{target}$) by matching industry relationships with upstreamness data to the Thomson SDC M&A information. We then construct variable MAUP_{it} cumulatively from the initial sample year of 2007, considering the possibility of multiple M&As by firms in the same year, as shown in the following equation.

$$\mathrm{MAUP}_{it} = \sum\nolimits_{j=2007}^{t} \sum\nolimits_{m=1}^{n} \mathrm{MAUP}_{imj}^{dummy} \tag{18}$$

$$\mathrm{MAUP}_{imj}^{dummy} = \begin{cases} 1, & \text{if } \mathrm{Upstreamness}_{it}^{acquiror} > \mathrm{Upstreamness}_{imt}^{target} \\ 0, & \text{if } \mathrm{Upstreamness}_{it}^{acquiror} \leq \mathrm{Upstreamness}_{imt}^{target} \end{cases} \tag{19}$$

Where, $\mathrm{MAUP}_{imj}^{dummy}$ is a dummy variable that records a single M&A activity, and subscript m denotes the target company and year. Each M&A activity is identified on the basis of the effective year. Where $\mathrm{Upstreamness}_{it}^{acquiror} > \mathrm{Upstreamness}_{imt}^{target}$ indicates the target is more upstream in the industry chain than the acquirer, which is an upstream M&A strategy motivated by supply chain integration. We retain samples of the acquired stake ⩾ 50%, enabling it to treat the target as an internally integrated supplier after the M&A.

The control variables include factors related to M&A decisions and corporate financial aspects. Regarding the M&A decision factors, we also identify the M&A activities of downstream MADOWN_{it} and those within the same industry MASAME_{it}①. Seven other control variables are related to the corporate financial situation: firm age, return on assets (ROA), return on equity (ROE), Tobin's Q ratio, equity concentration, financial leverage ratio, and cash flow ratio. Firm age $\ln \mathrm{age}_{it}$ is the natural logarithm of the number of years since establishment, ROA_{it} is the ratio of net income to total assets, and ROE_{it} is the ratio of net income to equity. We use the percentage of shares held by the top ten shareholders to represent equity concentration $\mathrm{Tophold}_{it}$, the financial leverage ratio Finlev_{it} is total liabilities divided by total assets, and the cash flow ratio $\mathrm{Cashrate}_{it}$ is operating cash flow divided by current liabilities. Additionally, our baseline specification includes fixed effects for firms μ_i, years δ_t, and province–industry interaction levels ξ_{ps}.

4.3. Samples and data

Our data come from three main sources: basic information on Chinese listed companies from CSMAR, M&A activities from Thomson SDC, and industry-level upstreamness calculated on the basis of USIO. We selected the A-share listed companies in CSMAR from 2007 to 2021 as the original sample. The original data underwent the following processing steps: ① Service sector samples that do not use energy inputs, such as banks, insurance, securities, etc. were excluded, and real estate industry samples were removed. ② We removed ST and delisted companies. ③ We excluded listed companies with annual revenue below 50 million yuan, samples with missing key information, or less than three years of continuous data. ④ We applied a 1% trimming to all continuous variables. We also constructed several concordance tables for different industry standards to consolidate datasets from different sources②.

Figures 1 and 2 present the flow and stock data of different types of M&A activities from 1995 to 2021. Figure 1 illustrates a significant increase in the M&A activities of Chinese listed companies since 2010, peaking in 2016. In most observed years, acquisitions of suppliers (i.e., upstream M&A) are often the most frequent, followed by customer acquisitions (i. e., downstream M&A), whereas acquisitions of competitors (i.e., horizontal M&A) are the fewest. M&A growth began declining in 2017, but this did not change the order of the three types of M&As by quantity. Figure 2 shows a similar viewpoint. As of 2021, among the M&A activities where Chinese listed companies obtained effective control (with a proportion ⩾ 50%), there were 6 310 upstream M&A transactions, 5 753 downstream M&As, and 4 511 horizontal M&As. These findings indicate that Chinese enterprises prefer upstream M&As for supply chain integration.

Table 1 summarizes the variable definitions and descriptive statistics used in the various sections of this paper.

5. Empirical analysis

5.1. Baseline result

We first analyzed the correlation between upstream M&A activities aimed at supply chain integration and corporate energy performance. We ran OLS regressions, adding fixed effects to Equation (10). The baseline results presented in Table 2 show that the coefficient of the upstream M&A variable (MAUP) remains consistently negative and significant at the 1% level with the addition of the fixed effects and control variables. This result indicates that companies engaged in

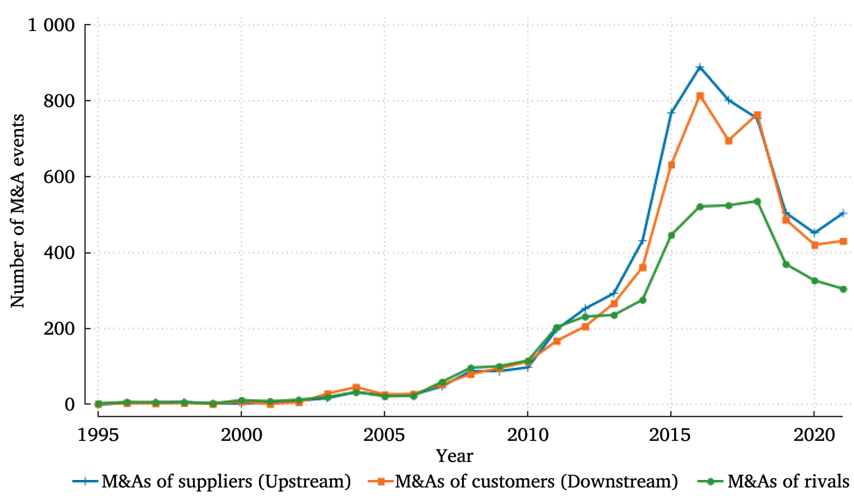

Figure 1. Flow of categorized M&A activities by Chinese listed companies from 1995 to 2021
Source: Thomson SDC.

①The industry-level upstreamness calculated based on the input–output data is ⩾ 1. However, there are a few cases where the upstreamness for different industries is equal to 1. Nevertheless, after screening our M&A samples, we did not encounter situations where the affiliated companies were both in industries with an upstreamness equal to 1. This particular case did not affect our identification of the upstream M&A decisions.
②Specifically, the M&A data recorded by Thomson SDC use the SIC standard industry classification, whereas the US Input–Output Table (USIO) data provide a concordance table between the input–output portions and NAICS. Therefore, we utilized the matching information provided by the US NAICS website to indirectly achieve the matching of the SIC–NAICS–USIO three-class industry standards.

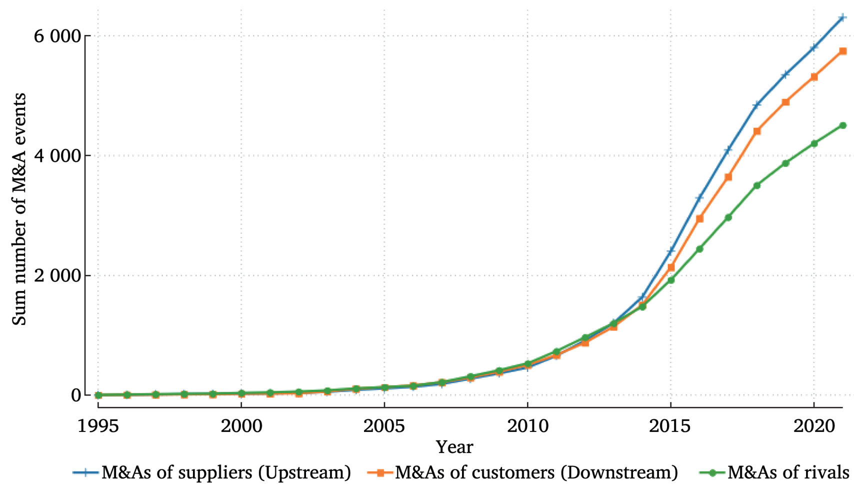

Figure 2. Stock of categorized M&A activities by Chinese listed companies from 1995 to 2021
Source: Thomson SDC.

Table 1
Variable definitions and summary statistics

Variables	Definition	Obs.	Max	Min	Mean	Std
EPerform	Firm's energy performance	23 516	40.771	0.010	6.334	9.646
MAUP	Number of upstream M&As	23 516	13.000	0.000	0.435	0.960
MADOWN	Number of downstream M&As	23 516	10.000	0.000	0.430	0.981
MASAME	Number of horizontal M&As	23 516	10.000	0.000	0.323	0.849
LNAGE	Natural logarithm of firm's age	23 516	3.401	0.000	2.011	0.872
ROA	Return on total assets	23 516	0.204	−0.194	0.042	0.058
ROE	Return on equity	23 516	0.328	−0.610	0.062	0.120
TOBINQ	Tobin's Q	23 516	7.852	0.877	2.045	1.217
TOPHOLD	Degree of equity concentration	23 516	93.500	23.33	58.98	15.055
FINLEV	Financial leverage ratio	23 516	0.896	0.000	0.421	0.253
CASHRATE	Cash flow ratio	23 516	0.246	−0.133	0.052	0.066
Grouping of upstream M&A variables						
MAUP_L	Number of upstream M&As where the targets are listed companies	23 516	2.000	0.000	0.005	0.075
MAUP_NL	Number of upstream M&As where the targets are nonlisted companies	23 516	13.000	0.000	0.430	0.950
MAUP_D	Number of domestic upstream M&As	23 516	13.000	0.000	0.406	0.927
MAUP_F	Number of cross-border upstream M&As	23 516	3.000	0.000	0.028	0.190
MAUP_B	Number of large-scale M&As	23 516	6.000	0.000	0.164	0.498
MAUP_S	Number of small- or medium-scale M&As	23 516	13.000	0.000	0.205	0.583
Mechanism variables						
TFP_OP	Productivity by Olley-Pakes	21 937	10.731	2.411	6.561	0.800
TFP_LP	Productivity by the Levinsohn-Petrin	21 937	11.807	3.783	8.185	0.971
TFP_FE	Productivity by FE	21 937	15.524	6.330	11.323	1.279
TFP_GMM	Productivity by the GMM	21 937	10.216	1.542	5.485	0.732
INPUT	Cost of intermediate inputs per unit of output	21 937	1.110	0.273	0.723	0.154
GIPUN	Number of self-owned invention green patents	23 516	5.412	0.000	0.119	0.431
GUPUN	Number of self-owned utility green patents	23 516	5.872	0.000	0.215	0.567
GIPUN_J	Number of joint-owned invention green patents	23 516	6.676	0.000	0.075	0.366
GUPUN_J	Number of joint-owned utility green patents	23 516	5.609	0.000	0.112	0.440

upstream M&As tend to exhibit better energy performance. We consider Column (6) to be the complete baseline regression result. For each additional upstream M&A transaction, the average energy performance increases by 0.531 units. This finding validates Hypothesis 1.

More than half of the control variables exhibited statistical significance. Downstream M&As (MADOWN) have are not significantly correlated with corporate energy performance, whereas the correlation for horizontal M&As (MASAME) is significantly negative. For corporate energy performance, horizontal M&As may generate negative synergy. From the perspective of corporate M&A motivations, strengthening market power may be one of the key reasons for merging competitors in the same industry (Perry and Porter, 1985; Salant et al., 1983). In such cases, corporate strategies may focus more on profitability than on the green and sustainable aspects of M&A projects (Herbohn et al., 2019). Corporate energy performance is positively correlated with firm age, ROA, Tobin Q, and financial leverage, but negatively correlated with equity concentration. In summary, a secure financial environment and development prospects provide a governance space for corporate green development.

Table 2
Baseline regression results

Dep. Var.	Energy performance					
	(1)	(2)	(3)	(4)	(5)	(6)
MAUP	2.458***	2.622***	0.524***	0.565***	0.606***	0.531***
	(0.172)	(0.178)	(0.152)	(0.153)	(0.156)	(0.153)
MADOWN					0.126	0.089
					(0.152)	(0.148)
MASAME					−0.398***	−0.336**
					(0.149)	(0.149)
LNAGE						0.743***
						(0.217)
ROA						4.459*
						(2.414)
ROE						−1.348
						(0.879)
TOBINQ						0.154**
						(0.065)
TOPHOLD						−0.041***
						(0.009)
FINLEV						1.373***
						(0.442)
CASHRATE						0.466
						(0.764)
Constant	6.315***	5.194***	6.106***	6.089***	6.145***	6.066***
	(0.179)	(0.077)	(0.066)	(0.067)	(0.089)	(0.793)
Firm FE	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes
Industry–Province FE	No	No	No	Yes	Yes	Yes
N	23 516	23 516	23 516	23 516	23 516	23 516
R^2		0.701	0.776	0.803	0.804	0.807

Notes: This table reports the relationship between the number of upstream M&As and the energy performances. The dependent variables used in the regression are all EPerform. We include enterprise fixed effects (FE), year fixed effects (FE), and industry-province-level interaction FE in Columns (4) to (6). Cluster-robust standard errors at the enterprise level are used. These settings are consistent across subsequent regressions in the paper. Standard errors are reported in parentheses. *** $P < 0.01$, ** $P < 0.05$, * $P < 0.10$.

5.2. Robustness test

5.2.1. Changing the measure of the dependent variable

Yu et al. (2023) and Caparrós et al. (2013) emphasized that the technology and R&D of an enterprise are equally critical for achieving emission reductions. Following the approach of Shen et al. (2020) and adapting to our requirements for calculating the dependent variable, the energy performance of enterprises considering the intensity of R&D investment can be represented as follows.

$$\mathrm{EPerform\_RD}_{it} = \frac{\mathrm{Revenue}_{it}}{\mathrm{CEmission}_{it} \times (\mathrm{AIR\&D}_{st}^{industry}/\mathrm{CR\&D}_{it})} \tag{20}$$

Where, $\mathrm{AIR\&D}_{st}^{industry}$ denotes the average R&D investment intensity of industry s in which the company operates, and $\mathrm{CR\&D}_{it}$ denotes the R&D investment intensity of the company itself. Weighting by R&D factors reveals that companies with higher R&D investments have better energy performance. The regression results using EPerform_RD as the dependent variable are presented in Column (1) of Table 3. We also employed the company's per capita carbon emissions as an alternative dependent variable, calculated by dividing the company's carbon emissions by the number of employees. The regression results are shown in Column (2) of Table 3, showing that the main results remain robust.

5.2.2. Excluding exceptional samples of observations

The Thomson SDC M&A information can be traced back to as early as 1995, while the basic information of the Chinese listed companies we used starts from 2007. Given this issue, we attempted to exclude those companies that had already engaged in upstream M&As before the initial year 2007 from our sample to optimize the comparability of the remaining companies in the sample. We also aimed to mitigate the uncertainty caused by the 2008–2009 global financial crisis by setting the sample period for regression from 2010 to 2021. The results are presented in Columns (3) and (4) of Table 3, respectively, showing findings similar to the baseline regression.

Table 3
Robustness test (changing dependent variable measurement and excluding special samples)

Dep. Var.	EPerform_RD	PCEmission	EPerform	
	(1)	(2)	(3)	(4)
MAUP	1.288***	0.008**	0.554***	0.497***
	(0.317)	(0.003)	(0.155)	(0.161)
MADOWN	0.323	−0.001	0.082	0.152
	(0.297)	(0.003)	(0.150)	(0.163)
MASAME	0.937**	−0.008	−0.326**	−0.459***
	1.288***	0.008**	(0.154)	(0.173)
Constant	2.991**	0.076***	6.179***	6.289***
	(1.474)	(0.021)	(0.796)	(0.853)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry–Province FE	Yes	Yes	Yes	Yes
N	23 090	23 509	23 380	21 152
R^2	0.722	0.894	0.807	0.814

Notes: In Column (1), the dependent variable used is EPerform_RD, which considers the R&D factor. In Column (2), the dependent variable used is the per capita carbon emissions at the enterprise level, PCEmission. Columns (3) and (4) use the same dependent variables as the benchmark regression. Enterprise-level clustering robust standard errors are presented in parentheses. *** $P < 0.01$, ** $P < 0.05$.

5.2.3. Changing the measure of the core independent variable

When conducting the robustness tests, we adjusted the measurement methods of the M&A variables to test the robustness. First, we adjusted the identification years of M&A activities, reidentifying them based on the announcement year of M&A. Second, we used the USIO 2007 and USIO 2012 to adjust the source of the industry-level upstreamness calculation. Finally, we adjusted the threshold for identifying effective M&A by modifying the identification ratio to ⩾ 25% or used the 100% wholly owned M&A standards for screening. The other settings remained unchanged. The results in Table 4 confirm the robustness of the baseline findings.

Table 4
Robustness test (changing the measure of the core independent variable)

Dep. Var.	Announce	USIO 2007	USIO 2012	⩾ 25% Share	100% Share
	(1)	(2)	(3)	(4)	(5)
MAUP	0.527***	0.568***	0.567***	0.528***	0.517**
	(0.151)	(0.149)	(0.153)	(0.127)	(0.216)
MADOWN	0.087	0.053	0.065	0.036	0.027
	(0.147)	(0.152)	(0.151)	(0.125)	(0.204)
MASAME	−0.348**	−0.353**	−0.357**	−0.272**	−0.342*
	(0.153)	(0.149)	(0.150)	(0.129)	(0.205)
Constant	6.043***	6.046***	6.032***	5.997***	6.147***
	(0.793)	(0.792)	(0.793)	(0.793)	(0.798)
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry–Province FE	Yes	Yes	Yes	Yes	Yes
N	23516	23516	23516	23516	23516
R^2	0.806	0.807	0.807	0.807	0.806

Notes: Enterprise-level clustering robust standard errors are in parentheses. *** $P < 0.01$, ** $P < 0.05$, * $P < 0.10$.

5.3. Endogeneity

The endogeneity of our model stems from two sources: First, sample selection bias from the exogeneity requirement of M&A shocks. Second, better energy performance indicates the healthy development state of companies, and improved business conditions may also prompt companies to engage in M&As, leading to the issue of reverse causality. To address the first source, the PSM-DID method was used to handle sample selection bias. For the second source, we use the instrumental variables.

5.3.1. PSM-DID

M&A activities may be nonrandom; thus, there may be a sample selection bias. We address this issue using the PSM-DID method, which has been widely used in emissions reduction (Huang et al., 2022; Yu et al., 2023; Zhang et al., 2019), to identify a control group of samples with characteristics most similar to those of the treated companies. Given that the feature variables of the treated and control group samples remain similar before the M&A events, the DID method is then used to reassess the impact of the upstream M&As on the energy performance.

Following Huang et al. (2022), we used firm characteristic variables observed before the first M&A event as matching covariates, including EPerform, Size, and Levrate. Specifically, we employed the lagged one- and two-period variables relative to the matching year, applying the nearest neighbor matching method with a ratio of 1:3. Observations from 2007 to 2008 were excluded from the matched regression. The probability of M&A is predicted using the probit model. Figure 3 and Table 5 show the differences between the treated and control groups before and after matching. Figure 3 indicates that the bias in each covariate exceeds 10%. However, after matching, the bias in the covariates was within 3%. Table 5 presents the PSM matching error test results for the covariates, indicating no significant differences between the two groups after matching. These results demonstrate that PSM successfully balanced the characteristics of the two groups. We then rerun the baseline regression Equation (12) and report the results of the PSM-DID in Columns (1)–(3) of Table 6. The results indicate that the core conclusion still holds.

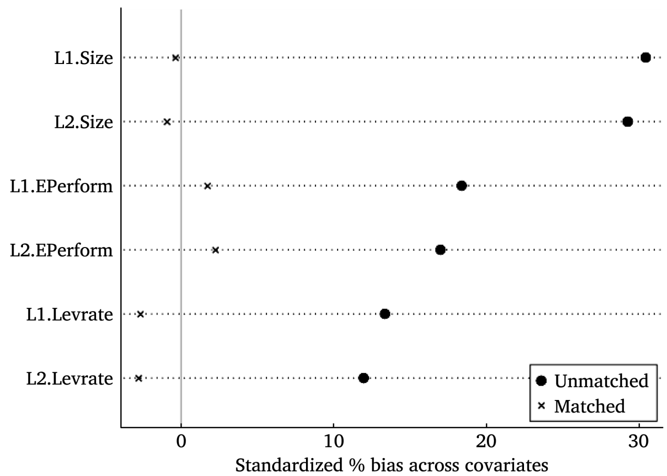

Figure 3. Covariate bias before and after matching

Table 5
PSM matching error test

Variables	Unmatched Matched	Mean Treated	Mean Control	Bias (%)	Reduct |bias| %	*T*-test *t*	*T*-test $P > \|t\|$
		(1)	(2)	(3)	(4)	(5)	(6)
L1.EPerform	U	7.089	5.385	18.400		12.110	0.000
	M	7.415	7.256	1.700	90.700	0.810	0.419
L2.EPerform	U	5.943	4.557	17.000		11.080	0.000
	M	6.175	5.992	2.200	86.800	1.070	0.286
L1.Size	U	22.350	21.960	30.400		19.52	0.000
	M	22.400	22.410	−0.400	98.800	−0.190	0.851
L2.Size	U	22.220	21.850	29.300		18.610	0.000
	M	22.250	22.260	−0.900	96.800	−0.470	0.642
L1.Levrate	U	0.429	0.403	13.300		8.460	0.000
	M	0.433	0.438	−2.700	79.900	−1.410	0.157
L2.Levrate	U	0.419	0.396	12.000		7.510	0.000
	M	0.421	0.426	−2.800	76.600	−1.460	0.145

Notes: Columns (1) and (2) display the average values of the covariates for the treated and control groups, respectively. Column (3) shows the sample bias before and after matching. Column (4) reports the reduction in the bias after matching. Columns (5) and (6) provide the *t*-test information for the paired samples.

5.3.2. Instrumental variable

To address the issue of reverse causality, we utilize the lagged one period of the core independent variable, L1.MAUP, as an instrument variable in the regression. The current period's energy performance does not influence the past M&A activities of the company and is strongly correlated with the current M&A decisions, meeting the requirement for instrumental variables. In Table 6, Column (4) utilizes L1. MAUP as a substitute and runs the OLS regression. We use L1.MAUP is the instrumental variable for MAUP, and the 2SLS regression is run, reporting the estimation results of the second stage in Column (5). Overidentification and the weak instrument test passed, with the coefficient of the independent variable remaining significant at the 1% level.

Table 6
Regression results of endogeneity issues

Dep. Var.	PSM-DID method			Lag	IV
	(1)	(2)	(3)	(4)	(5)
MAUP	0.494^{***}	0.550^{***}	0.549^{***}		0.625^{***}
	(0.181)	(0.176)	(0.184)		(0.200)
MADOWN	0.070	0.026	0.038	0.071	0.058
	(0.195)	(0.200)	(0.197)	(0.154)	(0.152)
MASAME	-0.365^{*}	-0.402^{**}	-0.405^{**}	-0.282^{*}	-0.314^{**}
	(0.206)	(0.205)	(0.206)	(0.158)	(0.159)
L1.MAUP				0.487^{***}	
				(0.158)	
Constant	6.044^{***}	5.991^{***}	6.010^{***}	5.435^{***}	
	(1.576)	(1.575)	(1.577)	(1.008)	
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry–Province FE	Yes	Yes	Yes	Yes	Yes
N	12 664	12 664	12 664	21 331	21 335
R^2	0.857	0.857	0.857	0.820	0.397

Notes: Columns (1) – (3) report the PSM-DID estimation results using USIO 2017, USIO 2007, and USIO 2012 as the data sources for the industry-level upstreamness calculation, respectively. Column (4) reports the OLS estimation results using L1. MAUP as an alternative independent variable. Column (5) reports the IV regression results using L1.MAUP as the IV. In Column (5), the Kleibergen–Paap r LM statistic value is 146.82, passing the overidentification test; the Kleibergen–Paap r Wald F statistic value is 6 308.69, passing the weak instrument test. Enterprise-level clustering robust standard errors are presented in parentheses. *** $P < 0.01$, ** $P < 0.05$, * $P < 0.10$.

5.4. Target firm characteristics and energy performance

We aimed to differentiate the characteristics of the target companies along three dimensions to analyze the sources of heterogeneity. First, we distinguished whether the target company was listed, as reported in Column (1) of Table 7. Only the estimated coefficient of MAUP_NLD is significantly positive, indicating that conducting upstream M&As is more beneficial when the target is a nonlisted company. Second, we distinguished whether the target company was domestic. With the coefficient of MAUP_D being significantly positive, the result suggests that integrating domestic upstream suppliers is more effective. From the estimated coefficients, the value of MAUP_F for upstream M&As targeting foreign companies is higher but insignificant. Although listed companies may pursue overseas upstream M&As to acquire advanced clean production technologies, applying technologies in production may take time. Generally speaking, the cost of integrating overseas suppliers is higher. From the perspective of corporate M&A motives, to offset the acquisition costs for companies after overseas upstream M&As may be to expand production rather than improve performance. Additionally, after integrating foreign suppliers, the internal procurement within the group still faces the issue of multinational trade costs, which may partly offset the input substitution effect of internalized procurement. In the sample observed, the proportion of Chinese listed companies initiating overseas M&As is relatively low (approximately 5.3% of the total number of M&As), suggesting that the acquisition targets of Chinese listed companies are still predominantly domestic firms, and vertical integration with overseas suppliers is uncommon.

Finally, we distinguished the scale of the M&A activities. Following Yu et al. (2023), we divided the sample of M&A activities into two groups based on median size. As shown in Column (3) of Table 7, only the regression coefficient of MAUP_L shows sufficient significance, indicating that upstream M&As must reach a certain scale threshold to be effective. We believe that for listed companies, suppliers as target entities must reach a particular scale to exert sufficient influence on the change in the acquirer's supply chain structure. Therefore, the capacity scale of the target company is equally important, even if the acquirer already gains control through an M&A.

5.5. Acquirer's characteristics and energy performance

Acquirer characteristics are also important sources of the heterogeneity effect of M&A, reflecting companies' different operating conditions and development goals. We differentiated acquirer characteristics along several dimensions: regional location, ownership structure, firm size, and financing constraint status. First, we grouped the acquirer sample into three regions. The regression results are shown in Columns (4)–(6) of Table 7. Second, we categorized the sample based on the ownership structure of the acquirer, with the results presented in Columns (1)–(3) of Table 8. Third, we divided the sample into 10 groups according to acquirer size, with the top three groups being small enterprises and the bottom three being large enterprises. Results are shown in Columns (4)–(5) of Table 8. Finally, by calculating the financial constraint index (Hadlock and Pierce, 2010) for companies, $\mathrm{SA} = -0.737 \times \mathrm{Size} + 0.043 \times \mathrm{Size}^2 - 0.04 \times \mathrm{Age}$, we grouped the sample based on the median and analyzed the differences in financing constraint levels on upstream M&A consequences, as shown in Columns (6)–(7) of Table 8.

In summary, companies in eastern China or those with state-owned/private ownership, larger development scales, and higher financing constraint levels significantly improved their energy performance through upstream M&As. We interpret this as follows: companies in the eastern region face stricter environmental regulations, leading to a greater willingness to implement energy-saving measures, even in M&A decisions; foreign-owned enterprises often have higher environmental performance requirements and utilize their unique multinational supply chains for production; larger enterprises may have more internal resources to coordinate M&As and energy-saving strategies; and companies with higher financing constraints tend to set higher required rates of return for projects, preferring higher-quality targets and focusing on evaluating M&A performance to avoid "investment waste".

5.6. Short-and-long-term impact

Using a method similar to the parallel trends test in event studies (Borusyak et al., 2024; Marcus and Sant'Anna, 2021; Schmidheiny and Siegloch, 2023), we demonstrate the impact of the distribution hysteresis M&A's impact on energy performance. This method allowed us to observe the differential effects of upstream M&As in the short and long term, as well as the trend before the events occurred. We specified the estimation model as follows.

Table 7
Heterogeneity analysis distinguishing target firm characteristics and acquirer size

Dep. Var.	Characteristics of the target			Characteristics of the acquirer		
	(1)	(2)	(3)	(4)	(5)	(6)
	Listed	Nation	M&A size	East	Middle	West
MAUP_LD	1.826					
	(1.686)					
MAUP_NLD	0.516***					
	(0.155)					
MAUP_D		0.493***				
		(0.160)				
MAUP_F		1.036				
		(0.638)				
MAUP_L			1.160***			
			(0.272)			
MAUP_S			0.199			
			(0.234)			
MAUP				0.506***	0.599	0.066
				(0.181)	(0.393)	(0.338)
MADOWN	0.091	0.094	0.093	0.289	−0.162	−0.868***
	(0.148)	(0.148)	(0.147)	(0.189)	(0.260)	(0.224)
MASAME	−0.337**	−0.339**	−0.313**	−0.341*	−0.715**	0.380
	(0.149)	(0.149)	(0.149)	(0.186)	(0.297)	(0.365)
Constant	6.055***	6.055***	6.073***	7.204***	4.691***	1.748
	(0.793)	(0.793)	(0.788)	(0.992)	(1.806)	(1.962)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry–Province FE	Yes	Yes	Yes	Yes	Yes	Yes
N	23 516	23 516	23 516	16 081	4 062	3 343
R^2	0.807	0.807	0.807	0.812	0.788	0.786

Notes: Columns (1) to (3) report the estimation results distinguishing the characteristics of target companies, including whether listed, whether domestic, and M&A scale. Columns (4) to (6) report the estimation results distinguishing the regions where the acquirer is located. MAUP_LD denotes the number of M&A transactions when the target company is listed, while MAUP_NLD denotes nonlisted. MAUP_D denotes the number of M&A transactions when the target company is domestic, while MAUP_F is used when the target is foreign. MAUP_L denotes the number of large-scale M&A transactions, whereas MAUP_S denotes small-scale. Enterprise-level clustering robust standard errors are presented in parentheses. *** $P < 0.01$, ** $P < 0.05$, * $P < 0.10$.

$$\text{EPerform}_{it} = \alpha_0 + \beta_k^{year} \Sigma_{k \geq -10, k \neq 0}^{10+} \text{MAUP}_{t_i+k} + \beta_2 \text{MADOWN}_{it} + \beta_3 \text{MASAME}_{it} + \beta' Z_{it} + \{\text{FE}\} + \upsilon_{it} \quad (21)$$

Where, k denotes the time interval from the first observation to the initiation of the upstream M&A. We simultaneously observed the performance in the windows before and after the first upstream M&A, with the year of the first upstream M&A ($k = 0$) set as the baseline period③. We report all the estimation results of β_k^{year} in Figure 4. Before the upstream M&A, the parameter estimates of β_k^{year} are mostly distributed around zero and are not significant; from the 2nd to the 8th period after the upstream M&A, β_k^{year} is positive and significantly effective. Considering the coefficient significance, the improvement in energy performance of enterprises is not significant in the short term after the upstream M&As but is effective in the medium to long term. With the postponement of M&As effective, improvement will weaken and become ineffective. Our results are supported by Altunbaş et al. (2023), who found that cost- and emission-reduction measures take time to implement; thus, energy performance may not improve immediately. Unlike Altunbaş et al. (2023), our result suggests the importance of M&A motivations for energy performance from the perspective of industrial chains.

5.7. Mechanism

This section explores the potential channels for improving energy efficiency after companies make upstream M&A decisions. To examine the mechanism, we use a two-stage verification approach as follows.

$$\text{Channel}_{it} = \alpha_0 + \beta_1 \text{MAUP}_{it} + \beta_2 \text{MADOWN}_{it} + \beta_3 \text{MASAME}_{it} + \beta' Z_{it} + \{\text{FE}\} + \upsilon_{it} \quad (22)$$

$$\text{EPerform}_{it} = \alpha_0 + \beta_1 \text{MAUP}_{it} + \beta_4 \text{Channel}_{it} + \beta_2 \text{MADOWN}_{it} + \beta_3 \text{MASAME}_{it} + \beta' Z_{it} + \{\text{FE}\} + \upsilon_{it} \quad (23)$$

Where, Channel_{it} represents the relevant mediating variables. The settings of the other variables remain the same as the baseline Model (10).

5.7.1. Effect of productivity

We first validate the productivity mechanism. We calculate firm-level productivity in four ways (OP, LP, GMM, and FE) and run two-stage regressions according to Equations (22) and (23). The results are presented in Table 9. The coefficients of the MAUP and TFP variables were positive and significant, indicating the effectiveness of both two-stage regressions. Increased productivity is essential for enterprises to improve their energy performance through upstream M&As. Thus, Hypothesis 3 is verified.

In addition, previous studies have demonstrated the benefits of M&A transactions on green technology innovation (Liang et al., 2022; Yang and Chi, 2023; Zhang et al., 2023), and technological progress has been widely considered part of productivity. As a supplement to the productivity channel analysis, we investigate whether upstream M&As can result in technology innovation. Green innovation helps companies save costs, reduce energy consumption in the short term, and lay the foundation for long-term sustainable development. By integrating green innovation into production, companies can optimize their processes and reduce reliance on natural resources, enhancing their competitiveness and long-term productivity. We treat a company's green patent applications as a proxy for productivity progress. Patent applications are largely related to the technological advancement of a company, and technology is a key productivity component. Importantly, green patent applications are likely driven by energy-saving motives; thus, the number of green patent applications is more aligned with our research objectives.

We set four proxy variables to measure green R&D innovation, including the number of independent green invention patents (GIP_I), independent green utility patents (GUP_I), joint green invention patents (GIP_U), and joint green utility patents (GUP_U). These variables were all calculated in logarithmic form using basic data from *CNRDS*. The regression results based on the same validation logic are presented in Columns (1)–(6) of Table 10, indicating a significant positive correlation between joint green innovation patents, upstream M&A, and energy performance, regardless of patent type. Our find-

③Equation (21) allows us to evaluate the effects before and after M&A separately over 10 years, which does not permit us to use the variable form of the number of M&A occurrences to assess the treatment effects. Therefore, MAUP_{t_i+k} are set as dummy variables. Our focus is on testing the distribution lag of the treatment effects.

Table 8
Heterogeneity analysis to distinguish M&A firm characteristics

Dep. Var.	Characteristics of the acquirer						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	State	Private	Foreign	Large	Small	High SA	Low SA
MAUP	0.543**	0.423**	0.018	0.801***	0.513	0.448**	0.404
	(0.216)	(0.215)	(1.118)	(0.240)	(0.504)	(0.210)	(0.280)
MADOWN	−0.292*	0.109	0.400	−0.224	0.901*	−0.056	0.460
	(0.175)	(0.204)	(0.723)	(0.186)	(0.547)	(0.183)	(0.323)
MASAME	−0.068	−0.401*	−0.975	−0.278	−0.031	−0.096	−0.025
	(0.206)	(0.234)	(0.740)	(0.184)	(0.696)	(0.192)	(0.336)
Constant	2.293	8.167***	7.874**	3.768***	8.782***	4.170***	6.765***
	(1.506)	(1.089)	(3.718)	(1.448)	(1.719)	(1.331)	(1.074)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry–Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	8 563	13 199	1 321	8 256	5 872	11 786	11 483
R^2	0.773	0.818	0.853	0.766	0.843	0.836	0.844

Notes: Enterprise-level clustering robust standard errors are presented in parentheses. *** $P < 0.01$, ** $P < 0.05$, * $P < 0.10$.

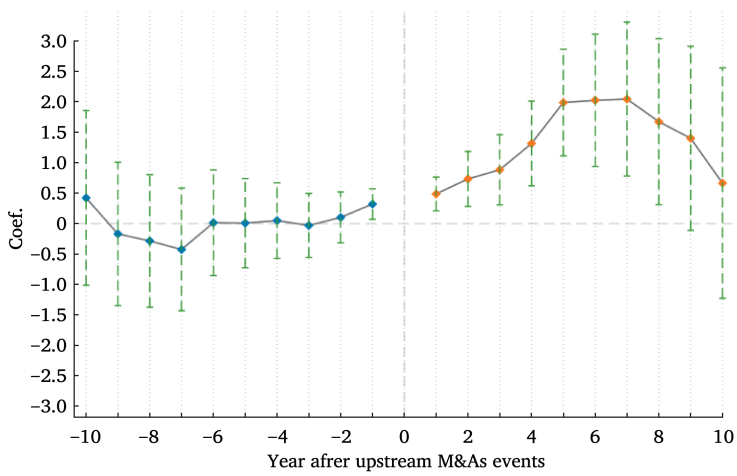

Figure 4. Short- and long-term impact of upstream M&As on energy performance
Notes: The horizontal axis represents the gap between the occurrence of the upstream M&As and the first instance. The vertical axis represents the estimated coefficients, with the midpoint of each vertical line indicating the parameter estimate, and the two endpoints indicating the confidence interval at a 95% confidence level.

ings are consistent with Shapiro and Walker (2018) and Long et al. (2017). In summary, upstream M&As have strong technological-seeking motivations and can lead to joint green technology innovation with target companies, improving energy performance. Thus, Hypothesis 4 is verified.

5.7.2. Input substitution effect

To test the input substitution effect, we define INPUT as a proxy variable for the overall cost of inputs, representing the intermediate input cost per unit of output, calculated as the ratio of the intermediate input to the total output. Results are presented in Columns (7) and (8) of Table 10. The estimates of MAUP in Column (7) and INPUT in Column (8) are both significantly positive, consistent with the meaning represented in the theoretical analysis section, indicating that upstream M&A activities aimed at supply chain integration can reduce the overall cost of inputs, improving enterprise energy performance. This validates Hypothesis 2 as proposed.

6. Conclusion

In the context of increasing external regulatory stringency and growing calls for green development, companies have prioritized improving energy efficiency as an essential task and seeking returns in energy conservation or emission reduction through M&A. As GVC production thrives, M&As driven by supply chain integration are also increasingly prevalent. However, the literature analyzing the impact of M&A activities on corporate energy performance from the perspective of the production chain is limited, especially considering upstream and downstream dynamics. In this study, we constructed a theoretical model at the firm level to analyze how upstream M&As affect corporate energy efficiency. Subsequently, using data from Chinese listed companies from 2007 to 2021, we identified and examined the effects of upstream M&As driven by supply chain integration on energy performance and its underlying mechanisms. Our results indicate that upstream M&As significantly improve corporate energy efficiency, whereas downstream and horizontal M&A activities affect energy per-

Table 9
Mechanism of the productivity Channel

Dep. Var.	OP		LP		GMM		FE	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	TFP_OP	EPerform	TFP_LP	EPerform	TFP_GMM	EPerform	TFP_FE	EPerform
MAUP	0.059***	0.480***	0.085***	0.445***	0.050***	0.488***	0.115***	0.420***
	(6.364)	(3.014)	(8.278)	(2.783)	(5.564)	(3.057)	(9.437)	(2.635)
MADOWN	0.062***	0.018	0.086***	−0.016	0.054***	0.026	0.115***	−0.039
	(6.755)	(0.119)	(8.208)	(−0.104)	(6.006)	(0.168)	(9.238)	(−0.250)
MASAME	0.024*	−0.305**	0.053***	−0.336**	0.015	−0.298*	0.086***	−0.363**
	(1.793)	(−1.969)	(4.152)	(−2.160)	(1.142)	(−1.921)	(5.758)	(−2.340)
TFP_OP		0.682***						
		(3.354)						
TFP_LP				0.891***				
				(4.372)				
TFP_GMM						0.649***		
						(3.217)		
TFP_FE								0.864***
								(4.579)
Constant	5.880***	−0.014	7.277***	−2.485	4.992***	0.760	9.890***	−4.551**
	(76.845)	(−0.009)	(88.451)	(−1.352)	(67.501)	(0.520)	(100.916)	(−2.098)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry–Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	21 931	21 931	21 931	21 931	21 931	21 931	21 931	21 931
R^2	0.882	0.817	0.909	0.817	0.859	0.816	0.935	0.817

Notes: Columns (1), (3), (5), and (7) run first-stage regressions based on Equation (19), with the dependent variable being the TFP measured using different methods. Columns (2), (4), (6), and (8) run second-stage regressions based on Equation (20) and use EPerform as the dependent variable. Enterprise-level clustering robust standard errors are presented in parentheses. *** $P < 0.01$, ** $P < 0.05$, * $P < 0.10$.

Table 10
Mechanism test of green innovation and input substitution

Dep. Var.	Green innovation patents						Intermediate input	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	GIP_I	GUP_I	GIP_U	EPerform	GUP_U	EPerform	INPUT	EPerform
MAUP	0.009	0.010	0.024***	0.500***	0.029***	0.516***	−0.003*	0.508***
	(1.311)	(1.109)	(3.163)	(3.348)	(3.238)	(3.386)	(−1.677)	(3.193)
MADOWN	−0.004	−0.005	0.004	0.084	0.008	0.085	−0.001	0.058
	(−0.371)	(−0.520)	(0.728)	(0.570)	(1.286)	(0.577)	(−0.372)	(0.378)
MASAME	0.007	−0.009	0.009	−0.347**	0.004	−0.338**	0.001	−0.283*
	(0.640)	(−1.025)	(0.872)	(−2.370)	(0.404)	(−2.269)	(0.573)	(−1.828)
GIP_U				1.294***				
				(4.012)				
GUP_U						0.511**		
						(2.167)		
INPUT								−4.119***
								(−4.341)
Constant	0.124***	0.231***	0.023	6.036***	0.060	6.035***	0.750***	7.089***
	(2.911)	(4.630)	(0.614)	(7.651)	(1.499)	(7.618)	(45.665)	(5.488)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry–Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	23 516	23 516	23 516	23 516	23 516	23 516	21 931	21 931
R^2	0.618	0.615	0.656	0.807	0.612	0.807	0.842	0.817

Notes: Columns (1), (2), (3), (5), and (7) of the table run first-stage regressions based on Equation (21). Columns (4), (6), and (8) run second-stage regressions based on Equation (20). For GIP_I and GUP_I, we did not run second-stage regressions based on Equation (20) because the first-stage estimates shown in Columns (1) and (2) are not significant. Enterprise-level clustering robust standard errors are presented in parentheses. *** $P < 0.01$, ** $P < 0.05$, * $P < 0.10$.

formance differently. Mechanism tests revealed that input substitution and productivity effects are important pathways to improve energy efficiency. Furthermore, M&A activities promote joint innovation in green technologies between companies and suppliers, improving energy performance by enhancing productivity.

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