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Online investor attention and firm restructuring performance: Insights from an event-based DEA-Tobit model

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ABSTRACT

Tourism firms frequently undergo restructuring to mitigate survival risks and enhance firm value. However, whether restructuring benefits for the formation of scale and synergistic effects remains unknown. In this paper, we aim to provide an approach to measure the scale effect brought by restructuring activities and investigate the determinants of performance from the scale effect of tourism firm restructuring. Drawing on efficiency theory, we propose an event-based data envelopment analysis method to measure restructuring performance by constructing dynamic event windows. Building on the complementarity of the attention-based view and the upper echelons theory, we uncover the transmission mechanism between managers and investors. Our results reveal that: (1) operating efficiency gains gradually decrease as event windows extend, while the proportion of increasing returns to scale grows across most tourism restructuring strategies; (2) Tobit regression analysis verifies an inverted U-shaped relationship between investor attention to online posting behavior and restructuring performance; and (3) the interaction between investor attention to online search and posting behavior strengthens the influence of investor attention on restructuring performance. This study sheds light on the complexities of restructuring in the tourism industry and highlights the importance of considering the impact of online investor attention on firm performance.

1. Introduction

Merger and acquisition activities commonly focus on the transfer of equity and corporate control, where two firms merge to create a new entity by combining their activities [1]. Asset restructuring, on the other hand, places extra emphasis on changing asset relationships and realigning resources. This may involve downsizing the former firm or creating a new entity dedicated to inherited activities [2]. In this paper, we treat all of these strategic activities, including mergers, acquisitions, consolidations, splits, divestitures, and equity transfers, as generalized restructuring. This refers to a strategic action in a business market where a homogeneous set of firms (i.e., pre-restructuring entities) undergo a restructuring event to generate a new group of post-restructuring entities to realize profitability or efficiency gains [3]. Tourism firms are frequently at the forefront of implementing restructuring activities due to their vulnerability to internal and external environments and shocks in uncertain tourism demands [4].

The evaluation of tourism firms' restructuring activities has been an ongoing debate, with the impact on firm value remaining unclear [5]. Operating measures, such as efficiency and productivity, and profitability measures, such as accounting and market returns, are often used as proxies for restructuring performance [6]. However, existing studies on tourism firms' restructuring performance have mainly focused on accounting and financial indexes, such as stock returns [4], financial incomes [7], or both [2]. While event studies are based on the efficient market hypothesis, which assumes that all valuable information is timely and accurately reflected in stock prices in a transparent and competitive stock market [8], classical market model estimation neglects individual stock performance relative to the specific market. Furthermore, using a single linear regression to capture intricate stock behavior is questionable [9]. Additionally, relying on multiple accounting ratios, such as return on assets and Tobin's Q, may provide

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limited insight, especially when considering the effect of economies of scale and identifying benchmarking strategies [10].

Current studies on tourism firms' restructuring activities have overlooked the scale and synergistic effects in the dimension of economies of scale and scope, which can rationalize asset and employee allocation, reduce transaction costs, and reallocate intangible assets [11]. Data envelopment analysis (DEA), an efficiency-based approach, can model the theory of production economics using operations research techniques to reveal firms' production and operation processes [12,13]. The classical CCR model proposed by Charnes et al. [14] assumes constant returns to scale (CRS), while the BCC model [15] accounts for variable returns to scale (VRS). The additive DEA model can evaluate decision-making units' (DMUs) efficiency using both input and output orientations, while also considering the CRS or VRS assumptions [16]. By executing these traditional DEA models and considering returns to scale, one can obtain scale efficiency or effect by calculating the ratio of technical efficiency (under the CRS assumption) and pure technical efficiency (under the VRS assumption) [17].

From the perspective of a reference set, the traditional DEA model is an analysis technique based on a self-evaluation system, and therefore cannot choose the reference set independently [18]. Additionally, due to the uncertainty of DMUs' reference set, the evaluation results given by traditional DEA models are relative and random [19]. Restructuring activities often span a time range or event period, generating short-term (less than a quarter), medium-term (between a quarter and a year), and long-term (over a year) measures of restructuring performance [7]. Therefore, the window DEA analysis can obtain dynamic efficiency scores in pre-set windows with variable width, improving the reliability of small sample data analysis [18]. Moreover, this method can increase the number of observations by generating a sequence of overlapping windows and enhance the robustness of estimated results [20]. This paper aims to propose an approach to measure the scale effect resulting from restructuring activities and examine the determinants of performance resulting from the scale effect of tourism restructuring.

Firms need to make effective management and investment decisions to improve their operating efficiency and resource allocation ability. The resources owned by each firm are typically heterogeneous, which determines the differences in their competitiveness [21]. The resource-based view focuses on the ability to acquire and deploy finite resources to maximize firm value during restructuring activities [22]. Additionally, effective integration of external resources such as investor attention, customer satisfaction, word-of-mouth and reputation is necessary to achieve the external scale effect. Attention, which requires time and effort, means gaining insights into a firm's internal and external environment and how to address it [23]. The attention-based view highlights the capacity of stakeholders, such as investors here, to process information and the distribution of their limited attention [24]. This paper combines two perspectives to provide a "measurement-determinants analysis framework" [25] in the context of tourism firm restructuring.

This paper contributes to the current understanding of tourism firm restructuring by introducing novel concepts and analytical tools. We develop a dynamic restructuring performance model within an event window framework to account for time-varying factors such as seasonal volatility, thus providing a more comprehensive analysis of restructuring activities. To analyze the medium- to long-term restructuring performance of listed tourism firms using fine-grained quarterly data, we adopt an event-based DEA method and set varying event window lengths. Specifically, we calculate the dynamic restructuring performance across three event windows with lengths of three, five, and seven quarters, which captures most of the duration of restructuring activities. Finally, we determine the scale efficiency scores under different event windows, as well as the operating efficiency gains and returns to scale of each restructured tourism firm.

Furthermore, this study aims to examine the effects of tourism investors' online behaviors, in the forms of online attention, on tourism firms' medium- or long-term restructuring performance, as indicated by scale efficiency scores. Specifically, we investigate the non-linear relationship between investors' posting behaviors (including different sentiment valences) and firms' restructuring performance. Our findings reveal that operating efficiency gains tend to decrease with the extension of the event windows, while the proportion of increasing returns to scale (RTS) tends to increase across most restructuring strategies. Using Tobit regression analysis, we confirm the existence of an inverted U-shaped relationship between investor attention from online posting behavior and restructuring performance, and find that the collaboration with investor attention from online search behavior moderates this relationship.

The structure of this paper is as follows: Section 2 provides a review of the literature and develops hypotheses. Section 3 presents the research design and methodology. Section 4 reports on the empirical analysis and results. Finally, in Section 5, we conclude and discuss the implications of our findings.

2. Literature review and hypotheses development

2.1. Tourism firm restructuring

Tourism firms often engage in restructuring activities to deal with the uncertainty of tourist consumption demand, the complexity of the internal and external environment, and fierce market competition [4]. There is a need to consider context characteristics in light of industrial heterogeneity [26], as the same restructuring strategies may produce diverse effects across different industries [27]. A restructuring announcement serves as a common indication of a tourism firm's undergoing reorganization. It entails the public and official disclosure of comprehensive restructuring matters that may significantly influence the firm's stock price [6]. How restructuring is beneficial for the improvement of firm value remains unclear, whether it is considered through accounting ratios or cumulative abnormal returns as a proxy for restructuring performance [6]. Restructuring can contribute to the improvement of firm value by facilitating the mutual sharing and communication of information, as well as integrating and optimizing various resources from both sides, thereby promoting production efficiency and competitiveness [11]. However, firm restructuring can also lead to negative outcomes [28]. For instance, the shareholders of restructured hotel firms did not receive excess returns in the short term, and the restructuring even had a negative impact on the stock price of the acquiring firm in the long term [29].

The event study method, commonly adopted to capture listed firms' market returns, is increasingly popular in the tourism context under the efficient market hypothesis [8]. It is commonly employed to examine the response of a particular firm's stock price (or market value) prior to and following a specific economic event, such as a merger or acquisition [30]. By analyzing the change in stock price returns before and after the event during a specific event window, the impact of the event on the stock price is quantified [31]. However, methodological challenges related to confounding events and adequate statistical tests are crucial to the inference validity of announcement effects, which makes this method more suitable for measuring short-term performance [32]. The tourism industry has industry-specific features, such as tourist consumption discretion, labor- and fixed assets-intensiveness, higher operating leverage, and vulnerability, which may affect the persistence (medium or long run) of firm value [33]. X-efficiency theory suggests that restructuring can obtain a synergistic effect and scale effect related to firms' management optimization and resource utilization [34]. However, the measurement of the scale effect of tourism firm restructuring and the possible determinants are important issues that have not been fully resolved or justified [35]. This paper provides an in-depth investigation of the medium or long-term restructuring performance of tourism firms from the perspective of scale and synergistic effects.

The theory of synergistic effect asserts that when a firm undergoes restructuring, the benefits generated by the new entity surpass the cumulative benefits of the original entities [36]. These synergistic effects enable firms to achieve a scale effect by leveraging shared information and resources, thereby realizing complementary advantages based on each firm's strengths [1]. These effects can be categorized into management synergies, which involve optimizing the comprehensive management system and improving communication efficiency; operational synergies, which enhance operational management ability and form economies of scope; and financial synergies, which improve capital management ability and reduce redundant financial costs. In support of the scale effect theory, research suggests that within a specific range, larger operating scales of firms result in lower average costs, leading to increased economic benefits and improved firm profitability [37]. Economies of scale can be categorized into internal economies of scale, which involve reducing production costs by optimizing the allocation of internal resources; external economies of scale, which involve reducing overall production costs after expanding the scale; and scale structure economy, which involves using regional cooperation to produce a scale effect. Restructuring activities present firms with an opportunity to attain a scale effect by optimizing internal operational mechanisms, enhancing market competitiveness, and accessing more financing channels and partners. This proactive approach also helps reduce the likelihood of external risk shocks [34].

2.2. Restructuring performance and benchmarking

Performance evaluation and benchmarking have become essential tools for business optimization and strategic measures, particularly in the context of firm restructuring, as firms strive to survive and thrive in a highly competitive and vulnerable industry [12]. DEA is a mathematical programming technique that identifies an efficient frontier or tradeoff curve, which serves as an empirical benchmark frontier (i.e., benchmarking) [38,39]. Based on the resource-based view [21,22], DEA has been shown to be an excellent tool for measuring and evaluating the relative efficiency of DMUs with multiple input and output variables, including in the tourism industry [13,40]. Benchmarking can establish a "standard of excellence" through the process of efficiency comparison among peer units and determine the relative positions of homogeneous DMUs [41]. The efficiency score of each DMU can be calculated by comparing their performance to the best-practice frontier [42]. However, the comparison object in the traditional DEA model is random and uncontrollable, as it consists of all DMUs under evaluation.

The literature on performance modeling has extensively explored the evaluation of operational efficiency gains resulting from generalized restructuring [43]. Frontier analysis approaches, which focus on efficiency and productivity, have been widely used by scholars to measure pre- and post-restructuring performance. These include the Bayesian random frontier model [44], Bootstrap DEA [45], inverse DEA [3], dynamic DEA [10], network DEA [46], directional distance function DEA [47], and Malmquist productivity index [48]. After measuring restructuring performance with different modeling specifications, exploring possible determinants is important. Researchers have employed robust regression techniques, such as Tobit, Simplex, and Beta, to investigate the effect of contextual variables on restructuring performance [46]. However, the existing literature on restructuring performance studies using DEA techniques mainly focuses on the banking sector and assumes the "additive scheme" to create virtual restructuring entities, which deviates from reality by simply combining corresponding inputs and outputs [49]. The operating efficiency gains are calculated by comparing pre- and post-restructuring performance to identify whether the restructuring is favorable, neutral, or unfavorable.

The announcement of restructuring presents an opportunity to distinguish sample firms from the non-restructuring group. The shift of DMUs' benchmarks calls for a new model to explore the efficiency changes resulting from the volatility of firm assets during the restructuring process. Cook et al. [41] extended the traditional DEA model by incorporating variable-benchmark and fixed-benchmark models to separate the evaluated set from the reference set. In other words, the best-practice frontier can be defined using a benchmark consisting of part units of all the DMUs (i.e., sample units) under evaluation. Following this line of analysis, the generalized DEA model can be defined using sample units to construct the production possibility set (PPS), thus achieving the separation of the evaluation object and comparison standard [19]. This model extends the reference object used for evaluation from the "standard of excellence" to "arbitrarily designated sample unit sets", overcoming the weakness of traditional DEA models that cannot independently choose a reference set according to the needs of decision makers [50]. During firm restructuring, managers may be more concerned about the performance of restructured firms relative to non-restructuring peer firms, making customized benchmarking practically significant.

The traditional DEA model evaluates the relative efficiency of DMUs using cross-sectional input-output data, which neglects the effect of time variations. Dynamic efficiency evaluation mainly encompasses dynamic DEA [51], DEA-based productivity index [52], and window DEA [20]. As a non-parametric panel approach, the window DEA technique treats each DMU in different periods as a separate entity following the principle of moving averages. This enables the evaluation of different DMUs in different periods in the process of calculating a sequence of overlapping windows [18]. The technique has the advantage of increasing the number of DMUs and acquiring better discrimination power, especially in limited sample scenarios, such as those involving listed tourism firms. In this paper, we propose an event-based DEA method that can depict real-world situations in strategic operations management. The reference set can be customized as the cluster of non-restructuring DMUs per period in each observed window. Since dynamic performance can be calculated in different periods and under diverse frontiers, the efficiency scores are not comparable in a time series for each window [10]. Thus, we extend the customized benchmarking to a global reference set by combining all the non-restructuring DMUs among each window as a cluster.

2.3. Online investor attention and restructuring performance

Most existing research focuses on the internal factors of firms, such as the payment method [53] and acquisition premiums [54] in restructuring transactions, executive attention [11] and institutional environment [55] of restructuring participants, and firm size [56] and financial characteristics [57]. However, these studies often overlook the influence of external factors on restructuring activities, except for macroeconomic determinants [58,59]. With the rapid development of information and communication technology, effective information dissemination has made public online attention an important external supervisor for listed tourism firms [60], thereby affecting their restructuring activities and performance [61]. Previous research has investigated two types of online attention related to tourism firms' restructuring performance: tourism investors' search behavior [6], as proxied by the Baidu index, and posting behavior [4], as proxied by sentiment volume and valence of posts in the stock forum of Eastmoney. However, these studies have failed to explore the non-linear relationship between online attention from tourism investors and restructuring performance, particularly in the presence of scale effects in restructuring activities.

Restructuring plays a crucial role in achieving profit or efficiency maximization within the appropriate scale of input and output resources, which is commonly referred to as the "optimal scale". Firm restructuring involves the optimal allocation of scarce resources, and the impact of managers' allocation of finite resources on tourism firms' scale efficiency is particularly critical. Upper echelons theory posits that managers make decisions and strategic choices based on their experience, attention, and values orientation [11]. The tourism industry is characterized by diverse stakeholders, and investor attention is considered a valuable and limited cognitive resource [4]. Restructuring activities are heavily scrutinized by investors, and the process is identified as expensive and complex. The online attention of tourism investors may capture the attention of managers and, consequently, influence the allocation of firm resources during restructuring, ultimately affecting scale efficiency. While firm expansion leads to improved operating efficiency and more financing channels, a firm should not blindly pursue scale expansion [3]. If a firm's scale exceeds a reasonable range, the economic benefits will gradually decline, which is not conducive to sustainable operation and development [45]. The attention of investor postings may aggregate and present by orders of magnitude and impact tourism firms' scale efficiency during restructuring similarly. Therefore, we hypothesize that:

H1: An inverted U-shaped relationship exists between the attention of investor postings and the scale efficiency of tourism firms during restructuring.

Scholars have yet to investigate the interaction effect between investor attention in searches and postings in the context of tourism firm restructuring. Baidu search engine and Eastmoney stock forum are two typical Internet platforms that can easily generate network synergistic effects, meaning that the value of a product increases with the number of stakeholders who buy or use the product. The network scale effect suggests that the more participants, the lower the marginal cost and the higher the marginal benefit. In the case of tourism firm restructuring, an increase in investor searches may indicate a higher scale of online investor attention toward a firm's restructuring event, which managers can capture and take note of. Additionally, investors' search behavior inevitably increases the transparency of discussions regarding the restructuring event in the stock forum [60], which can inspire tourism investors to participate and post their views or attitudes on restructuring activities. As a result, managers may actively pay attention to investors' concerns and opinions on restructuring events and adjust the allocation of resources in tourism firm restructuring. Therefore, investor searches may enhance the relationship between investor postings on scale efficiency. Thus, we hypothesize that:

H2: The attention of investor searches significantly moderates the impact of the attention of investor postings on the scale efficiency of tourism firms during restructuring.

3. Research design and methodology

3.1. Generalized additive DEA

Let the set of tourism firms be $\text{DMU}_j (j = 1,2,...,J)$, each DMU having m inputs and s outputs. The vectors of inputs and outputs for DMU_j are denoted by $\mathbf{x}_i = (x_{1j}, x_{2j}, ..., x_{mj})^T$, $i = 1,2,...,m$ and $\mathbf{y}_r = (y_{1j}, y_{2j}, ..., y_{sj})^T$, $r = 1, 2, ..., s$. Accordingly, $\mathbf{X} = (\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_J) \in R^{m\times J}$ and $\mathbf{Y} = (\mathbf{y}_1, \mathbf{y}_2, ..., \mathbf{y}_J) \in R^{s\times J}$ represent the input and output matrices, respectively. All data are assumed to be positive, i.e., $\boldsymbol{X} > 0$ and $\boldsymbol{Y} > 0$. The PPS in the traditional DEA model is equal to the evaluated set, indicating that the traditional DEA model is subject to a self-evaluation mechanism. On the other hand, the PPS in a generalized DEA model consists of the reference set, which enables the separation of the evaluation object and reference standard [41].

The traditional DEA model is utilized to evaluate the relative efficiency of DMUs, where the reference set is the same as the evaluated set. In contrast, the generalized DEA model allows for the comparison between the evaluated set and a predetermined sample of units. In this case, the relationship between the reference set and the evaluated set may be equal, intersecting, or irrelevant [19]. For the evaluated $\text{DMU}_k (k = 1,2,...,K)$, the relationship between the evaluated set ($k \in P$) and the reference set ($j \in R$) can take several forms: (1) the evaluated set is equal to the reference set, which corresponds to the traditional DEA model ($P = R$); (2) the evaluated set is a subset of the reference set ($P \subset R$); (3) the reference set is a subset of the evaluated set ($R \subset P$), and so on.

Under CRS assumption, the PPS of the evaluated set P and the reference set R can be defined using the nonnegative combination of the DMUs as: $\widehat{P} = \{(\mathbf{x}, \mathbf{y}) | \mathbf{x} \geq \sum_{j\in P} \lambda_j \mathbf{x}_j, \mathbf{y} \leq \sum_{j\in P} \lambda_j \mathbf{y}_j, \boldsymbol{\lambda} \geq \mathbf{0}\}$ and $\widehat{R} = \{(\mathbf{x}, \mathbf{y}) | \mathbf{x} \geq \sum_{j\in R} \lambda_j \mathbf{x}_j, \mathbf{y} \leq \sum_{j\in R} \lambda_j \mathbf{y}_j, \boldsymbol{\lambda} \geq \mathbf{0}\}$. The intensity vector is denoted by $\boldsymbol{\lambda} = (\lambda_1, \lambda_2, ..., \lambda_J)^T$. The PPS considering the VRS assumption can be obtained by adding the constraint $\sum_{j\in P} \lambda_j = 1$ and $\sum_{j\in R} \lambda_j = 1$, respectively. To avoid the dilemma of having to set the input or output orientation in the traditional DEA model, we have opted for an additive DEA model that can simultaneously evaluate both input and output indicators [16]. The generalized additive DEA model, under the CRS assumption, can be formulated as follows:

$$
\begin{aligned}
E_k^{CRS} &= \min \sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+, \\
s.t. &\sum_{j\in R} x_{ij}\lambda_j + s_i^- = x_{ik}, \\
&\sum_{j\in R} y_{rj}\lambda_j - s_r^+ = y_{rk}, \\
&\lambda_j \geq 0; j \in R; k \in P, \\
&i = 1,2,...,m; r = 1,2,...,s.
\end{aligned}
\tag{1}
$$

Parameters $s_i^- \geq 0$ and $s_r^+ \geq 0$ are input and output slacks. Model (1) is assumed to have a best-practice frontier of constant returns to scale (CRS), which means that a best-practice decision-making unit (DMU) is both technically and scale efficient [41]. If there is scale inefficiency, the model can be modified to consider VRS by adding the constraint $\sum_{j\in R} \lambda_j = 1$ to model (1). Specifically, if the evaluated DMU_k is not in the reference set (i.e., $k = (x_k, y_k) \notin R$) and also the PPS of the reference set (i.e., $k = (x_k, y_k) \notin \widehat{R}$), then the generalized additive DEA model becomes a super efficiency model [62]. As a result, unlike the traditional DEA model, the efficiency scores obtained by the generalized additive DEA model can exceed one. Fig. 1(a) illustrates the frontier of the generalized additive DEA model, where the reference set's frontier (convex curve ABD) is part of the evaluated set's frontier (convex curve ABCD). The super efficiency model can be viewed as a particular case in which the efficiency scores of the evaluated DMU are derived from the frontier composed of other DMUs (i.e., excluding the evaluated DMU itself).

After solving model (1), we can obtain the efficiency scores under CRS and VRS assumptions and identify the returns to scale (RTS) status of each DMU. In the DEA model, the shape of the frontier is determined by the setting of RTS. Fig. 1(b) illustrates the various status of returns to scale of the DEA model using a single input-output model and input orientation. Under CRS assumption, the frontier is ray OC; DMU_B and DMU_C are deemed as efficient. Under VRS assumption, the frontier is constituted by convex curve MABCD; DMU_A, DMU_B, DMU_C, and DMU_D are deemed as efficient. When focusing on the convex curve, we can observe that the horizontal projection of point A and F is located at an increasing RTS status, while the horizontal projection of point B, G, and C is located at a constant RTS status. Moreover, the horizontal projection of point E and D is located at a decreasing RTS status.

3.2. Event-based DEA method

The efficiency scores generated by the generalized additive DEA model can only be compared statically across cross-sections. However, dynamic performance evaluation based on panel data can capture efficiency changes over time [18]. Using the moving average method, the window analysis framework constructs diverse reference sets to dynamically evaluate the performance of each DMU, treating it as a different entity in different periods [20]. Let DMU_k^t denotes an observation $k (k = 1, 2, ..., n)$ in period $t (t = 1, 2, ..., T)$ with m dimensional

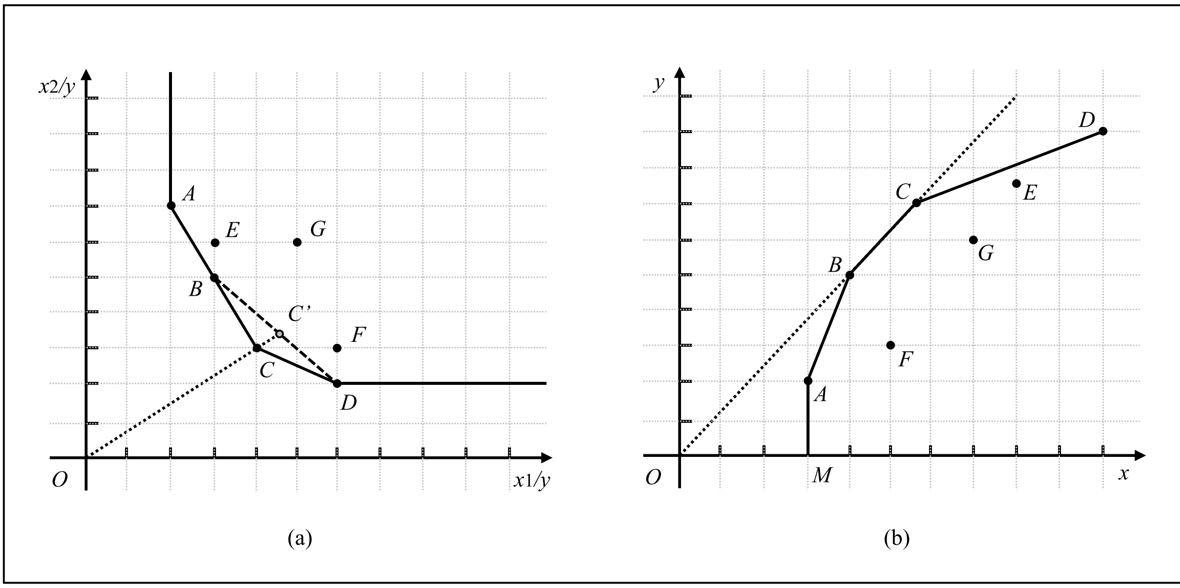

Fig. 1. Reference frontier and returns to scale.

input vector $\mathbf{x}_k^t = (x_{1k}^t, x_{2k}^t, ..., x_{mk}^t)^T$ and s dimensional output vector $\mathbf{y}_r^t = (y_{1k}^t, y_{2k}^t, ..., y_{sk}^t)^T$. Suppose that $\alpha\beta$ represents the window start in period $\alpha(1 \leq \alpha \leq T)$ with width $\beta(1 \leq \beta \leq T - \alpha)$. Accordingly, the matrices of inputs $\mathbf{X}_{\alpha\beta}$ and outputs $\mathbf{Y}_{\alpha\beta}$ for the specific window are defined as follows:

$$\mathbf{X}_{\alpha\beta} = \begin{bmatrix} x_1^{\alpha} & x_2^{\alpha} & \cdots & x_K^{\alpha} \\ x_1^{\alpha+1} & x_2^{\alpha+1} & \cdots & x_K^{\alpha+1} \\ \vdots & \vdots & \ddots & \vdots \\ x_1^{\alpha+\beta} & x_2^{\alpha+\beta} & \cdots & x_K^{\alpha+\beta} \end{bmatrix} \mathbf{Y}_{\alpha\beta} = \begin{bmatrix} y_1^{\alpha} & y_2^{\alpha} & \cdots & y_K^{\alpha} \\ y_1^{\alpha+1} & y_2^{\alpha+1} & \cdots & y_K^{\alpha+1} \\ \vdots & \vdots & \ddots & \vdots \\ y_1^{\alpha+\beta} & y_2^{\alpha+\beta} & \cdots & y_K^{\alpha+\beta} \end{bmatrix}$$

We refer to the generalized additive DEA model under the window analysis framework as the event-based DEA method, as events can be used to define the reference set, and diverse windows can be set to generate observation periods. The event-based DEA model under CRS assumption can be formulated as model (2). The superscript (or subscript) $\alpha\beta$ denotes the focused event window. The model considering the VRS assumption can be obtained by adding the constraint $\sum_{j \in R_{\alpha\beta}} \lambda_j^{\alpha\beta} = 1$ to model (2). When $E_{k\alpha\beta} \geq 1$, and all the optimal solution of slack variables $s_i^{-,\alpha\beta} = 0, s_r^{+,\alpha\beta} = 0$, then the evaluated DMU_k is efficient and can be deemed as a best-practice DMU. Scale efficiency can be calculated by the ratio of technical efficiency (i.e., CRS assumption) and pure technical efficiency (i.e., VRS assumption), that is $E_{k\alpha\beta} = E_{k\alpha\beta}^{CRS}/E_{k\alpha\beta}^{VRS}$.

$$\begin{aligned} & E_{k\alpha\beta}^{CRS} = \min \sum_{i=1}^{m} s_i^{-,\alpha\beta} + \sum_{r=1}^{s} s_r^{+,\alpha\beta}, \\ & s.t. \sum_{j \in R_{\alpha\beta}} x_{ij}^{\alpha\beta} \lambda_j^{\alpha\beta} + s_i^{-,\alpha\beta} = x_{ik}^{\alpha\beta}, \\ & \quad \sum_{j \in R_{\alpha\beta}} y_{rj}^{\alpha\beta} \lambda_j^{\alpha\beta} - s_r^{+,\alpha\beta} = y_{rk}^{\alpha\beta}, \\ & \quad \lambda_j^{\alpha\beta} \geq 0; j \in R_{\alpha\beta}; k \in P_{\alpha\beta}, \\ & \quad i = 1, 2, ..., m; r = 1, 2, ..., s. \end{aligned} \tag{2}$$

For a balanced panel data, we can calculate the number of windows $\xi = T - \beta + 1$, the number of diverse DMUs per window $\omega = K \times \beta$, and the total number of diverse DMUs $N = K \times \beta \times \xi$, respectively. Table 1 shows the window analysis framework of the evaluated DMU_k and the scale efficiency scores $E_{k\alpha\beta}$ derived from the event-based DEA model. Suppose that there are 10 DMUs ($K = 10$), which are observed in five periods ($T = 5$), and the window width is set to three periods ($\beta = 3$). We can derive $\xi = 3$, $\omega = 30$, and $N = 90$. By using the moving average method, we can calculate the average efficiency scores based on the column average, row average, and total average E_{**}. Fig. 2(a) demonstrates that windows with a width of seven periods move backwards, with each window deleting the first period and adding a new one.

Table 1
Window analysis framework.

DMU_k	Period 1	Period 2	Period 3	Period 4	Period 5	Row average
Window 1	E_{11}	E_{12}	E_{13}			E_{1*}
Window 2		E_{22}	E_{23}	E_{24}		E_{2*}
Window 3			E_{33}	E_{34}	E_{35}	E_{3*}
Column average	E_{*1}	E_{*2}	E_{*3}	E_{*4}	E_{*5}	E_{**}

In the context of tourism firm restructuring, we can customize benchmarking by setting two clusters: the restructuring and non-restructuring clusters for each observed period. The window analysis framework generates different overlapping restructuring event windows, which constitute the Bootstrap-like sample DMUs. Based on the occurrence-to-completion cycle of a restructuring event, we divide it into three quarters (Win3), five quarters (Win5), and seven quarters (Win7) event windows. We choose the symmetrical event window to facilitate the measurement of the average trend (efficiency) change before and after the restructuring event. In Fig. 2(b), the restructuring performance of the evaluated DMUs can be calculated by referring to the global reference frontier of non-restructuring DMUs in each restructuring event window. To aggregate multiple dynamic efficiency scores in the focused window, we can use the row average method under the window analysis framework.

3.3. Panel Tobit regression model

Regression analysis is used to analyze *Scale Efficiency* (SE), a dependent variable with truncated data, which is calculated using an event-based DEA model. Two types of online investor attention are used as independent variables: investors' search volumes on Baidu search engine (*Search*) and posting volumes on the stock forum of Eastmoney (*SumPost*). Web crawlers are designed to collect day-level data from

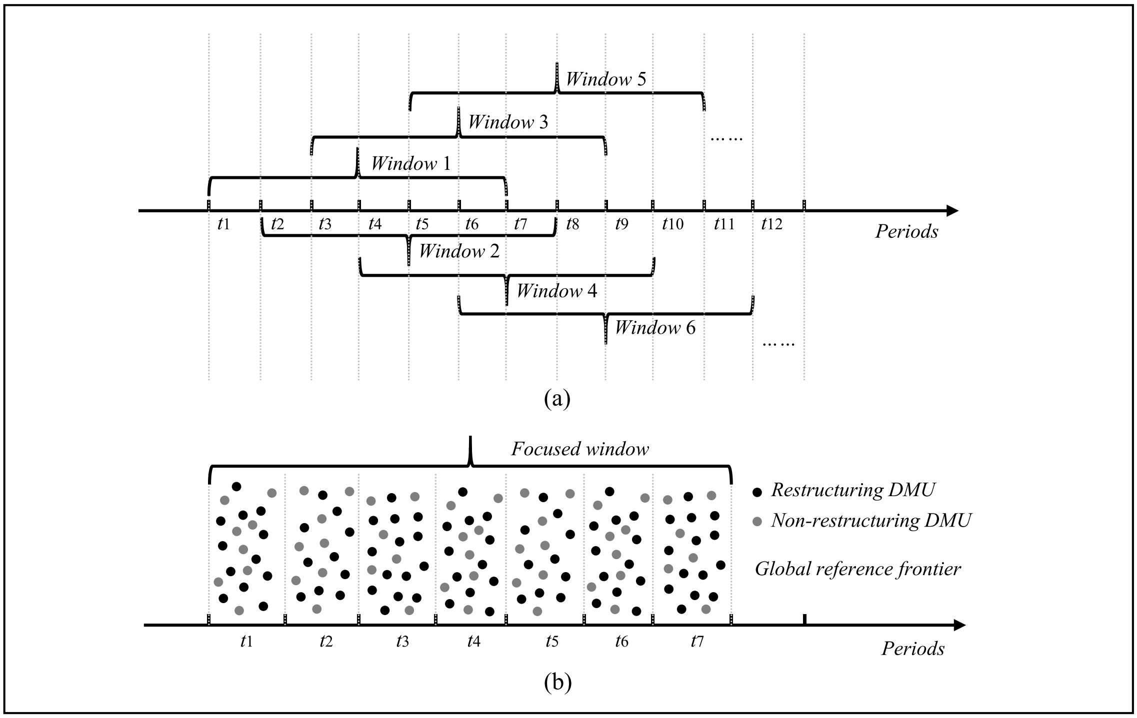

Fig. 2. Window analysis rule and customized benchmarking.

Baidu index by importing keywords for each firm and collecting data from the stock forum page of each firm on the Eastmoney website, such as the text of a post, and the volume of reads (*Reads*) and comments (*Comment*). Regarding the selection of keywords for each firm, we utilize the full name, abbreviation, and ticker symbol of the company as keywords in order to capture a more comprehensive assessment of investors' search volumes. Subsequently, we combine the daily search volumes for each tourism firm associated with specific keywords and aggregate them on a quarterly basis.

Besides, each post undergoes standard text cleaning and sentiment polarity identification and labeling by a pre-trained support vector machine (SVM) model. After conducting standard data collection and preprocessing, the next step involves feature extraction, where the textual data is transformed into numerical feature vectors suitable for inputting into the SVM classifier. Following this, a manual annotation process is performed on a randomly selected subset of samples, assigning sentiment labels to the preprocessed data. The labeled dataset is then divided into a training set and a test set. The SVM algorithm is subsequently applied to train the classifier using the labeled training data. Once the SVM classifier is trained and evaluated, it can be utilized to predict the sentiment of new, unseen text samples. This process enables us to determine the volume of positive (*PosPost*), negative (*NegPost*), and neutral (*NeuPost*) posts. We also control for posting and firm-related variables, such as *Read, Comment, ROA, Growth*, and window effects within a specific event window. The regression model specifications are as follows:

$$\begin{aligned}\text{ModelI}: SE_{it} &= \alpha + \beta_1 Search_{it} + \beta_2 SumPost_{it} + \gamma_1 Read_{it} \\ &+ \gamma_2 Comment_{it} + \gamma_3 ROA_{it} + \gamma_4 Growth_{it} + Win_t + \varepsilon_{it}\end{aligned} \tag{3}$$

$$\begin{aligned}\text{ModelII}: SE_{it} &= \alpha + \beta_1 Search_{it} + \beta_2 PosPost_{it} + \beta_3 NegPost_{it} + \beta_4 NeuPost_{it} \\ &+ \gamma_1 Read_{it} + \gamma_2 Comment_{it} + \gamma_3 ROA_{it} + \gamma_4 Growth_{it} + Win_t + \varepsilon_{it}\end{aligned} \tag{4}$$

$$\begin{aligned}\text{ModelIII}: SE_{it} &= \alpha + \beta_1 Search_{it} + \beta_2 SumPost_{it} + \delta SumPost\_sqr_{it} + \gamma_1 Read_{it} \\ &+ \gamma_2 Comment_{it} + \gamma_3 Comment\_sqr_{it} + \gamma_4 ROA_{it} + \gamma_5 Growth_{it} + Win_t + \varepsilon_{it}\end{aligned} \tag{5}$$

$$\begin{aligned}\text{ModelIV}: SE_{it} &= \alpha + \beta_1 Search_{it} + \beta_2 PosPost_{it} + \beta_3 NegPost_{it} + \beta_4 NeuPost_{it} \\ &+ \delta_1 PosPost\_sqr_{it} + \delta_2 NegPost\_sqr_{it} + \delta_3 NeuPost\_sqr_{it} + \gamma_1 Read_{it} \\ &+ \gamma_2 Comment_{it} + \gamma_3 Comment\_sqr_{it} + \gamma_4 ROA_{it} + \gamma_5 Growth_{it} + Win_t + \varepsilon_{it}\end{aligned} \tag{6}$$

$$\begin{aligned}\text{ModelV}: SE_{it} &= \alpha + \beta_1 Search_{it} + \beta_2 SumPost_{it} + \delta SumPost\_sqr_{it} \\ &+ \xi_1 SeaSum_{it} + \xi_2 SeaSum\_sqr_{it} + \gamma_1 Read_{it} + \gamma_2 Comment_{it} \\ &+ \gamma_3 Comment\_sqr_{it} + \gamma_4 ROA_{it} + \gamma_5 Growth_{it} + Win_t + \varepsilon_{it}\end{aligned} \tag{7}$$

where SE_{it} represents the scale efficiency of the i th firm in the t-th quarter under a specific event window, Win_t denotes the window (i.e., each quarter in an event window) effects, and ε_{it} is an error term. *SumPost_sqr, SeaSum*, and *SeaSum_sqr* represent the quadratic term of *SumPost*, the interaction term of *Search* and *SumPost*, and the interaction term of *Search* and *SumPost_sqr*, respectively.

4. Empirical analysis and results

4.1. Variable and descriptive statistics

The main analysis is based on an unbalanced panel dataset comprising 2057 firm-quarter observations (830 units undergoing restructuring activity) for 56 listed tourism firms publicly traded on China's stock market from 2010 to 2019. According to Fig. 3, tourism firms have frequently undergone restructuring activities in order to avoid bankruptcy or failure and achieve growth and value creation [6]. The use of restructuring announcements helps identify whether a restructuring event has occurred in a specific firm-quarter, and allows for differentiation between the restructuring group and non-restructuring group. Restructuring information and firm-specific financial data, such as return on assets (*ROA*) and business revenue growth rate (*Growth*), are collected from the China Stock Market & Accounting Research database [4]. The dataset is further refined by retaining only firms with at least 12 consecutive firm-quarter observations and removing poorly performing firms that have been specially treated.

We use the proposed event-based DEA model to calculate the

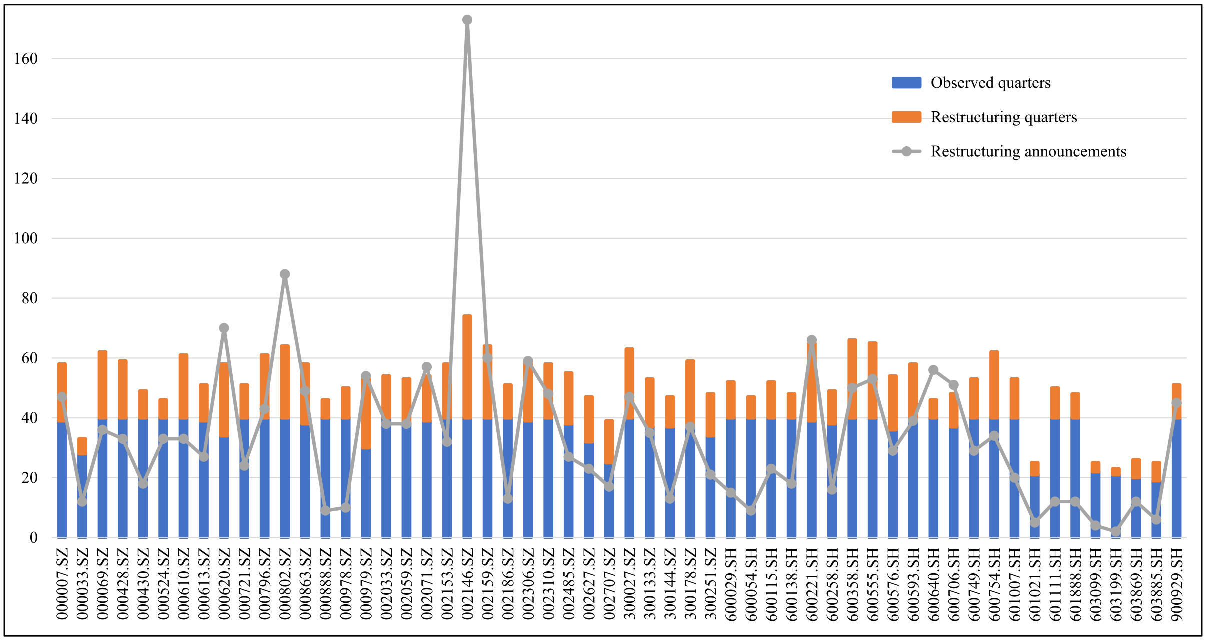

Fig. 3. Restructuring related information of listed tourism firms.

technical efficiency, pure technical efficiency, and scale efficiency of each restructuring activity in the tourism firm context. This model allows us to determine the status of returns to scale and the gains in operating efficiency, whether increasing, decreasing, or constant. We analyze quarter-level input and output data to illustrate the model's operating mechanism. According to Yin et al. [63], we determined the input and output indicators. The goal of the event-based DEA model in tourism firm restructuring is to increase desirable output, denoted by *Income*, while reducing consumption of input resources, such as fixed assets (*Capital*), total liabilities (*Liability*), and operating costs (*Cost*). To meet the dynamic modeling requirements of the proposed event-based DEA model, we transformed the dataset into a series of rolling-window structures, such as three-quarter (5880 observations), five-quarter (9313 observations), and seven-quarter (12,346 observations) event windows.

We transformed all the magnitude variables into quarter-level by summarizing daily data, and then converted them into logarithmic form for regression analysis. Table 2 displays the descriptive statistics for the DEA and regression variables after applying a winsorize measure (with a criterion of 1% quantile). Table 3 provides the results of the Pearson correlation analysis. Our findings show that *Growth* has no significant correlation with SE, but is positively correlated with TE and PTE. Furthermore, *Search* and *SumPost* are negatively related to SE. To investigate the determinants of the scale efficiency of tourism firm restructuring, we employed a panel Tobit regression model with random effects [25]. This was necessary because obtaining consistent estimates from nonlinear models with fixed effects is usually impossible [63]. Moreover, we compute the variance inflation factor (VIF) to examine

Table 2
Descriptive statistics for the DEA and regression variables.

Variable	Obs.	Mean	Std. Dev.	Min.	Median	Max.
DEA variables						
Capital	2057	8817.01	28,863.36	0.02	502.54	175,675.00
Liability	2057	15,738.56	40,643.53	8.49	967.68	284,626.61
Cost	2057	4955.29	15,079.88	0.00	332.33	136,016.00
Income	2057	6295.17	17,945.78	0.01	605.64	154,322.00
Efficiency scores						
Technical efficiency	5880	0.58	0.27	0.09	0.55	1.41
Pure technical efficiency	5880	0.73	0.37	0.14	0.70	2.56
Dependent variable						
Scale efficiency	5880	0.84	0.22	0.19	0.95	1.00
Independent variables						
Search*	5880	11.76	1.16	7.74	11.69	14.27
SumPost*	5880	7.08	1.05	3.81	7.11	9.51
PosPost*	5880	5.93	0.99	2.89	5.93	8.24
NegPost*	5880	5.60	1.09	1.95	5.67	8.06
NeuPost*	5880	6.26	1.12	2.89	6.29	8.74
Control variables						
Read*	5880	14.27	1.20	11.12	14.23	17.04
Comment*	5880	7.69	1.26	3.99	7.71	10.59
ROA	5880	0.046	0.069	−0.224	0.036	0.255
Growth	5880	0.281	1.243	−0.895	0.026	9.187

Note: Superscript * denotes the logarithmic data; the unit of DEA variables is million CNY; Obs. 2057 means the original firm-quarter observations used for executing event-based DEA model; Obs. 5880 represents the total firm-quarter observations under a three-quarter event window.

Table 3
Pearson correlation analysis.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
TE (1)	1.000											
PTE (2)	0.686***	1.000										
SE (3)	0.322***	−0.383***	1.000									
Search (4)	−0.181***	0.067***	−0.358***	1.000								
SumPost (5)	0.024*	0.171***	−0.233***	0.524***	1.000							
PosPost (6)	0.061***	0.176***	−0.196***	0.493***	0.981***	1.000						
NegPost (7)	0.004	0.168***	−0.257***	0.546***	0.960***	0.927***	1.000					
NeuPost (8)	0.014	0.166***	−0.235***	0.516***	0.991***	0.956***	0.931***	1.000				
Read (9)	0.101***	0.214***	−0.211***	0.475***	0.845***	0.845***	0.813***	0.829***	1.000			
Comment (10)	0.042***	0.179***	−0.235***	0.447***	0.712***	0.732***	0.762***	0.655***	0.724***	1.000		
ROA (11)	0.338***	0.366***	−0.097***	0.166***	0.047***	0.063***	0.046***	0.038***	0.022*	0.065***	1.000	
Growth (12)	0.064***	0.048***	0.012	0.043***	0.040***	0.040***	0.045***	0.037***	0.032***	0.052***	0.098***	1.000

Note: TE=Technical efficiency, PTE=Pure technical efficiency, SE=Scale efficiency; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

bias estimates derived from multicollinearity and find that all variables are less than 5. It indicates that multicollinearity is not a major issue in this paper.

4.2. Restructuring performance with an event-based DEA model

In the panel dataset, there are 830 restructured observations. The efficiency scores (TE, PTE, and SE) are calculated using row averages in each event window (three-quarter, five-quarter, and seven-quarter) and the statistics are shown in Fig. 4. The median value of TE, PTE, and SE in Win3 is 0.55, 0.74, and 0.92, respectively. This indicates that restructuring performance, measured by PTE (VRS assumption), is higher than TE (CRS assumption), and restructuring activities lead to higher scale efficiency. Similar results are observed in Win5 and Win7.

We analyze the operating efficiency gains by comparing the pre- and post-restructuring scale efficiency scores. Fig. 5(a) shows that, on average, 41.32% of restructured observations gain an increase in scale efficiency, 50% gain a reduction, and 8.68% show no change. Fig. 6(a) shows that, on average, 46.31% of restructured observations present increasing RTS, 53.49% present decreasing RTS, and 0.2% present constant RTS. We further divide firm restructuring activities into three types: merger and acquisition, divestiture, and equity transfer, which represent different firm strategies, i.e., expansion, shrinkage, and stabilization [4]. Figs. 5(b-d) show that operating efficiency gains gradually decrease with the extension of the event windows, regardless of the restructuring strategies implemented. On the other hand, Figs. 6 (b-d) show that the proportion of increasing RTS is gradually growing across most of the restructuring strategies.

4.3. The direct and interaction effects of online investor attention

To analyze the direct and interaction effects of online investor attention on firm restructuring performance, we have adopted a panel Tobit regression model with random effects as described in the model specifications. Table 4 presents the estimation results of the main effect under three different event windows, which serves as a way to check the robustness. Specifically, we used Model I to estimate the linear effect of *Search* and *SumPost* on firm restructuring's scale efficiency. This includes regression (1) in Win3, regression (3) in Win5, and regression (5) in Win7. The regression results demonstrate a significant positive effect of *Search* and *SumPost* on restructuring's scale efficiency under all three event windows.

Table 5 presents regression results using a non-linear assumption and exploring possible moderating effects under three different event windows, which also provides a way to check for robustness. Model III in the model specifications is used to estimate the non-linear effect of *SumPost* on the scale efficiency of firm restructuring, as demonstrated in regression (1) in Win3, regression (4) in Win5, and regression (7) in

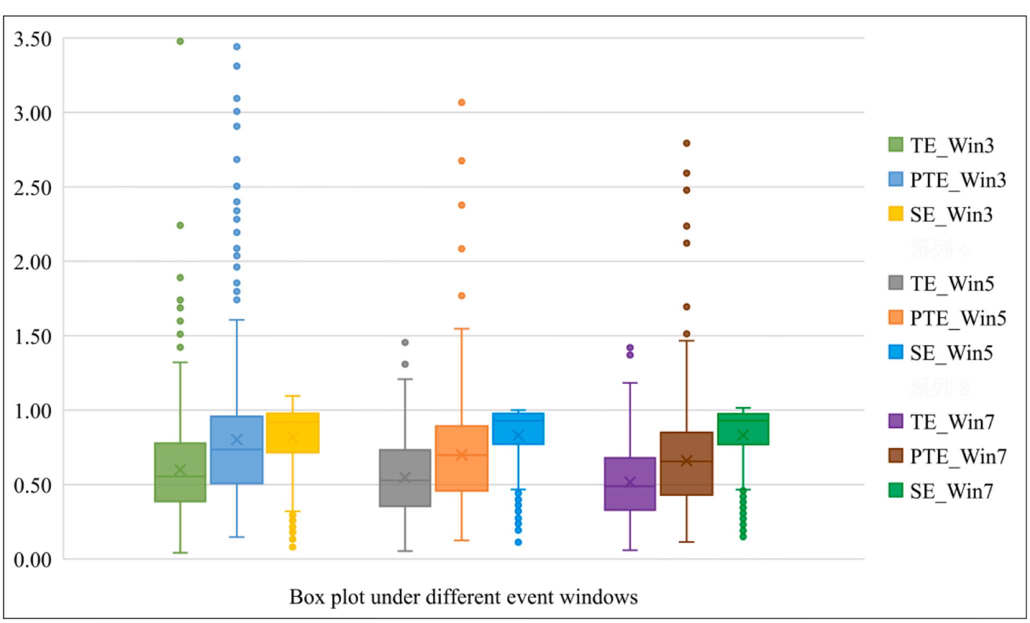

Fig. 4. Statistics of static panel data for 830 restructured observations.

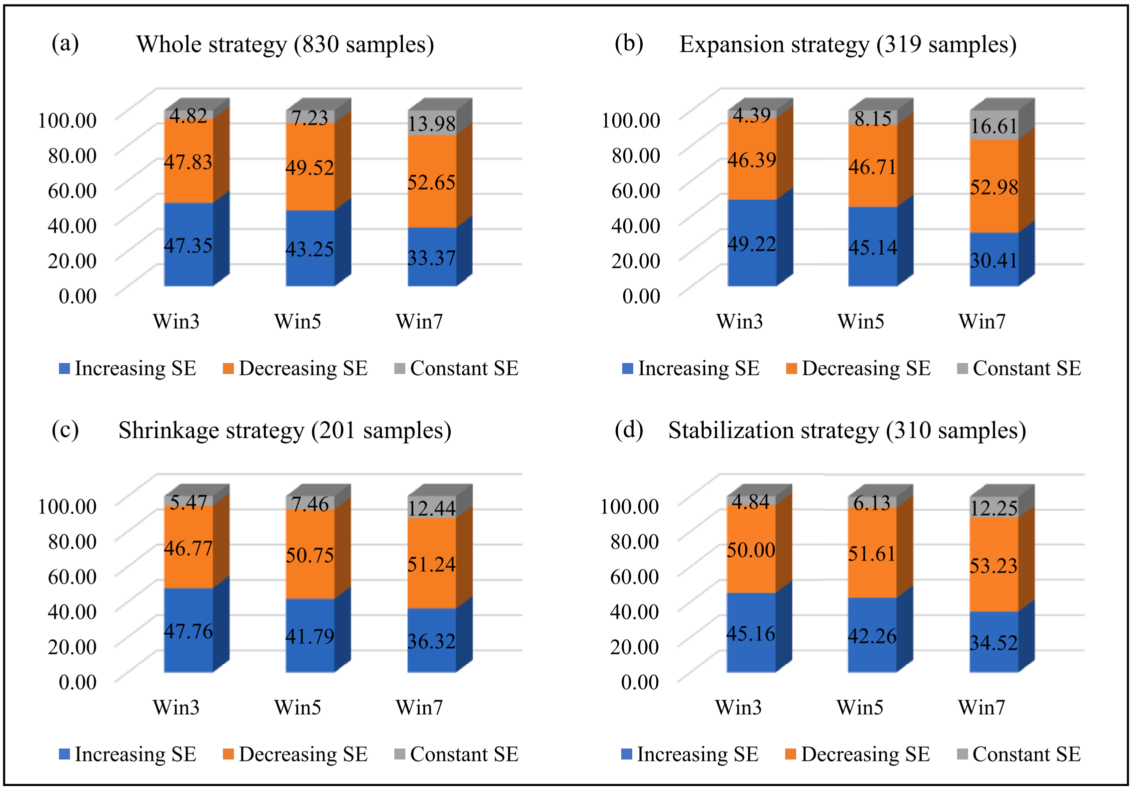

Fig. 5. Operating efficiency gains under different restructuring strategies.

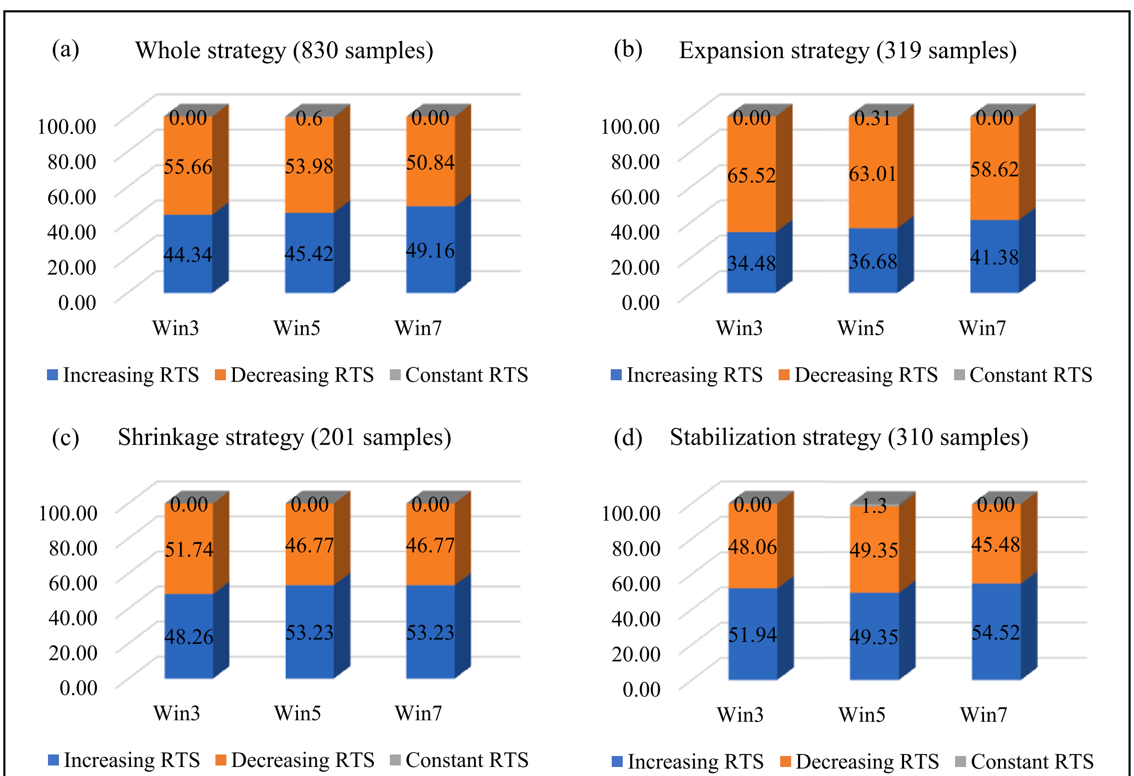

Fig. 6. Returns to scale under different restructuring strategies.

Win7. The results show an inverted U-shaped relationship between *SumPost* and scale efficiency of firm restructuring under Win3 and Win5, while this relationship is not supported under Win7. These findings partially support the previous assumption that an inverted U-shaped relationship exists between investor attention and tourism firms' scale efficiency in restructuring. Thus, H1 is partially supported. If investor

Table 4
Baseline regression results under different event windows.

Variables	SE (Win3)		SE (Win5)		SE (Win7)	
	(1)	(2)	(3)	(4)	(5)	(6)
Search	0.014**	0.018***	0.013***	0.016***	0.015***	0.016***
	(0.006)	(0.006)	(0.004)	(0.004)	(0.003)	(0.003)
SumPost	0.012***		0.013***		0.018***	
	(0.004)		(0.003)		(0.002)	
PosPost		0.043***		0.034***		0.024***
		(0.009)		(0.006)		(0.005)
NegPost		0.003		0.011**		0.016***
		(0.006)		(0.004)		(0.004)
NeuPost		−0.025***		−0.023***		−0.016***
		(0.008)		(0.006)		(0.005)
Read	−0.006	−0.007**	−0.001	−0.002	−0.003	−0.002
	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)
Comment	−0.007***	−0.012***	−0.010***	−0.015***	−0.012***	−0.017***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
ROA	0.114***	0.103***	0.076***	0.067***	0.079***	0.072***
	(0.034)	(0.034)	(0.025)	(0.025)	(0.021)	(0.021)
Growth	−0.001	−0.001	−0.000	−0.000	−0.001	−0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Window fixed	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.845***	0.846***	0.859***	0.859***	0.863***	0.863***
	(0.025)	(0.025)	(0.025)	(0.025)	(0.026)	(0.026)
Sigma_u	0.183***	0.183***	0.187***	0.187***	0.191***	0.191***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Sigma_e	0.144***	0.144***	0.130***	0.130***	0.124***	0.124***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Chi-square	30.500	51.490	84.850	114.060	194.370	223.250
Prob > Chi2	0.000	0.000	0.000	0.000	0.000	0.000
Log likelihood	2197.344	2207.771	4611.517	4625.957	6803.353	6817.543
Observations	5880	5880	9313	9313	12,346	12,346

Notes: Standard errors are in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

attention exceeds a reasonable range, the scale effect brought by firm restructuring will gradually decline, and there can be too much of a good thing.

We also examined the moderating effect of *Search* on the non-linear relationship between *SumPost* and the scale efficiency of firm restructuring by estimating Model V. The results, presented in regression (3) in Win3 and regression (5) in Win5, indicate that *Search* strengthens the non-linear relationship between *SumPost* and scale efficiency. Thus, H2 is supported. Fig. 7 illustrates the interaction effect between *Search* and *SumPost* (−1 SD and +1 SD) on scale efficiency under Win3 and Win5. High *Search* makes the reversal point of the relationship between *SumPost* and scale efficiency appear at a higher level of *SumPost* (i.e., moving backwards). Additionally, the steepness of the inverted U-shaped relationship between *SumPost* and scale efficiency becomes smoother under a high level of *Search*.

4.4. Further analysis: the heterogeneity of posting types

The primary objective of firm restructuring is to generate synergies and economies of scale, which can lead to cost savings, improved quality of products and services, and ultimately better performance and higher efficiency gains [45]. Analysis of bank sector restructuring performance indicates that acquiring firms fail to improve X-efficiency after restructuring, while acquiring banks experience moderate scale efficiency gains [34]. Although restructuring activities resulted in rapid expansion of firms' operating scale, they failed to bring about medium- and long-term earnings and efficiency improvements [63].

Investor posts that express positive, negative, and neutral attention demonstrate corresponding attitudes toward restructuring activities. Typically, investors with extreme attitudes (positive or negative) focus more on short-term market returns, while investors with a neutral attitude tend to care more about the long-term value creation ability. As presented in Table 4, Model II is adopted to estimate the linear effect of *Search, PosPost, NegPost*, and *NeuPost* on firm restructuring's scale efficiency, such as regression (2) in Win3, regression (4) in Win5, and regression (6) in Win7. The regression results reveal that *Search* and *PosPost* have a significant positive effect, while *NeuPost* has a significant negative effect on firm restructuring's scale efficiency under three different event windows. Moreover, the positive effect of *NegPost* exhibits time heterogeneity, as *NegPost* shows no effect under Win3 and its significant effect gradually appears with the extension of event windows (i.e., Win5 and Win7).

It is possible that different types of investor attention in online postings have a non-linear effect on scale efficiency. Therefore, we hypothesize that there may be a non-linear relationship between positive, negative, and neutral attention in investor postings and the scale efficiency of firms during restructuring. In Table 5, Model IV estimates the non-linear effect of *PosPost, NegPost*, and *NeuPost* on the scale efficiency of firm restructuring, as demonstrated in regression (2) in Win3, regression (5) in Win5, and regression (8) in Win7. Regression results indicate a U-shaped relationship between *PosPost* and scale efficiency, an inverted U-shaped relationship between *NeuPost* and scale efficiency, and no non-linear relationship between *NegPost* and firm restructuring's scale efficiency. Empirical results confirm the existence of a non-linear relationship between positive and neutral attention in investor postings and the scale efficiency of tourism firms during restructuring, while negative attention in investor postings is not supported. Moreover, the neutral attention of investor postings, which constitutes the main component of total investor postings, has a similar impact as suggested in H1.

5. Discussion and implications

As one of a firm's key dynamic capabilities, restructuring emphasizes the importance of recombining and reconfiguring organizational assets and structures to achieve sustainable, profitable growth [64]. A primary motivation for firm restructuring is gaining efficiencies, which can be achieved by spreading fixed costs, eliminating redundancies, and

Table 5
Analysis of non-linear relationship and possible moderating effect.

Variables	SE (Win3)			SE (Win5)			SE (Win7)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Search	0.014**	0.017***	0.011*	0.013***	0.015***	0.010**	0.016***	0.016***
	(0.006)	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)
SumPost	0.008**		0.007	0.012***		0.010***	0.018***	
	(0.004)		(0.004)	(0.003)		(0.003)	(0.002)	
SumPost_sqr	−0.005***		−0.005**	−0.002**		−0.002**	−0.001	
	(0.002)		(0.002)	(0.001)		(0.001)	(0.001)	
PosPost		0.050***			0.041***			0.031***
		(0.009)			(0.007)			(0.006)
NegPost		−0.002			0.009*			0.016***
		(0.007)			(0.005)			(0.004)
NeuPost		−0.030***			−0.028***			−0.020***
		(0.008)			(0.006)			(0.005)
PosPost_sqr		0.016***			0.014***			0.012***
		(0.004)			(0.003)			(0.003)
NegPost_sqr		−0.005*			−0.003			−0.001
		(0.003)			(0.002)			(0.002)
NeuPost_sqr		−0.011***			−0.009***			−0.007***
		(0.003)			(0.002)			(0.002)
SeaSum			0.001			0.000		
			(0.002)			(0.002)		
SeaSum_sqr			0.003**			0.003***		
			(0.001)			(0.001)		
Read	−0.004	−0.006	−0.005	−0.001	−0.001	−0.001	−0.003	−0.002
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Comment	−0.005*	−0.010***	−0.005**	−0.009***	−0.015***	−0.010***	−0.012***	−0.018***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Comment_sqr	0.003***	0.002	0.003***	0.001	−0.000	0.001	−0.000	−0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ROA	0.108***	0.099***	0.107***	0.075***	0.068***	0.074***	0.080***	0.074***
	(0.034)	(0.034)	(0.034)	(0.025)	(0.025)	(0.025)	(0.021)	(0.021)
Growth	−0.001	−0.000	−0.001	−0.000	−0.000	−0.000	−0.001	−0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Window fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.845***	0.847***	0.846***	0.860***	0.861***	0.861***	0.865***	0.865***
	(0.025)	(0.024)	(0.025)	(0.025)	(0.025)	(0.025)	(0.026)	(0.026)
Sigma_u	0.183***	0.181***	0.184***	0.187***	0.185***	0.188***	0.192***	0.190***
	(0.018)	(0.017)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Sigma_e	0.144***	0.143***	0.144***	0.130***	0.130***	0.130***	0.124***	0.124***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Chi-square	41.890	78.250	48.470	89.530	137.390	108.610	196.850	246.120
Prob > Chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Log likelihood	2203.008	2221.053	2206.278	4613.837	4637.507	4623.2725	6804.576	6828.842
Observations	5880	5880	5880	9313	9313	9313	12,346	12,346

Notes: Standard errors are in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

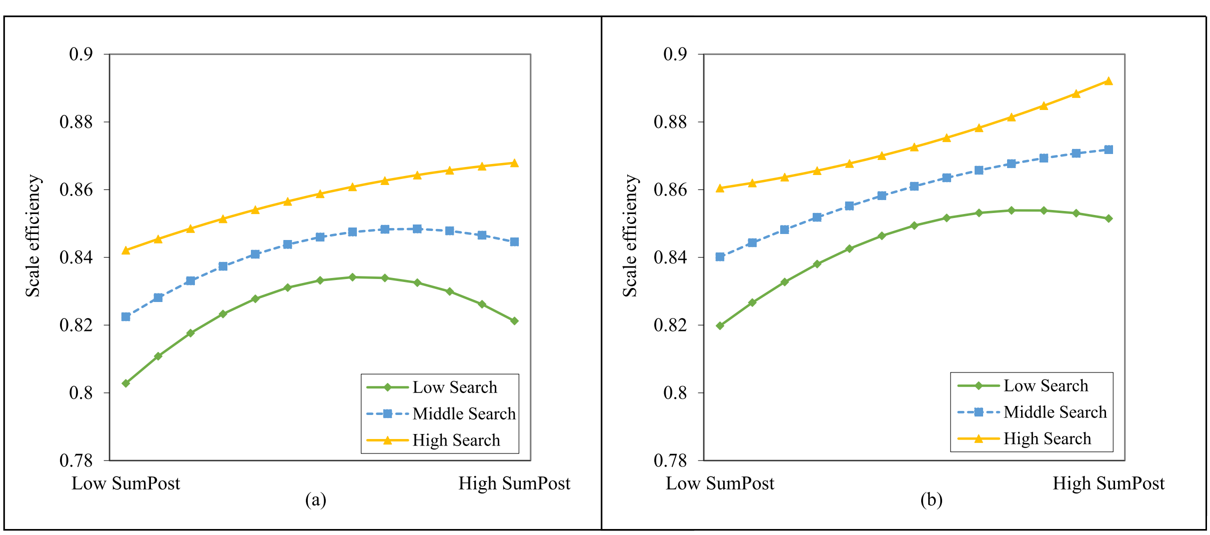

Fig. 7. The interaction effect between *Search* and *SumPost* on scale efficiency.

exploiting scale-related synergies to provide cost benefits [63]. Prior research has concluded that firm restructuring is value-enhancing if it enables firms to achieve operating efficiency gains and scale and synergistic effects [10]. However, operating efficiency gains typically have an inconsistent relationship with returns to scale. Therefore, the validity of restructuring should prevent the generation of an oversized entity and pursue higher efficiency gains [37]. In the context of tourism firm restructuring, there is a scarcity of studies investigating tourism firms' operating efficiency gains in restructuring activities, let alone the scale and synergistic effects.

In this paper, we present an event-based DEA model for measuring the scale efficiency of tourism firms during restructuring. We have developed a dynamic restructuring performance model within an event window framework, incorporating varying event window lengths. This approach enables us to conduct a more comprehensive analysis of restructuring activities. The proposed approach can be deemed as an alternative method for evaluating the performance of tourism firm restructuring, similar to the principles of an event study. Drawing on efficiency theory, our proposed method explores the impact of restructuring activities on the medium- and long-term operating efficiency gains of firms. Our model offers several advantages, including enhanced discriminatory power and the ability to analyze a larger number of DMUs, particularly in cases where sample sizes are limited, such as those observed in listed tourism firms. Moreover, we conduct a micro-level analysis of changes in operating efficiency and RTS within the tourism economy. It is worth noting that this method can be extended and applied to other industries to test its applicability.

Existing studies have demonstrated that restructuring efforts in the Canadian banking industry have led to improved overall efficiency [10]. Similarly, the consolidation period in Nigeria has resulted in increased cost-efficiency among banks [44]. Furthermore, it has been observed that a majority of Greek bank restructuring initiatives have yielded short-term operating efficiency gains [45]. However, the restructuring endeavors of Chinese listed firms have failed to generate medium- and long-term efficiency improvements [63]. In contrast to the aforementioned studies, we find that restructuring activities do not lead to significant operating efficiency gains or changes in RTS. The possibility of increasing or decreasing SE or RTS is approximately 50%. Previous studies have indicated that an appropriate restructuring can have a temporary "stimulant" effect in the short term. However, as the effectiveness of this stimulus diminishes over time, the impact of the restructuring gradually weakens [65]. Our findings partially align with this perspective. When considering the restructuring strategies of expansion, shrinkage, and stabilization, we find that operating efficiency gains gradually decrease as the event windows extend, while the proportion of increasing RTS generally increases across most of the restructuring strategies.

To further explore the impact of online investor attention on restructuring performance of tourism firms, we use a Tobit regression model. Different from previous linear relationship [4,6,60], we find an inverted U-shaped relationship between the investor attention of online posting behavior and the scale efficiency of tourism firm restructuring. Excessive investor postings may lead to information overload for managers, and scale efficiency is optimal only within reasonable limits. We also observe a U-shaped relationship between *PosPost*, an inverted U-shaped relationship between *NeuPost*, and firm restructuring's scale efficiency under three different event windows. The inverted U-shaped effect of investor attention of online posting behavior only exists under Win3 and Win5 and disappears under Win7, displaying time heterogeneity under different event windows. Furthermore, the non-linear relationship can be moderated by another type of online investor attention, i.e., search attention. This amplification effect makes the investor postings have stronger communication power and generate greater attention. Overall, our study sheds light on the complexities of restructuring in the tourism industry and highlights the importance of considering the impact of online investor attention on firm performance.

5.1. Theoretical implications

This paper has several theoretical implications. Firstly, it contributes to the interface between operations research and tourism management by providing an in-depth analysis of the scale effect of tourism firms' restructuring activities. Previous studies have commonly adopted the event study approach to capture cumulative abnormal return, which reflects investors' expectations of a firm's fundamentals under event-induced volatility [66]. However, restructuring performance is driven not only by profit-enhancing motivations but also by efficiency-enhancing synergies and returns to scale related to scale expansion, which supports the restructuring motivation of pursuing a synergistic and scale effect [1]. Most importantly, building upon the resource-based view, we provide an event-based DEA model to dynamically measure restructuring performance by constructing different event windows.

Secondly, this paper identifies the influencing mechanism of online investor attention on firm restructuring performance by exploring the complementarity of attention-based view [24] and upper echelons theory [11]. We classify two distinct types of attention among tourism investors: search attention and posting attention. According to the upper echelons theory, managers' individual characteristics and attention orientation can influence a firm's strategic decisions and outcomes. Investor attention behaviors can bring about manager attention, which acts as a precursor to firm strategy and resource allocation. In turn, this transmission mechanism can impact firms' scale efficiency in restructuring. This paper identifies the influencing mechanism of online investor attention on firm restructuring performance by combining the attention-based view and upper echelons theory. Our research highlights the importance of considering the impact of attention behaviors on managerial decision-making and sheds light on the transmission mechanism of investor attention in corporate governance.

Thirdly, this paper uncovers the non-linear relationships between tourism firms' scale efficiency in restructuring and investor attention towards their online posting behavior. Additionally, it investigates the moderating effect of investor searches on this relationship. The findings show an inverted U-shaped relationship between investor attention of online posting behavior and firms' scale efficiency in restructuring. The interaction mechanism between investors' online search behavior and posting behavior is examined, considering the network synergistic effect and scale effect. Furthermore, the study finds that investor attention towards online search behavior can amplify the positive effect and mitigate the negative effect of the inverted U-shaped relationship. Investor searches inevitably increase the transparency of discussions regarding the restructuring event in stock forums. As a result, investors are more likely to participate and post their views or attitudes on specific restructuring activities.

5.2. Practical implications

This paper presents three practical implications for managers and practitioners in the tourism industry, and the regulators from public departments. Firstly, scale efficiency of tourism firms in restructuring provides valuable information for medium- and long-term firm value to managers and investors. Restructuring has become a major means of resource allocation for tourism firms to cope with external uncertainties, resist the risk of survival, and promote business returns growth [27]. If a firm cannot achieve optimal scale, it can acquire another firm to achieve optimal scale. Similarly, if a firm becomes too large, it can achieve optimal scale by shedding some of its assets or production capacity. To focus more on long-term firm value, managers and investors need to pay attention to the scale and synergies effects brought by restructuring activities, rather than just short-term market profits.

Secondly, managers should actively consider investors' concerns and opinions on restructuring events and adjust resource allocation during the process of tourism firm restructuring. The tourism industry is characterized by diverse stakeholders, and investor attention is a valuable and limited cognitive resource [4]. Restructuring activities are heavily scrutinized by investors, and the process is identified as expensive and complex. By monitoring the volume and tone of investor postings on stock forums, managers can carefully evaluate the strategy outcomes and make subsequent decisions for restructuring activities. Although online investor attention can bring managers' attention to external stakeholders' opinions, excessive information can lead to information overload and affect managers' judgment of current restructuring activities and subsequent decisions. Therefore, encouraging investor attention to contain valid information and more investor attention to online search behavior can help mitigate negative impacts.

Thirdly, from the perspective of regulatory authorities, it is crucial to proactively facilitate the development of internet infrastructure and establish a standardized online environment. This facilitates external investors in accessing tourism firm's information more conveniently, while enabling firms to gage investor interest, thereby enhancing multi-party communication. Additionally, it assists regulatory authorities in effectively monitoring tourism firm's information disclosure practices, ensuring that investors can access genuine and relevant information on online exchange platforms. Simultaneously, it enables supervision of investors' comments on exchange platforms, such as the stock forum of listed firms, thereby regulating investor behavior and promoting rational attention. Through such measures, regulatory authorities can continuously guide investors towards adopting long-term investment concepts.

5.3. Limitations and research directions

This paper focuses solely on measuring the scale efficiency in restructuring to serve as a proxy for medium- or long-term restructuring performance. It does not compare this method with the mainstream event study approach. A more valuable research project in the future would be to compare these two event-induced performance measurement methods and analyze the influence of antecedent conditions on two different types of firm value: market performance and operating performance in tourism firm restructuring. Moreover, this paper only examines the online behavior of tourism investors as an antecedent variable. The role of other key stakeholders, such as employees, consumers, and suppliers, who are involved in tourism firms' business operations and strategic adjustments, needs to be considered. Furthermore, the interactions between different stakeholders are also directions that warrant further study. Last but not least, the proposed generalized DEA approach may yield unfeasible solutions when dealing with VRS condition. In fact, researchers have introduced several modified super-efficiency models that assume VRS to address these infeasibility concerns [67,68]. In this paper, the methodology employed by Ma and Zhao [50] can be adopted to tackle the infeasibility challenges when computing the generalized DEA model. Subsequent research endeavors will delve into this issue at a theoretical level.

Declaration of Competing Interest

None.

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