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eWOM platforms as productivity catalyzers in the travel industry: a two-stage double bootstrap data envelopment analysis

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Abstract: In a fast-paced digitalization context, travel agencies face a challenge to increase productivity. Electronic word of mouth (eWOM) could allow better learning processes, improve communication with customers, and serve as a remarkable diffusion channel. However, this channel is not yet fully embraced by the sector. This research, delimited to Spanish travel agencies in the period 2012-2019, applies a two-stage double bootstrap data envelopment analysis to assess whether eWOM and how firms manage eWOM, contributes to achieving higher levels of efficiency. Results show that firms with higher valence and volume of online reviews tend to be closer to the efficiency frontier. Moreover, results show that proactively managing eWOM, by asking customers for their online reviews, answering negative reviews, doing so promptly, as well as investing in eWOM, positively and significantly contributes to achieving higher levels of efficiency.

Keywords: efficiency, eWOM, productivity, travel agencies.

Introduction

Back in 1995, Amazon began letting their users post reviews on their purchases online, which soon became one of the flagships of the e-commerce titan. Every day, new user-generated content (UGC) is posted online. Some of this content consists of opinions on products and services and is therefore considered electronic word of mouth (eWOM). This concept is defined as a pronouncement, either positive, neutral, or negative, about a product or service posted online by an individual and shared with other potential customers (Hennig-Thurau et al, 2004). The most structured channel through which eWOM actually takes form is online reviews (ORs).

The helpfulness of eWOM and UGC goes without question. 78% of United States' e-commerce customers declared that ORs of products played a major role in their decisions (Hong & Pittman, 2020). From a demand

perspective, learning what other individuals think of a product, service, or company is very valuable in the decision-making process (Senecal & Nantel, 2004). But from a business perspective, receiving feedback on the product, service, or operation is essential to raising clients' satisfaction, improving processes, and ultimately, achieving higher levels of productivity. In this way, information technologies, and in particular eWOM, represent an outstanding chance for companies to learn from their customers and improve their processes (Melián-González & Bulchand-Gidumal, 2016).

The objective of this research is, therefore, to examine to what extent eWOM contributes to increasing the productivity of travel industry firms. In particular, this study focuses on travel agencies, due to the constant threat of disintermediation that accrued as a result of the COVID-19 pandemic. The research is delimited to Spanish travel agencies, observed throughout the period 2012-2019. The main

hypothesis is that eWOM contributes to increasing the productivity of firms for two reasons. First, by increasing the trust of consumers in given products, services and/or companies (Hong & Pittman, 2020), which is especially critical for intangibles (Litvin et al, 2008). Second, by giving firms the chance to detect opportunities for improvement or development of products (Lee & Yang, 2015) and to engage in a deeper relationship with their customers (Park & Allen, 2012) by proactively managing eWOM. The following section digs deeper into how eWOM might contribute to firms' performance, and presents a brief review of previous research that studied this topic in the tourism industry.

Literature review

Word of mouth (WOM) is frequently considered to have more potential impact on customers than any other communication channel (Godes & Mayzlin, 2004), and to be the most effective medium to influence customers' behaviour because of the high reliability and credibility the customer has on the opinion-sharing party (Huete-Alcocer, 2017). WOM itself has been considered a key diffusion channel in marketing, but when adding internet reach to the equation, this medium has escalated to new horizons. Most ORs have a numeric value (valence) that makes the messages easy to convey. Furthermore, eWOM has several characteristics, such as its persistence, observability, and dispersion, that creates a volume that WOM lacked (King et al, 2014).

To this day, most studies on eWOM have focused on customers' behaviour, and in particular, on how it influences tourist decision-making processes (Hernández-Ortega et al, 2020). However, fewer studies have analyzed the impact of eWOM on businesses' performance (Schuckert et al, 2015; Phillips et al, 2016). Of the latter, research in the travel industry has focused almost exclusively on the hospitality sector, overlooking the importance these channels have to the rest of the travel industry players (Sann et al, 2020).

In regards to the impact of eWOM on businesses' performance, previous research has

confirmed this is heavily dependent on the category of the product (Lee et al, 2011). For services, since customers have fewer ways of pre-assessing its quality, they find an increased value in using these communication channels to reduce pre-purchase doubts (Litvin et al, 2008; Pourfakhimi et al, 2020). The existing literature on eWOM has identified that valence (rating of reviews), variance (dispersion of reviews according to the rating) and volume (quantity of reviews) have a direct impact on the customers' decision-making processes, and ultimately, on firms' productivity or performance (Magnani, 2020; Mariani & Borghi, 2020).

There is an increasing number of companies that are realizing the need to join the online conversation on their products and proactively manage eWOM. However, while some companies perceive responding to eWOM better to be done as discreetly and privately as possible, other companies choose to answer publicly to engage in a deeper relationship with clients (Park & Allen, 2012). Previous research has identified that the presence of management responses increases reviews' helpfulness (Cox et al, 2009), and has a positive impact on the volume of subsequent content (Chen et al, 2019). Moreover, it was identified that management responses tend to positively impact the firms' performance (Xie et al, 2014). However, contradictory evidence has shown that the presence of management responses may have a negative impact on customers' purchasing intentions (Mauri & Minazzi, 2013).

Although most literature recommends companies to include eWOM as a business strategy (Cox et al, 2009; Herrero et al, 2015; Zhang et al, 2020), these recommendations seem to drift from the actual use of eWOM by travel businesses. Only 11,05% of companies identified as part of the Spanish Travel Industry in Trustpilot request their customers to share their experiences with other potential customers. And just 12,37% of firms reply to customers who have shared a negative experience. The travel industry might be missing an outstanding opportunity to increase its productivity.

Previous research has analysed productive efficiency in the tourism industry by means of the increasingly popular two-stage data

envelopment analysis. In this sector, it has been applied to assess the efficiency of hotels (Barros & Dieke, 2008; Barros et al, 2009; Assaf & Agbola, 2011; Oukil et al, 2016; Pulina & Santoni, 2018; Kularatne et al, 2019), touristic destinations (Barros et al, 2011; Benito et al, 2014; Chaabouni, 2018; Nurmatov et al, 2020), and trade shows (Alberca-Oliver et al, 2015). Furthermore, previous studies have analyzed how eWOM has contributed to increasing the productive efficiency of firms in the hospitality industry (Fernández-Miguélez et al, 2020; Mariani & Borghi, 2020, Xie et al, 2014). However, the contribution of eWOM to firms' productivity in other sectors of the travel industry has not yet been addressed.

Methods

This work intends to explore whether eWOM platforms may help travel companies increase their productivity in two ways. First, by employing eWOM as a peer-trusted diffusion channel. Second, by allowing companies to proactively manage eWOM to improve their processes.

Following previous research on eWOM's and productivity in the tourism industry (Chaabouni, 2018; Kularatne et al, 2019; Nurmatov et al, 2020; Pulina & Santoni, 2018), this research employs a two-stage double bootstrap data envelopment analysis.

First stage: Data Envelopment Analysis

This research applies, as a first stage, the Data Envelopment Analysis (DEA) to assess travel

agencies' efficiency, as well as to analyze the contribution of eWOM and eWOM management to achieving higher levels of efficiency. DEA, first introduced by Charnes et al (1978) consists of a linear programming technique that converts different inputs and outputs to compare the efficiency of decision-making units (DMUs) by building an efficiency frontier envelope. DMUs can be efficient by maximizing outputs while keeping inputs constant, by minimizing inputs by keeping outputs constant, or by doing both alternatives at the same time. This analysis provides a single value per DMU, called efficiency score, that ranges from 0 for non-efficient DMUs, to 1, for those at the efficiency frontier. Here, labour and capital are considered the main inputs, with turnover as the main output. DEA can either be made through an input-oriented model or an output-oriented model. Given the nature of the travel agency business, the first was employed, since these firms may achieve higher levels of efficiency by optimizing their inputs.

Second stage: Double bootstrap regression

The data envelopment analysis, although functional, has been criticized for being a deterministic technique, as it doesn't provide a random error term when estimating efficiency. In this way, it doesn't allow assessing the determinants of efficiency. Complementing the DEA, and to this effect, Simar and Wilson (2007) have proposed a solution to double bootstrap DEA scores in a truncated regression, which allows incorporating explanatory variables into the analysis of efficiency scores. The truncated regression employed is as follows:

$$\lambda_{i,t} = \alpha \text{ INN}_{i,t} + \beta_1 \text{ FO}_{i,t} + \beta_2 \text{ AGE}_{i,t} + \beta_3 \text{ HK}_{i,t} + \beta_4 \text{ ASK}_{i,t} + \beta_5 \text{ PAY}_{i,t} + \beta_6 \text{ RENG}_{i,t} + \beta_7 \text{ QKNG}_{i,t} + \beta_8 \text{ VOL}_{i,t} + \beta_9 \text{ VAL}_{i,t} + \beta_{10} \text{ FIVE}_{i,t} + \beta_{11} \text{ ONE}_{i,t} + \beta_{12} \varepsilon_{i,t}$$

Here, i and t represent the cross-section and time-series observations, being individual firms and years of operation respectively. λ , the dependent variable, is the technical efficiency. Following, the control variables are INN which represents the innovation efforts of each firm.

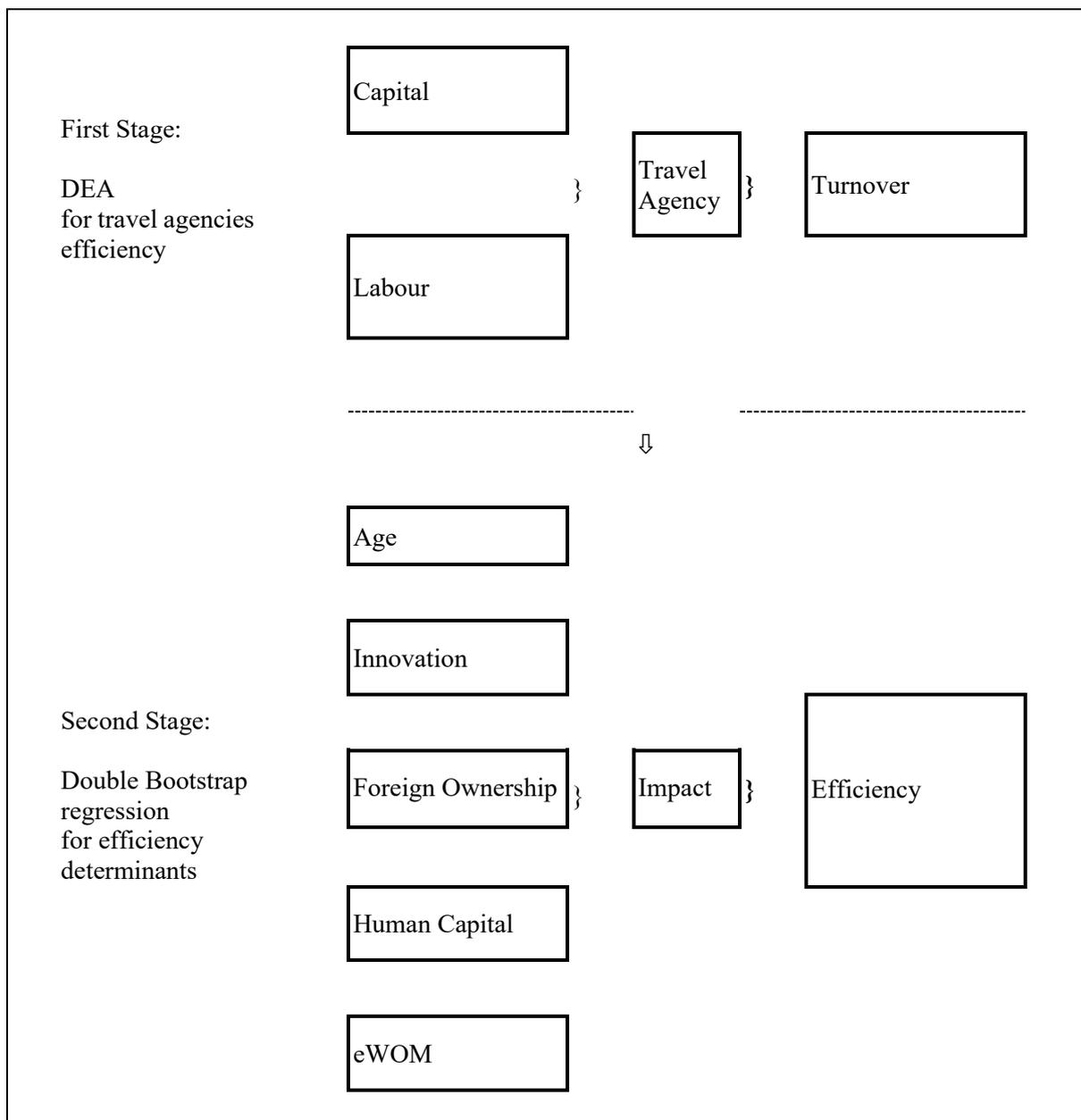
FO denotes foreign majority ownership. AGE represents the number of years since the firm began operating. HK is the average cost per employee, used as a proxy for human capital. Following are dichotomous variables denoting whether the company asks their clients for their

ORs (ASK), if they engage in further investments in eWOM (PAY), if they indeed respond to the majority of the negative ORs (RENG), and if they quickly respond to negative ORs (QKNG). Next, the research-specific variables for eWOM are VAL, VOL and FIVE, and ONE, representing the valence, volume and variance of the ORs each observed company has in Trustpilot. Last, ε is the error term.

preceding figure, as a first stage, a data envelopment analysis is conducted. In it, capital and labour are considered the main inputs employed by travel agencies to obtain the main output, turnover. The result of this first stage is a productive efficiency score. This is employed in the truncated regression of the second stage, to analyze the impact of the explanatory variables of age, innovation, foreign ownership, human capital and eWOM, on achieving higher levels of efficiency.

The framework of this study can be summarized in Figure 1. As described in the

Figure 1. Research framework.



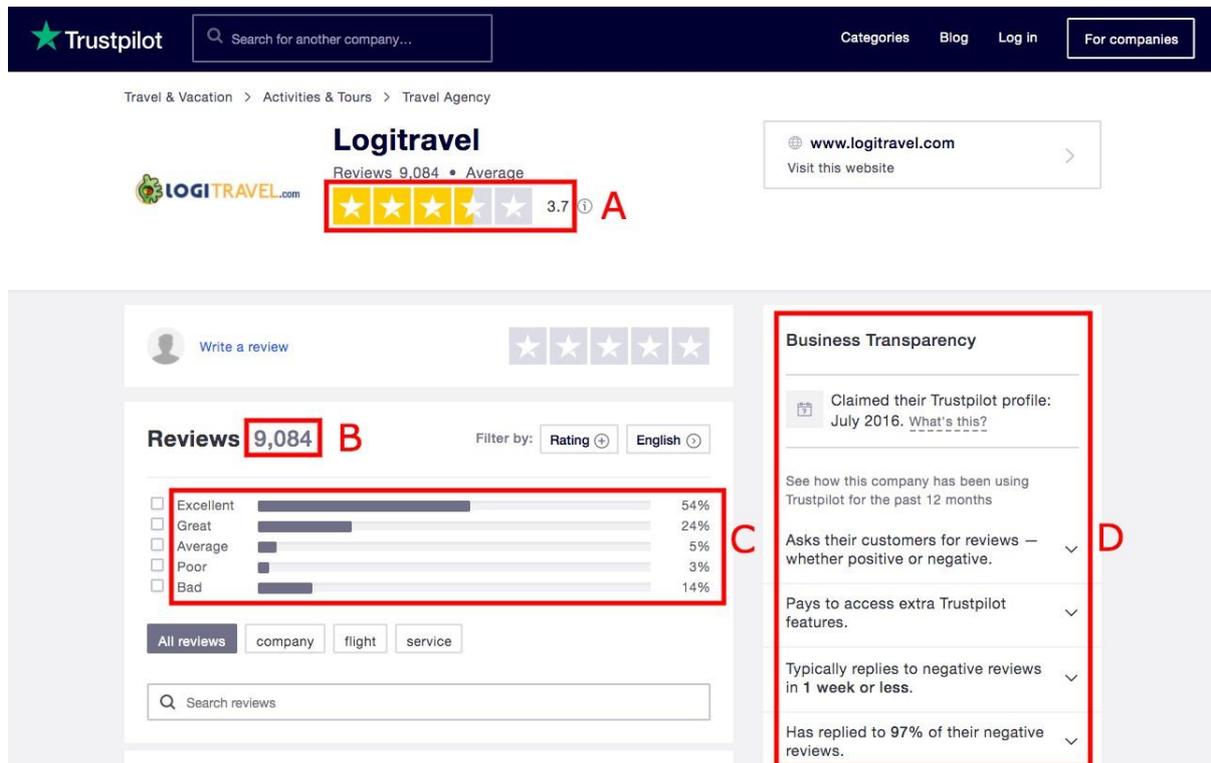
Data

The microdata employed in this research was obtained from two main sources.

First, firm-level financial and corporate information was obtained from the Orbis database. Following previous studies that have set the basis to perform productivity analysis on the firm level using the Orbis database (Ahmad et al, 2018; Gal, 2018), the total firm’s revenue was retrieved for output, while the total number of employees for labour, and the tangible fixed assets for capital. In addition, data regarding firms’ age, innovation efforts, ownership and human capital was also retrieved. Due to data availability restrictions, the average employee cost was employed as a proxy for human capital, and the number of patents as a proxy for the innovation efforts.

Second, firm-level data on eWOM was scraped from Trustpilot. Trustpilot is a leading eWOM platform founded in Denmark in 2007 and currently accumulates more than 120 million reviews from customers for over 529.000 websites (Trustpilot, 2022). This eWOM platform was chosen among others for different reasons. First, it's an eWOM platform that specialises in ORs on a firm level, whereas other platforms support ORs on a product level. Second, at the time of conducting the research Trustpilot does not limit the accessibility to its information through web scraping techniques in its terms and conditions. Last, Trustpilot offers a “business transparency” section that is of high value to assess the proactive management of eWOM from the firms’ perspective. The data scraped from Trustpilot, refers both to the eWOM on each company, as well as to how each individual company manages eWOM, as follows:

Figure 2. Data scraped from Trustpilot.



For each company, 12 pieces of data were obtained. Regarding the eWOM and UGC, the following data was obtained:

- Valence (A): Overall qualification of the business
- Volume (B): Amount of online reviews posted on the business
- Variance (C): Amount of online reviews categorized as each of the 5 star ratings

Regarding the way the business manages eWOM (D), the following data was procured.

- The business claimed their profile on Trustpilot
- The business asks their customers for their reviews, whether positive or negative
- The business pays to access extra features on Trustpilot
- The business replies to negative reviews within a week
- The business replies to most negative reviews

The first variable identifies the month when the company first started managing their Trustpilot profile. The rest of the data pieces are assigned

by a dummy variable represented by 1s for positive and 0s for negative actions.

Regarding delimitation, this research focuses on Spanish travel agencies. Spain has been chosen to delimit this study because of its worldwide leadership position in the travel industry. Moreover, the only previous study that has analysed the productivity of travel agencies employing a DEA methodology has also focused on this economy (Fuentes, 2011), setting the ground for this study. The sample consists of 47 firms, which is the total number of firms that had both an active profile on Trustpilot and available financial data on the Orbis database. These firms were analyzed throughout the period 2012-2019. The time series was defined to observe the evolution of travel agencies' productivity. It analyses until 2019 because of the severe impact that the COVID-19 pandemic has had on travel agencies' performance, which would interfere with the study.

Results and discussion

In table 1, the variables employed in the analysis are presented, followed by their descriptive statistics, presented in table 2.

Table 1. Variables description.

Variable	Description
TURNOVER	firms' turnover
LABOUR	Total number of the firms' employees
CAPITAL	Value of the firms' tangible fixed assets
AGE	Years since foundation
HK	Average cost of the firms' employees
FO	Dichotomous variable indicating foreign majority ownership
INN	Number of patents owned by the firm
CLA	Dichotomous variable indicating if the firm has claimed their Trustpilot profile
ASK	Dichotomous variable indicating if the firm asks travellers for their reviews
RENG	Dichotomous variable indicating if the firm answers negative reviews
QKNG	Dichotomous variable indicating if the firm quickly answers negative reviews
PAY	Dichotomous variable indicating if the firm pays to access further functionalities in Trustpilot
VOL	Volume of reviews in Trustpilot
VAL	Overall rating in Trustpilot in a scale of 1 to 5
FIVE	Share of five star reviews in the overall reviews
FOUR	Share of four star reviews in the overall reviews
THREE	Share of three star reviews in the overall reviews
TWO	Share of two star reviews in the overall reviews
ONE	Share of one star reviews in the overall reviews

Table 2. Descriptive statistics.

Variable	Obs.	Mean	Std. Dev.	Min	Max
TURNOVER	376	126,000,000.00	396,000,000.00	79600.88	2,470,000,000
LABOUR	376	709.10	2,241.41	1	13,732
CAPITAL	376	142,000,000.00	462,000,000.00	49953.86	4,390,000,000
HK	376	33.46	11.65	0.0654962	110.3012
AGE	376	23.14	17.43	5	116
FO	376	0.21	0.41	0	1
INN	376	0.06	0.32	0	2
ASK	376	0.15	0.36	0	1
RENG	376	0.15	0.36	0	1
QKNG	376	0.09	0.28	0	1
PAY	376	0.15	0.36	0	1
VOL	376	1,013.75	3,305.47	0	17000
VAL	376	2.63	1.53	0	4.8
FIVE	376	0.32	0.34	0	1
ONE	376	0.30	0.36	0	1

Next, the results for the DEA study are presented in table 3. Two models were estimated, considering both constant results of scale, as well as variable results of scale. This

table presents the mean value of the technical scores of the studied firms, depending on how they manage eWOM.

Table 3. DEA results.

Variable	Description	Condition	CRS model	VRS model
valence	Valence over 4 star	Y	0.450682	0.398070
		N	0.328375	0.241277
volume	More than 50 reviews	Y	0.537458	0.414114
		N	0.265618	0.201211
postive variance	More than 50% of 4 and 5 star reviews	Y	0.341472	0.272805
		N	0.349769	0.259554
negative variance	More than 50% of 1 and 2 star reviews	Y	0.420878	0.271329
		N	0.315076	0.261786
ask	The firm asks their clients for their reviews	Y	0.523519	0.405221
		N	0.315629	0.240025
pay	The firm pays to access further functionalities of TrustPilot	Y	0.479275	0.338452
		N	0.323372	0.251710
reng	The firm replies to most negative reviews	Y	0.586965	0.483849
		N	0.304526	0.226265
qkng	The firm quickly replies to negative reviews	Y	0.700947	0.602807
		N	0.313628	0.233170

Next are the descriptive statistics of the technical efficiency:

Table 4. Descriptive statistics of technical efficiency.

	CRS model	VRS model
# Efficient DMUs	6	19
# Inefficient DMUs	370	357
Mean all sample	0.264629	0.346591
Median all sample	0.171033	0.259488
Mean inefficient unit	0.252704	0.311816
SD	0.245257	0.286754
Observations	376	376

Last, table 5 presents the results of the Simar & Wilson estimation for the determinants of efficiency.

Table 5. Simar & Wilson results.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
INN	-0.180759 (0,212771)	-0.221608 (0,233197)	-0.167771 (0,194409)	-0.190440 (0,222953)	-0.266304 (0,250112)	-0.270770 (0,246673)	-0.379367 (0,255783)	-0.2755511 (0,245465)
FO	0.196901 (0,150994)	-0.007319 (0,158929)	0.232938 (0,156664)	0.288100 (0,153383)	0.203669 (0,182681)	0.294714 (0,191621)	0.281595 (0,188717)	0.280021 (0,198351)
AGE	-0,012064 *** (0,005348)	-0,012156 ** (0,005032)	-0,010446 ** (0,004736)	-0,009445 ** (0,004852)	-0,015644 ** (0,006338)	-0,016227 ** (0,006395)	-0,015629 ** (0,005758)	-0,016617 ** (0,006476)
HK	0,022787 *** (0,009413)	0,025351 ** (0,010401)	0,019945 ** (0,009287)	0,018839 ** (0,008211)	0,027456 ** (0,011818)	0,028724 ** (0,047184)	0,027422 ** (0,011406)	0,029400 ** (0,011649)
ASK	0,570164 *** (0,237166)							
PAY		0,533161 ** (0,253965)						
RENG			0,636014 ** (0,289834)					
QKNG				0,826295 ** (0,351463)				
VOL					0,000028 (0,000020)			
VAL						-0,032195 (0,581754)		
FIVE							0,351498 (0,225585)	
ONE								0,105315 (0,193091)
_cons	-0.765595 (0,501)	0.484657 (0,536871)	-0,677841 (0,508598)	-0,646502 (0,444637)	-0,907993 (0,606509)	-0,857566 (0,5817538)	-0,995647 (0,6250007)	-0,988631 (0,6002033)
/sigma	0,454671 *** (0,08975)	0,484657 *** (0,088041)	0,437918 *** (0,087448)	0,438508 *** (0,083355)	0,508758 *** (0,102477)	0,516181 *** (0,10265)	0,504744 *** (0,097997)	0,517109 *** (0,102268)

Note: *Significant at 10%; **significant at 5%, ***significant at 1%
Number of bootstrap replications = 1000

Results from the DEA have shown that travel agencies that have a higher valence, or overall qualification, tend to be closer to the efficiency frontier. This relates to higher levels of customer satisfaction, and in time, more credibility for acquiring new customers, in consonance with previous theory on the matter (Senecal & Nantel, 2004; Hong & Pittman, 2020). In line with this, travel agencies that have high volumes of online reviews are also on average twice as efficient as those with few reviews. According to previous literature on online reviews, a higher volume increases firms' credibility by having more customers try out the firms' services, therefore validating the firm (Mariani & Borghi, 2020; Sann et al, 2020), which could explain this finding. This research could not confirm the relationship between review variance and firms' efficiency. Also, when studying the factors determining firms' efficiency, no causal relationship was found between valence, volume, and variance, and firms' efficiency. Regarding how travel agencies manage eWOM, the DEA has shown that firms that proactively manage eWOM tend to be considerably closer to the efficiency frontier. As previous research has confirmed, asking customers for their feedback on eWOM platforms not only helps businesses increase diffusion and validate their services but also allows firms to better understand their perceived performance, leading to better learning processes (Melián-González & Bulchand-Gidumal, 2016).

These results were further confirmed by the second stage bootstrapped regression, which revealed a positive and significant impact of asking customers for their ORs on firms' productive efficiency. Previous academic literature has revealed a contradiction in how to deal with negative reviews (Park & Allen, 2012). While some managers prefer not to answer publicly to solve problems directly and discreetly with the unsatisfied customer, others prefer to show their proactiveness and their problem resolution processes publicly by answering online to the negative OR. Additionally, this contradiction regarding how to deal with negative ORs has also been identified in the literature, with research on diverse sectors such as gastronomy or hospitality pointing in different directions (Mauri & Minazzi, 2013; Xie et al, 2014). The present research shows that, for travel agencies,

answering publicly to negative ORs has a positive and significant impact on firms' efficiency, and that firms that do so tend to be, on average, twice as efficient as those that don't engage in eWOM communication. These results are even more evident when travel agencies quickly respond to negative ORs. Doing so in a prompt manner also contributes positively and significantly to achieving higher levels of efficiency, and firms that do so tend to be almost three times as efficient as those that don't reply quickly to negative ORs. Last, results also showed that firms that decide to invest in eWOM, such as those that pay to access further functionalities in the eWOM platform under study, also tend to be considerably closer to the efficiency frontier. Investing in these channels has a positive and significant impact on travel agencies' efficiency.

Conclusion

The travel industry has traditionally been characterized as a low (labour) productivity sector. With the accelerated digitalization and innovation processes across industries, productivity is on the rise throughout most sectors. The travel industry, therefore, faces a challenge not to fall behind. What is more, the COVID-19 crisis has severely impacted this industry beyond most others, which calls for an urgent tackling of productivity challenges. The travel industry, but in particular the distribution sector, faces one additional obstacle within this challenge, which is its delocalization. Since most customers book their trips in advance, the learning processes that could lead to improving procedures and ultimately productivity is harder to systematize. Previous literature has identified that eWOM could potentially become a powerful tool to help firms boost their productivity by learning from their customers (Melián-González & Bulchand-Gidumal, 2016), engaging in a deeper relationship with them (Park & Allen, 2012), as well as reaching out to new audiences, and validating their services (Hong & Pittman, 2020). However, there is a literature gap regarding the effect of eWOM on the travel agency and tour operation sector (Sann et al, 2020). This research has addressed this issue and applied a two-stage double bootstrap data envelopment analysis to

identify if eWOM helps travel firms achieve higher levels of productive efficiency. The main innovation of this paper is to apply this methodology to travel firms beyond the hospitality sector, as well as intersecting this analysis with eWOM data scrapped from an eWOM digital platform. This research has confirmed that eWOM and the proactive management of eWOM positively and significantly contribute to achieving higher levels of productive efficiency for travel agencies.

Implications

Regarding implications on the managerial level, the data envelopment analysis has shown that there is still great room for optimizing efficiency in the sector. This challenge must be faced by an arsenal of actions, to which eWOM should be a pillar. Not only travel agencies must be vigilant to the ORs as a marketing and diffusion channel, but they should also systematize customer relationship management actions. This includes, but is not limited to, asking users to share their opinions online, implementing claim-solving processes on eWOM platforms and answering (fast) to negative experiences shared online. This will help capitalise on the learning opportunities raised by eWOM and reach a more extensive audience.

From a theoretical perspective, this paper has tested the eWOM and ORs research stream in a previously unexplored area, the travel agency sector. Its findings contribute to the existing theory by highlighting the need for firms to proactively manage eWOM. This need might be more pressing in sectors in which learning processes are harder to systematize, such as the travel agency sector.

Limitations and future research lines

There are different limitations to this study. First, this research focuses on the Spanish case, and therefore, its conclusions might not be applied to other regions. Second, this research is delimited only to travel agencies within the extended ecosystem of the travel industry. Last, due to data availability restrictions, information on eWOM at the firm level is only captured for the last available period. Future research lines should continue to explore the contribution of

eWOM to achieving higher levels of productivity in other sectors of the travel industry that this study did not cover, such as attractions or transportation. Furthermore, further research could address one of the limitations of this study, which is its delimitation to the Spanish case. Analyzing different contexts would provide a more comprehensive context for understanding the contribution of eWOM to the productivity of the tourism industry.

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