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THE REVIEW SENTIMENT GARDEN: BLOSSOMING LOSS AVERSION AND DIMINISHING SENSITIVITY ACROSS TIME AND CRISIS

Abstract

Adopting an approach grounded in prospect theory, this article tests the principles of loss aversion and diminishing marginal sensitivity in hotel review sentiment. While prospect theory has been extensively tested in other areas, its application to review sentiment is novel, thereby extending our understanding of how hotel guests perceive and evaluate their service experiences. Simultaneously, this study examines whether the predictions of prospect theory hold to the same extent in post-Covid-19 reviews as they do in pre-Covid-19 reviews. The analysis is conducted on a sample of 416,756 reviews from 375 hotels in 14 European cities posted between 2000 and 2022. The findings show that a significant level of loss aversion and diminishing sensitivity characterizes reviews from both the pre-pandemic as well as post-pandemic periods. However, the effect of loss aversion becomes even more accentuated after Covid-19, with a gradual return to pre-pandemic levels.

Keywords: prospect theory; loss aversion; diminishing sensitivity; reference dependence; online reviews; sentiment.

1. Introduction

The proliferation of electronic word of mouth in recent years has transformed how consumers interact (Bang and Jang, 2024; Line et al., 2024; Liu et al., 2024). Traditional communication flows have been radically altered with information sharing among individuals now an integral component of the consumption experience. In the past, word of mouth communication regarding one's interest in commodities and experiences was mostly restricted to one's offline social network. However, the shift toward more interactive internet-based platforms has facilitated more widespread consumption dialogues that now also connect consumer bases that were previously isolated from one another. Perhaps most striking in this context has been the evolution of online consumer reviews into what is now a key medium that individuals use for the dissemination of information pertaining to consumption. Online consumer reviewers are especially relevant in the realm of hotels. In fact, in a survey, 95% of respondents reported having read online reviews before making travel bookings (see Hotel News Resource, 2015). In fact, Cho et al. (2024) find that the booking performance of a hotel is influenced not only by its own reviews but also by those of its competitors.

It is certainly not surprising that online consumer reviews have become a key area of interest in the hotel scholarship (Cho et al., 2024; Choi et al., 2024; Kirilenko et al., 2024; Labsomboonsiri et al., 2022; Lv et al., 2024; Shin et al., 2024; Wu et al., 2024). At the same time, one must keep in mind that online consumer reviews are merely a pathway for individuals to communicate. Accordingly, as with any form of human communication, there exists the possibility that certain reviews may not be as objective as intended, and may potentially have been distorted by the judgements, sentiments, and behavioral dispositions of those involved in the communication. In this study, we investigate whether prospect theory (Kahneman & Tversky, 1979) – the now dominant albeit nontraditional explanation of decision making under risk, is able to uncover certain cognitive inconsistencies as reflected in the sentiment underlying hotel reviews.

The paper has two specific objectives. First, we test for whether the prospect theory principles of loss aversion and diminishing marginal sensitivity are present in hotel review sentiment. These two principles are central to the reference dependent framework of prospect theory, which contends that individuals evaluate outcomes against a reference point which determines how they classify gains and losses. Loss aversion refers to the propensity of individuals to avoid losses over acquiring gains of equal magnitude (where gains and losses are determined based on the reference point). The other principle – the principle of diminishing sensitivity – asserts that changes in outcomes have more of an impact closer to the reference point compared with changes that occur farther away.

Second, we examine whether the predictions of prospect theory hold to the same extent in post Covid-19 reviews as they do in pre-Covid-19 reviews. Prospect theory is, at its core, a theory of decision making under risk. Given that the pandemic in many ways constituted an unprecedented systemwide elevation in travel risk, an opportunity emerges to study how the tenets of prospect theory apply when a macro-level shift in parameters relating to risk occurs. That is, with regard to hotel review sentiment, have the levels of loss aversion and diminishing marginal sensitivity changed with the onset of the pandemic? In recent years, prospect theory has become increasingly among hospitality and tourism researchers (Nicolau and Sharma, 2022), and we believe that it offers a powerful theoretical framework to understand aspects of reviewer behavior that are of interest in this study.

This study is meaningful for three key reasons. First, it contributes to understanding how crises shape consumer behavior. The Covid-19 pandemic was an unprecedented global event that fundamentally altered consumer perceptions of risk, service expectations, and decision-making processes. By applying prospect theory to online hotel reviews, this study provides empirical evidence of how a systemic crisis affects behavioral biases such as loss aversion and diminishing sensitivity. These insights are not just about Covid-19 but about how consumers react to major disruptions in general, including health crises, economic instability, and global events affecting travel behavior. Second, the study captures the dynamic nature of behavioral shifts. Our results show that loss aversion and diminishing sensitivity were most pronounced immediately after the pandemic but gradually returned to pre-pandemic levels. This transition is meaningful because it highlights that behavioral shifts caused by crises are dynamic rather than permanent. Even if consumer attitudes continue to normalize in the future, understanding the trajectory of these changes provides valuable insights for both scholars and industry professionals in anticipating and responding to future disruptions. Third, this study extends prospect theory into the domain of review sentiment, a novel application that enhances our understanding of how consumers evaluate service experiences over time. The finding that external shocks can temporarily reshape well-established behavioral biases offers a framework for future research on consumer decision-making in fluctuating risk environments.

2. Literature Review

Theoretical Framework: Prospect Theory

Behavioral models that follow from the rationality assumption of neoclassical economics would essentially be based on the hypothetical notion that reviewers possess immense reasoning ability that consistently enables them to engage in optimal decision-making behavior. Of course, the reality is that behavioral phenomena that diverge from the rigid theoretical framework of neoclassical economics can frequently be observed in the everyday world. Neoclassical theory would deem such deviations to be idiosyncratic, if not irrational. However, the broader economics literature also encompasses behavioral approaches that are either entirely independent of the neoclassical school or only loosely rooted in it (see for instance, Fehr and Schmidt, 1999; Lowenstein et al., 2001; Rabin, 1993; Thaler, 1985). It may be argued that several of these alternative models of human behavior offer more definitive explanations for human preferences that would appear incongruent under the mainstream lens. These alternative models recognize that human decision making, and indeed human communication, is often molded by the heuristics, proclivities, and sentiments of the parties involved.

Traditional models of decision making under risk also assume that individual preferences are solely motivated by the maximization of expected utility. Indeed, such models do not incorporate reference points into how outcomes of different probabilities are perceived. Additionally, traditional models assume linearity in human preferences. In most of these models, potential outcomes x_i that entail probabilities p_i are linearly valued by the individual i in the $\sum p_i u(x_i)$ form, with u used to denote the satisfaction (utility) the person obtains from x . Under the prospect theory (Kahneman & Tversky, 1979) formulation, on the other hand, the individual values ‘prospects’ as $\sum \pi(p_i)v(x_i - r)$, with π denoting the non-linear decision weights the individual assigns to the probabilities. The value function $v(x - r)$ describes gains and losses, valued against the individual’s reference point, r , which provides the basis for prospect theory’s reference dependent framework.

The two central principles of prospect theory, i.e., loss aversion and diminishing marginal sensitivity, can be observed in this $v(x - r)$ value function. The first is the principle of loss aversion. The principle of loss aversion asserts that the disutility induced by losses relative to the individual's subjective reference point is greater than the utility provided by gains of equal magnitude relative to the same reference point. Loss aversion explains, in other words, why a \$50 loss in wealth would have a greater net impact on a person's satisfaction than a \$50 gain in wealth. This principle argues that the value function has a greater slope on the loss side than it does on the gain side, where gains and losses are, as previously noted, defined by the deviations from the reference point. This means that $v'(x) < v'(-x)$. Loss aversion illustrates why individuals prefer to avoid losing a certain sum, rather than win the same amount. This principle similarly explains the propensity of human beings to turn down gambles that are symmetrically fair, like a coin toss where $(x, 0.5; -x, 0.5)$. When introducing prospect theory, Kahneman and Tversky (1979) also demonstrated that as the stakes increase, levels of loss aversion increase. Mathematically, this means that if $x > y \geq 0$, then individuals, in general, prefer $(y, 0.5; -y, 0.5)$ over $(x, 0.5; -x, 0.5)$. That the stakes matter is particularly relevant in the context of this paper, as a key objective of this paper is to assess how the tenets of prospect theory predict different levels of loss aversion and diminishing sensitivity in post-Covid-19 hotel reviews as compared to pre-Covid-19 reviews.

The second principle associated with prospect theory, and one that is also satisfied in the $(x - r)$ value function is that of diminishing marginal sensitivity. The principle of diminishing marginal sensitivity suggests that for both gains and losses, increases in distance from the aforementioned reference point result in decreasing marginal changes to satisfaction. It is this principle that gives the value function the S shaped curvature – concave for deviations above the reference point, and convex for deviations below the reference point. Mathematically, this means that $v''(x) < 0$ when $x > 0$, and $v''(x) > 0$ when $x < 0$. Diminishing marginal sensitivity explains why, for example, a change in wealth from \$100 to \$120 (or \$120 to \$100) has a greater impact on net satisfaction than a change from \$1,000 to \$1,020 (or \$1020 to \$1000). In both instances – whether moving from \$100 to \$120, or \$1,000 to \$1,020, the change is \$20. Yet, because the shift from \$100 to \$120 occurs closer to the reference point, it results in a larger impact on the individual's utility than is the case when wealth moves from \$1,000 to \$1,020. In a follow up to their original paper, Tversky and Kahneman (1981) similarly found that individuals were more willing to drive 20 minutes for a discount of \$5 on a \$15 item, than to save \$5 on a \$125 item.

Applications of Prospect Theory

The applications of prospect theory are not restricted to preferences involving monetary outcomes, however. Prospect theory has been used to understand behavior in a wide variety of domains. The applications include, for instance, advertising tactics (Berger and Smith, 1998), health insurance choices (Kairies-Schwarz et al., 2017), adoption of subscription services (Day et al., 2020), political decisions (Haas, 2001), guessing behavior in multiple choice tests (Bereby-Meyer et al., 2002), climate change responses (Osberghaus, 2017), etc. The sheer range of applications of prospect theory is emblematic of the power of its power as a theoretical framework. It is no wonder that the theory has been found to be highly relevant in hospitality and tourism, as evidenced by Nicolau and Sharma's (2022) review of this literature. Even without having invoked prospect theory, it has repeatedly been demonstrated that tourists evaluate travel experiences against various points of reference (Neal and Gursoy, 2008; Petrick and Backman, 2002; Wang

and Wu, 2011). Travel decisions often involve outcomes associated with various levels of risk (Reisinger & Mavondo (2005); Supernak, 1992; Williams & Baláž, 2015), and this is perhaps an important reason behind the popularity of prospect theory in the hospitality and tourism research.

As a platform where consumer preferences are expressed, electronic word of mouth constitutes an attractive area of study for behavioral researchers. Like other forms of human communication, electronic word of mouth is replete with emotions, judgements, and sentiments (Kim and Gupta, 2012). Indeed, there is a substantial literature that examines behavioral aspects of internet communication between consumers (see for instance Chen et al, 2020; Pera et al., 2019). Despite the popularity of electronic word of mouth, a number of studies have demonstrated that this communicational format may sometimes be distorted by cognitive biases like the *anchoring effect* (Book et al., 2016) and *confirmation bias* (Yin et al., 2016). As tends to be the case with cognitive biases, these behavioral distortions are not intentional in that individuals committing such behavioral biases do not deliberately misrepresent their preferences when committing the biases. These biases thus do not encompass the purposeful manipulations of online reviews by reviewers with vested interests. Nonetheless, the aforementioned biases – as well as the biases predicted by prospect theory, do have the potential to alter online consumer communication among along unintended lines.

Prospect theory has frequently been employed in the online consumer communication scholarship to understand the preferences of various parties involved. In fact, researchers have long known about certain fundamental asymmetric effects associated with online reviews (see, for instance, Lee and Cranage, 2014; Park and Nicolau, 2015). A study by Yoon et al. (2017) found that consumers build expectations about movies (reference point) from exposure to pertinent social media, and that specific consumer behaviors during the movie being watched tend to be consistent with the prospect theory principles of loss aversion and diminishing marginal sensitivity. With regard to inconsistent consumer behavior in online reviews specifically, Mellinas et al. (2019) observed that guest assessments of hotel location are influenced by their evaluation of other attributes in a manner that reflects the loss aversion principle. Loss aversion has also been detected in user decisions to post in online knowledge sharing repositories (Shankar, 2022). In a more recent study, Nicolau et al. (2023) investigated the relationship between online review sentiment and hotel performance. The authors observed a diminishing sensitivity pattern with the effect of sentiment increasingly positive only up to a certain point, before tapering off.

3. Hypotheses Development

An important issue pertains to how the reference point - a critical aspect of prospect theory - could be measured. While prospect theory is immensely elegant in its mathematical formulation, the measurement of any real-world deviations in terms of losses and gains is contingent on the identification of explicit points of reference against which evaluations can be made.

In general terms, two widely recognized comparison standards have been established: i) internal reference points, wherein people assess an outcome by comparing it with information based on past experiences (internal memory-based standards); and ii) external reference points, where the comparison standard is a value—or the current distribution of values—observed in the purchasing environment (stimulus-based reference benchmarks). While in the context of pricing, both types of benchmarks have been used in the literature (Mazumdar et al, 2005), in the case of ratings, observing internal reference points is not easily attainable because one should know the rating an individual believes that a hotel should have. For this reason, external reference points are used, as researchers only need to look at the information available at the time an individual is

staying at the hotel. As explained later, in this empirical study we consider the average rating in the month the individual stayed at the hotel as a proxy of the rating that they saw on the Internet.

Previous studies have detected loss aversion in multiple aspects of consumer behavior. This includes brand choice (Hardie et al., 1993), destination choice (Nicolau, 2011), savings behavior (Fisher et al., 2011), and responses to promotions (Das and Dutta, 2022). Even before the Covid-19 pandemic one can expect the prospect theory principle of loss aversion to be inherent in the sentiment underlying hotel reviews. This results from the propensity of individuals to overweigh the negative.

In this study, we specifically predict that the sentiment scores resulting from a sentiment analysis of hotel reviews would be impacted to a greater extent when the hotel service received falls below expectations by a certain magnitude, as compared to the scenario in which service received exceeds expectations by the same magnitude. If a value function were to be graphically constructed using the sentiment scores obtained, the slope (steepness) for negative deviations from expectations would be greater than the slope for positive deviations. In terms of the slopes for gains and losses, the graph obtained would be consistent with the classic value function associated with prospect theory. Thus, prior to the Covid-19 pandemic, negative deviations (losses) in ratings from the reference point (service expectation) have a greater absolute impact on online hotel review sentiment than equivalent positive deviations (gains), in line with the prospect theory principle of loss aversion. Accordingly, we state hypothesis 1 as follows:

H1. *Prior to the Covid-19 pandemic, loss aversion is present in the effect of ratings on review sentiment.*

Loss aversion, however, is only one condition that must be met for the graphical representation of the obtained sentiment scores to follow the archetypical prospect theory graph. In order to truly be described as a prospect theory value function, the graph must also exhibit an *S* shape resulting from diminishing marginal sensitivity. This resulting *S* shaped value function is concave for gains, and convex for losses. Diminishing marginal sensitivity pertains to Kahneman and Tversky's (1979) assertion that for both gains and losses, distance from the reference point is inversely related to the marginal change in utility induced. Like loss aversion, diminishing marginal sensitivity has been detected in a multitude of domains. This includes consumer expenditures at wineries (Sellers and Nicolau, 2021), price sensitivity to advertising positioning (Kalra and Goldstein, 1998), responses to website speeds (Gallino et al., 2022) amongst others. In the context of this research, the presence of diminishing sensitivity would mean that, despite the different slopes of positive and negative deviations with regards to the reference point, the marginal impact on satisfaction diminishes as service received increasingly diverges from expectations.

We expect this to be true for both losses and gains. Thus, prior to the Covid-19 pandemic, for both losses and gains, deviations closer to the expectation have a greater marginal impact on online hotel review sentiment than deviations of equal magnitude away from the reference point, in line with the prospect theory principle of diminishing marginal sensitivity. Hypothesis 2 is stated as follows:

H2. *Prior to the Covid-19 pandemic, diminishing sensitivity is present in the effect of ratings on review sentiment.*

The relevant stakes for the consumer have certainly not decreased since the onset of the pandemic. The prospect theory principle of loss aversion is expected to endure in post pandemic hotel review sentiment. That is, reviewers can still be expected to exhibit greater sensitivity to losses than to

gains with respect to the reference point as defined by expectations of service. Graphically, this once again means that in the plotted value function, the slope for the reviews where service received exceeds expectations will be lower than the slope corresponding to reviews where the service received fell short of expectations. As with pre-Covid-19 reviews, this results from the propensity of reviewers to avoid losses rather than to acquire equivalent gains. In the research framework adopted in this study, this would mean that consumers would rather avoid service shortfalls (with regards to what was expected) rather than experience services that exceed expectations by an equal magnitude, in line with the adage that “losses loom larger than gains.” Thus, after the Covid-19 pandemic, negative deviations (losses) in ratings from the reference point (service expectation) have a greater absolute impact on online hotel review sentiment than equivalent positive deviations (gains), in line with the prospect theory principle of loss aversion. Hypothesis 3, pertaining to post-pandemic loss aversion in hotel reviews is stated as:

H3. *After the Covid-19 pandemic, loss aversion is present in the effect of ratings on review sentiment.*

Just as we expect hotel reviews after the pandemic to be characterized by loss aversion, we also expect that post-pandemic hotel reviews would continue to exhibit a statistically significant level of the prospect theory principle of diminishing marginal sensitivity. This means that deviations in service from expectations can be expected to have a lower marginal impact on hotel review sentiment as the size of the deviations increase. Once again, one anticipates this to be the case for gains as well as losses, i.e., positive as well as negative deviations. Therefore, the post pandemic value function would still be characterized by the prototypical S shape, which is integral to prospect theory. In other words, we predict that the post pandemic value function for hotel review sentiment would still be concave for gains, and convex for losses. Thus, after the Covid-19 pandemic, for both losses and gains, deviations closer to expectations have a greater marginal impact on online hotel review sentiment than deviations of equal magnitude away from the reference point, in line with the prospect theory principle of diminishing marginal sensitivity. Hypothesis 4, pertaining to post-pandemic diminishing sensitivity, is stated as follows:

H4. *After the Covid-19 pandemic, diminishing sensitivity is present in the effect of ratings on review sentiment.*

Not only do we expect loss aversion to persist in post-pandemic hotel reviews, but we anticipate that loss-aversion will be even more pronounced in post-pandemic reviews than in pre-pandemic hotel reviews. That is, we expect that post-Covid-19 consumer satisfaction will be impacted to an even greater net extent by losses than by the same level of gains, compared with the period before Covid-19.

This expectation is in line with the well-documented phenomenon that increased uncertainty and perceived risk amplify loss aversion (Barberis, 2013; Köszegi & Rabin, 2006). The COVID-19 pandemic disrupted normal consumer experiences in travel and hospitality, elevating risk perceptions and making consumers more sensitive to potential losses (Rather, 2021). Research in behavioral economics has shown that individuals tend to react more strongly to negative experiences when their perceived stakes are high (Tversky & Kahneman, 1991), which was particularly relevant in the post-pandemic recovery phase. Along these lines, recall that Kahneman and Tversky (1979) demonstrated that an increase in stakes results in individuals becoming more loss averse. As previously mentioned, this pertains to situations like a coin toss, where for $x > y \geq 0$, then individuals, in general, prefer $(y, 0.5; -y, 0.5)$ over $(x, 0.5; -x, 0.5)$. More

simply, this means that individuals tend to prefer a simple game – like a coin toss – wherein the stakes are \$10, rather than a coin toss where the stakes are \$20.

In many ways, it might be argued that the ‘stakes’ went up with the onset of the pandemic. During this period, travelers faced increased uncertainty regarding cleanliness, safety, and overall service reliability, reinforcing a greater psychological cost for negative experiences (Jiang & Wen, 2020; Shin and Kang, 2020). Studies have found that consumer trust in travel and hospitality brands was severely affected during COVID-19 (Wen et al., 2022), further exacerbating negative reactions when expectations were not met. Steffeen and Chang (2021) found that participants were more inclined to adopt Covid-19 preventive measures when the message was framed in terms of loss rather than gains. Consumers placed even more importance on wanting to avoid hotel stays where expectations were not met. This is consistent with research showing that during crises, consumers place disproportionate weight on avoiding perceived risks rather than seeking potential benefits (Yang et al., 2020). We presume that many of these expectations had to do with safety and hygiene measures, which for many individuals became more of a priority in post-pandemic. Once again, the expectations would be reflected in the reference point, and assessments of the stay, in terms of prospect theory, could be described in terms of deviations from the reference point.

Prior research in online reviews suggests that loss aversion manifests more prominently when consumers perceive higher stakes in service encounters. Studies on electronic word-of-mouth (eWOM) have shown that negative experiences tend to have a stronger impact on review sentiment than positive ones, particularly in industries where perceived risk is high (Chevalier & Mayzlin, 2006; Mauri & Minazzi, 2013). Given that hospitality services involve considerable experience-based attributes that cannot be assessed before purchase, negative deviations from expectations are more salient than positive ones (Chan et al., 2017). In the post-COVID-19 context, consumers who perceived a hotel as failing to meet their basic needs were more likely to respond with disproportionately negative sentiment, reinforcing our hypothesis.

Accordingly, Hypothesis 5, pertaining to post Covid-19 loss aversion, is stated as:

H5. *Loss aversion is more pronounced in post Covid-19 hotel reviews than in pre-Covid-19 hotel reviews.*

In addition to expecting higher levels of loss aversion in post-Covid-19 hotel review sentiment, we also anticipate that levels of diminishing marginal sensitivity will increase. That is, marginal sensitivity will diminish at a more accelerated rate than before. In the Covid-19 period, deviations from expectations are likely to have a profound impact on consumer satisfaction, but the marginal impact on satisfaction will decrease quickly with the discrepancy between what is expected and what is actually experienced increases. This argument is in line with findings in consumer psychology showing that after an initial strong reaction to an unexpected event, individuals gradually adjust their expectations and become less reactive to subsequent deviations (Walasek et al., 2018; Gächer et al., 2022).

Of course, this in no way implies that increases in deviations from the reference point can be expected to result in reductions in *overall* utility – we are instead concerned with how net utility is impacted. Stronger reactions elicited by small deviations from the reference point would also mean that people would have become more tolerant – less sensitive – than before about larger deviations. This, of course, would only be the case because of the expected overweighting of smaller deviations. Goldstein et al. (2021) observed diminishing sensitivity in Covid-19 lockdowns – initially lockdowns have highly desirable impacts on reducing cases, but as they are increasingly implemented, the marginal effects decrease. The authors attribute this to diminishing

marginal sensitivity. Similar effects have been observed in tourism, where consumers display increased sensitivity to service quality changes in the early stages of a disruption, but over time, their responsiveness to fluctuations diminishes (Brouder, 2020).

Prior literature on online reviews also supports this notion. Studies have shown that consumers react more strongly to small deviations from expected service levels than to larger deviations, a pattern consistent with diminishing marginal sensitivity (Piriyakul et al., 2024; Sharma et al., 2020). For example, in the post-COVID-19 period, as hygiene measures became standardized and risk perceptions stabilized, consumers may have adjusted their reference points, leading to a faster decline in sensitivity to service quality deviations. This argument suggests that while strong negative reactions persisted initially, consumers eventually adapted, leading to a sharper decline in marginal sensitivity compared to pre-pandemic trends.

Hypothesis 6 pertains to diminishing marginal sensitivity in post Covid-19 reviews and is stated as follows:

H6. *Marginal sensitivity diminishes at a more accelerated rate in post Covid-19 reviews for losses, than in pre Covid-19 reviews.*

4. Research design

4.1. Methodology

To test the prospect theory principles of loss aversion and diminishing sensitivity in the relationship between ratings and sentiments scores ($-1 < Sent_i < 1$), the following regression model is built:

$$Sent_i = \delta_0 + \delta_1 \cdot Gain_i + \delta_2 \cdot Loss_i + \delta_3 \cdot Gain_i^2 + \delta_4 \cdot Loss_i^2 + \varepsilon_i$$

We define Gain and Loss variables in a reference dependent fashion. Specifically, *Gain* captures positive deviations in ratings relative to the expected rating (reference point). It is defined as:

$Gain_i = (Actual\ Rating_i - Expected\ Rating_i)$ if $Actual\ Rating_i > Expected\ Rating_i$ and $Gain_i = 0$ if $Actual\ Rating_i < Expected\ Rating_i$.

And *Loss* captures negative deviations in ratings relative to the expected rating (reference point). It is defined as:

$Loss_i = (Actual\ Rating_i - Expected\ Rating_i)$ if $Actual\ Rating_i < Expected\ Rating_i$ and $Loss_i = 0$ if $Actual\ Rating_i > Expected\ Rating_i$.

Also, $\delta_0, \delta_1, \delta_2, \delta_3, \delta_4$, are the reference dependent parameters such as if $\delta_2 / \delta_1 > 1$ then loss aversion would be confirmed, and significance of δ_3 and δ_4 imply that diminishing sensitivity is also detected. Finally, ε_i is a random term.

To reflect the effects of Covid-19 we have created dummy variables that takes value 1 for each month from June 2020 to March 2022. We also capture hotel's stars with categorical variables to reflect 3, 4 and 5 stars (with 5 stars being the baseline) in line with Abrate et al. (2019) and Alcalde-González et al. (2021). The models also include controls for city, month, and year. In the regression analysis, Berlin, January, and years 2000, 2001, 2002 and 2003 are used as baselines. We will append interactions to the set of independent variables as described in the results section.

Importantly, the interactions between months and prospect theory variables will enable us to assess changes in the magnitudes of loss aversion and diminishing sensitivity in the post-Covid-19 period. The formulation that allows for a comprehensive analysis, capturing the dynamic effects of loss aversion and diminishing sensitivity across time, different hotel categories, and geographic locations is as follows:

$$\begin{aligned}
Sent_i = & \delta_0 + \sum_{j=1}^4 \delta_j X_{ij} \\
& + \sum_{m=2}^{12} \sum_{y \in \{2020, 2021, 2022\}} \sum_{k=1}^4 \delta_{ymk} (Year_y \times Month_m \times X_{ik}) \\
& + \sum_{s \in \{3,4\}} \sum_{l=1}^4 \delta_{sl} (X_{il} \times Stars_s) + \sum_{s \in \{3,4\}} \sum_{l=1}^4 \delta_{slc} (X_{il} \times Stars_s \times AfterCovid) \\
& + \sum_{c=1}^{13} \delta_c City_c + \sum_{t=20}^{2022} \delta_t Year_t + \sum_{m=1}^{12} \delta_m Month_c + \epsilon_i
\end{aligned}$$

where X_{ij} represents the core independent variables: $Gain_i$ ($j=1$), $Loss_i$ ($j=2$), $Gain_i^2$ ($j=3$), $Loss_i^2$ ($j=4$).

The second summation captures the interactions of each independent variable with monthly dummies from June 2020 to March 2022:

$(Year_y \times Month_m \times Gain_i)$

$(Year_y \times Month_m \times Loss_i)$

$(Year_y \times Month_m \times Gain_i^2)$

$(Year_y \times Month_m \times Loss_i^2)$

The third summation accounts for star rating effects:

$(Gain_i \times Stars_s)$

$(Loss_i \times Stars_s)$

$(Gain_i^2 \times Stars_s)$

$(Loss_i^2 \times Stars_s)$

The fourth summation models the effect of star ratings after Covid-19:

$(Gain_i \times Stars_s \times AfterCovid)$

$(Loss_i \times Stars_s \times AfterCovid)$

$(Gain_i^2 \times Stars_s \times AfterCovid)$

$(Loss_i^2 \times Stars_s \times AfterCovid)$

Where $AfterCovid$ is a dummy variable that takes value 1 for those observation after March 10, 2020 (as the declaration of the Covid-19 pandemic by the World Health Organization occurred on March 11, 2020).

The fifth summation includes city fixed effects for cities, the sixth summation incorporates year fixed effects from 2024 to 2022, the seventh summation accounts for month fixed effects, and ϵ_i is the error term.

4.2. Sample and variables

A sample of 416,756 English language reviews pertaining to 375 hotels (127 five-star hotel, 120 four-star hotels, and 128 three-star hotels) located in the following European cities was obtained from TripAdvisor between 2000 (year that TripAdvisor started) and 2022 (year that we obtained the data): Barcelona, Milan, Rome, Paris, Vienna, Frankfurt, Lisbon, Madrid, Berlin, Prague, Brussels, Edinburgh, Dublin and London. These major cities were selected to ensure a minimum number of hotels and travelers, and consequently, of reviews. In the same vein, we excluded 1- and 2-star hotels because there were relatively fewer hotels under these categories on TripAdvisor. Moreover, we found that 1- and 2-star hotels tended to receive a smaller number of reviews, which is expected when one considers that these properties are usually smaller in size. For such hotels, reliable analyses cannot be conducted with a sufficient level of confidence. Table 1 shows the distribution of hotels per city and reviews per year.

Table 1. Hotels per city and reviews per year

City	Hotels per city				Reviews per year	
	5-star	4-star	3-star	Total	Year	Number of reviews
Barcelona	10	10	10	30	2000	6
Milan	10	10	10	30	2001	0
Rome	10	10	10	30	2002	30
Paris	10	8	10	28	2003	249
Vienna	9	8	10	27	2004	929
Frankfurt	9	9	9	27	2005	1651
Lisbon	9	8	10	27	2006	2385
Madrid	10	8	8	26	2007	3286
Berlin	9	9	8	26	2008	3381
Prague	8	8	10	26	2009	5388
Brussels	8	8	9	25	2010	7478
Edinburgh	9	8	8	25	2011	13837
Dublin	8	8	8	24	2012	22043
London	8	8	8	24	2013	28044
Total	127	120	128	375	2014	34078
					2015	46999
					2016	57827
					2017	55596
					2018	50243
					2019	49401
					2020	12552
					2021	16404
					2022	4949

The dependent variable in this study represents the sentiment score obtained through the Linguistic Inquiry Word Count program (Boyd et al., 2022). This program calculates the percentage of sentiment words based on its dictionary and provides a sentiment score ranging from -1 (negative) to +1 (positive) for a given text (Tausczki & Pennebaker, 2010). The sentiment score generated by Linguistic Inquiry Word Count is widely utilized in various online review studies due to its accuracy and validity (Kong & Lou, 2023; Park et al., 2023; Wang et al., 2023). Text sentiment can be a more reliable measure of customer sentiment than an overall rating because the sentiment embedded in an online review can be represented through a broader range of textual data (Kim, 2021). Additionally, by using the artificial intelligence-based sentiment analysis (“sentiment.ai”), two extra deep learning-based algorithms (“en.large” (-1,+1) and “multi.large” (0,+1)) are employed to obtain additional dependent variables, thereby testing the robustness of the results.

Regarding the independent variables, the overall rating (from 1 to 5) the reviewer posted is compared to the “expected rating.” Critical to this analysis is the definition of this expected rating. We define a specific monthly reference point for each hotel by using the mean value of the ratings for each month in the sample. Note that we cannot access the average rating the hotel published on its website in the past. Therefore, to obtain a proxy for the rating of a specific month in a particular year, we calculate the rating by averaging all the ratings that individuals posted in that month and year. Ultimately, this is essentially how hotels obtain the ratings that they publish online.

Our choice of the monthly average rating as a reference point follows the logic of prospect theory as a descriptive model. Rather than seeking the “true” reference point, we adopt a specification that is consistent with how consumers are likely to form expectations about service quality before writing their reviews. The monthly average rating serves as a reasonable external benchmark because it reflects the aggregated perception of hotel quality at the time of a guest’s stay, making it one of the most visible and accessible heuristics for consumers when forming expectations (Anderson, 2012; Nicolau et al., 2024; Xie et al., 2014). In fact, hotels typically calculate and publicly display their overall ratings based on an average of past reviews, reinforcing the relevance of this measure as a reference point (Han & Mikhailova, 2024; Liu et al., 2018). Consumers are exposed to such reference points before writing their reviews since hotel ratings on platforms and booking websites are highly visible at the time of booking and often referenced post-stay when writing a review (Wu et al., 2024; Xu et al., 2025). While it is not possible to directly measure how each individual reviewer forms their expectations, the prevailing monthly average serves as a reasonable proxy for expectations at the time of the stay.

Once we calculate this average rating (expected rating), we compare each individual’s rating against the expected rating in that particular period, thereby obtaining gain and loss variables. Table 2 presents the descriptive statistics.

Table 2. Descriptives of dependent variables and prospect theory-related independent variables

	Dependent variable 1 (LIWC)	Dependent variable 2 (en.large)	Dependent variable 3 (multi.large)	Gain	Loss
Mean	0.7044	0.1897	0.2792	0.2827	-0.2827
Max	0.9800	1.0000	1.0000	3.1000	0.0000
Min	-0.9800	-0.6857	0.0000	0.0000	-3.9047
SD	0.4576	0.0866	0.0414	0.3351	0.5928

5. Results

Table 3 presents the parameter estimates obtained through Ordinary Least Squares to test the hypotheses. Four models are estimated: Model 1 uses sentiment scores obtained through the Linguistic Inquiry Word Count program, while Models 2 and 3 employ sentiment scores obtained through deep learning-based algorithms (“en.large” and “multi.large”, respectively). Out of these three models, Model 1 outperforms the other two, showing higher R-squared and adjusted R-squared values. In all models, robust standard errors are used to estimate the significance of the parameter estimates. Still, out of prudence, Model 4 re-estimates Model 1 by applying a 1% trimming function to discard the potential effect of outliers. The results of Models 1 and 4 are similar.

Additionally, potential endogeneity may emerge as there may be a two-way relationship between sentiment scores and review ratings. While people may assign higher sentiment scores when they give higher ratings, the reverse may also occur: the sentiment expressed in the review could influence the assigned rating. This raises the concern that ratings may not be fully exogenous, necessitating an approach to control for endogeneity. Thus, it is crucial to control for endogeneity. Our model is based on the premise that ratings reflect a structured cognitive evaluation, whereas sentiment captures the emotional expression associated with the experience. Since our objective is to test whether reference-dependent shifts in expectations (the overall rating that the individuals saw when making the reservation) influence sentiment, we treat sentiment as the dependent variable.

However, recognizing the potential for a reverse relationship, we employ Gaussian copulas, a method that does not depend on instrumental variables and directly captures the joint distribution of variables that could be endogenous and the error term (Park & Gupta, 2012). This approach is particularly advantageous as it allows us to address endogeneity concerns without requiring strong exclusion restrictions typically necessary for instrumental variable techniques. By leveraging the copula-based framework, we effectively model the joint dependence structure between sentiment scores and review ratings while ensuring that our estimation remains robust to potential biases. The computation of copula terms for gains (G) and losses (L) is performed as follows:

$$G_i^c = \Phi^{-1}[H_G(G_i)]$$

$$L_i^c = \Phi^{-1}[H_L(L_i)]$$

Here, Φ^{-1} denotes the inverse of the cumulative normal distribution. Additionally, $H_G(G_i)$ and $H_L(L_i)$ signify the empirical distribution functions for gains and losses, respectively.

Should the copulas exhibit significant parameters, it indicates the presence of endogeneity. Consequently, those copulas characterized by significant parameters should be incorporated into the regression model to correct for potential bias in our estimates. The results reveal that both copulas are significantly different from zero (see bottom of Table 3), confirming the need to control for endogeneity in our model. By including these copula terms, we mitigate concerns regarding simultaneity between sentiment and ratings, ensuring that our estimates of loss aversion and diminishing sensitivity remain reliable and robust.

As Model 1 is found to be optimal after addressing endogeneity concerns, we proceed with the interpretation of its parameters, ensuring that our findings regarding reference-dependent effects in online review sentiment are not confounded by reverse causality or omitted variable bias.

Table 3. Effect of loss aversion and diminishing sensitivity on hotel review in pre- and post-pandemic scenarios*

	Model 1	Model 2	Model 3	Model 4
<i>Loss aversion and diminishing sensitivity</i>				
Gain	0.056 ^a (0.008)	0.018 ^a (0.002)	0.004 ^a (0.001)	0.058 ^a (0.008)
Loss	0.484 ^a (0.006)	0.076 ^a (0.001)	0.03 ^a (0.0001)	0.483 ^a (0.006)
Gain ²	-0.027 ^a (0.006)	-0.013 ^a (0.001)	-0.003 ^a (0.001)	-0.028 ^a (0.006)
Loss ²	0.028 ^a (0.002)	0.01 ^a (0.0001)	0.002 ^a (0.0001)	0.028 ^a (0.002)
Constant	0.656 ^a (0.029)	0.168 ^a (0.005)	0.275 ^a (0.002)	0.653 ^a (0.03)
<i>Controlling for endogeneity - copulas</i>				
Copula Gain	0.002b (0.001)	0.0004b (0.0001)	0.0005a (0.0001)	0.003a (0.001)
Copula Loss	0.006a (0.001)	0.0009a (0.0001)	0.0007a (0.0001)	0.006a (0.001)
R-squared	0.3243	0.1605	0.1621	0.3240
Adjusted R-squared	0.3241	0.1602	0.1618	0.3237
F-statistic	1481.08 ^a	589.84 ^a	597.09 ^a	1449.29 ^a

^a=p<0.01. * For the sake of space, the full set of parameter estimates is provided in a five-page table in the appendix (supplementary file).

The gain and loss parameters are significantly different from zero, with the latter (0.484) being significantly greater than the former (0.056) (Wald test=1198.1; p<0.001). This means that consumers hate dissatisfaction more than love an equivalent satisfaction, thereby supporting Hypothesis 1 that loss aversion exists in online hotel reviews. In other words, finding a service with quality that is lower than expected leads to a negative reaction in the review sentiment that is stronger than the reaction derived from finding a service with a quality that is better than expected. In fact, when examining the magnitudes of these parameters, the finding that the loss parameter is almost nine times greater than the gain parameter strongly suggests that loss aversion is a cognitive bias that is deeply ingrained in hotel reviews.

The quadratic terms associated with gains and losses are also significant—the gain parameter with a negative sign (-0.027) and the loss parameter with a positive sign (0.028)—giving rise to

diminishing sensitivity, thereby supporting Hypothesis 2 that diminishing sensitivity exists in online hotel reviews. In other words, the marginal effect of a change in ratings closer to the reference point is greater than an equivalent change that is further away for that same reference point; and this situation occurs for gains and losses.

The interactions between months and prospect theory variables allow us to determine the magnitude of loss aversion and diminishing sensitivity in the post-Covid-19 period. Starting in June 2020 (when some countries began lifting lockdowns), we observe that all the interactions present either significantly positive or non-significant parameters, meaning that pre-Covid-19 loss aversion and diminishing sensitivity still exist or are accentuated in the post-Covid-19 period, in line with Hypotheses 3, 4, 5 and 6.

Focusing on Hypotheses 5 and 6, it is relevant to observe whether there is a gradual return to pre-pandemic norms. The results show that, in the instances where loss aversion was greater than normal (see parameters in boldface in Model 1), there is a clear decreasing pattern: the highest parameter occurs in September 2020 (parameter=0.255), followed by June 2021 (0.230), August 2021 (0.206), September 2021 (0.147), October 2021 (0.155), November 2021 (0.118) and December 2021 (0.074). Until the end of the study period (March 2022), no other month shows loss aversion above normal values. A similar decreasing pattern is found for diminishing sensitivity: September 2020 (parameter=0.094), June 2021 (0.77), August 2021 (0.060), October 2021 (0.046), March 2022 (0.062).

Additionally, in an attempt to further unearth the effects of loss aversion and diminishing sensitivity, we implemented two actions:

1) we introduced the number of stars in Model 1 (where 5-star hotels is the base category to which 4- and 3-star hotels are compared). The loss aversion parameters associated with 4- and 3-star hotels exhibit significant and negative values (-0.118 and -0.122, respectively), indicating that 5-star hotels present the largest loss aversion effect. This means that failing to service expectations in high-quality hotels (5 stars) brings about the greatest negative reaction. Interestingly, these parameters are no longer significant after Covid-19, meaning that people staying in 4 and 3-star hotels became more sensitive to negative discrepancies than before. Exactly the same pattern is found for diminishing sensitivity. It seems that people became more demanding regarding the basic services provided by 4- and 3-star hotels, especially considering the safety measures that were expected.

2) we use quantile regression (Koenker & Bassett, 1978) to test whether non-constant effects of loss aversion exist over the conditional distribution of the dependent variable (Table 4)—singularity issues prevented the inclusion of quadratic terms in the model, resulting in the unavailability of estimates for the diminishing sensitivity parameters. The results show that, in line with the results obtained earlier, loss aversion existed before Covid-19 and is accentuated after the onset of the pandemic (notice that the parameter associated with losses increases after Covid-19). However, for the 10th, 25th, 50th, 75th, and 90th quantiles, we observe a differentiated effect over the conditional distribution of sentiment. In particular, the decreasing size of the parameters across the different quantiles suggests that the lower the sentiment score the higher the effect of loss aversion. It seems that it is especially at lower levels of satisfaction when tourists tend to penalize the hotel more harshly for mistakes than commend it lavishly for good service.

To be more specific regarding the heterogeneous impact of loss aversion—varying across different levels of sentiment—it is important to note that at lower quantiles (Q10 and Q25), loss

aversion is particularly strong, suggesting that highly dissatisfied consumers penalize service failures more intensely than they reward positive experiences. At the median quantile (Q50), the effect remains significant but at a lower magnitude, reflecting a more balanced response to deviations from expectations. However, at higher quantiles (Q75 and Q90), the influence of loss aversion weakens considerably, meaning that consumers who are already highly satisfied are less affected by negative deviations.

This pattern is visualized in Figure 1, where the post-Covid-19 (solid) lines at lower quantiles exhibit a steeper decline, indicating a stronger penalty for negative experiences after the pandemic. At higher quantiles, however, the slopes flatten, reinforcing that consumers with higher sentiment scores are less sensitive to reference-dependent losses. Moreover, the Loss x AfterCovid interaction term in Table 4 confirms that loss aversion became more pronounced post-pandemic, particularly at lower sentiment levels.

Additionally, the results for gains show a contrasting pattern. The coefficients for gains are consistently lower than those for losses, reinforcing the asymmetric nature of consumer responses in line with prospect theory. More importantly, gains have little to no effect at higher quantiles, suggesting that once consumers express high levels of satisfaction, further positive deviations do not substantially increase sentiment. The Gain x AfterCovid interaction term further reveals that post-pandemic, consumers became even less responsive to positive surprises, emphasizing that their primary concern was avoiding negative experiences rather than rewarding superior service.

These findings are relevant for hotel management because (i) service failures seem to affect consumers higher at lower sentiment levels, meaning that hotels must prioritize minimizing negative experiences, and (ii) attempting to exceed expectations for already satisfied customers may yield diminishing returns. Furthermore, the post-pandemic amplification of loss aversion highlights the need for stronger service recovery strategies, as consumers became more sensitive to disappointments.

Table 4. Pre- and post-pandemic loss aversion with Quantile regression
(Standard errors in parenthesis)

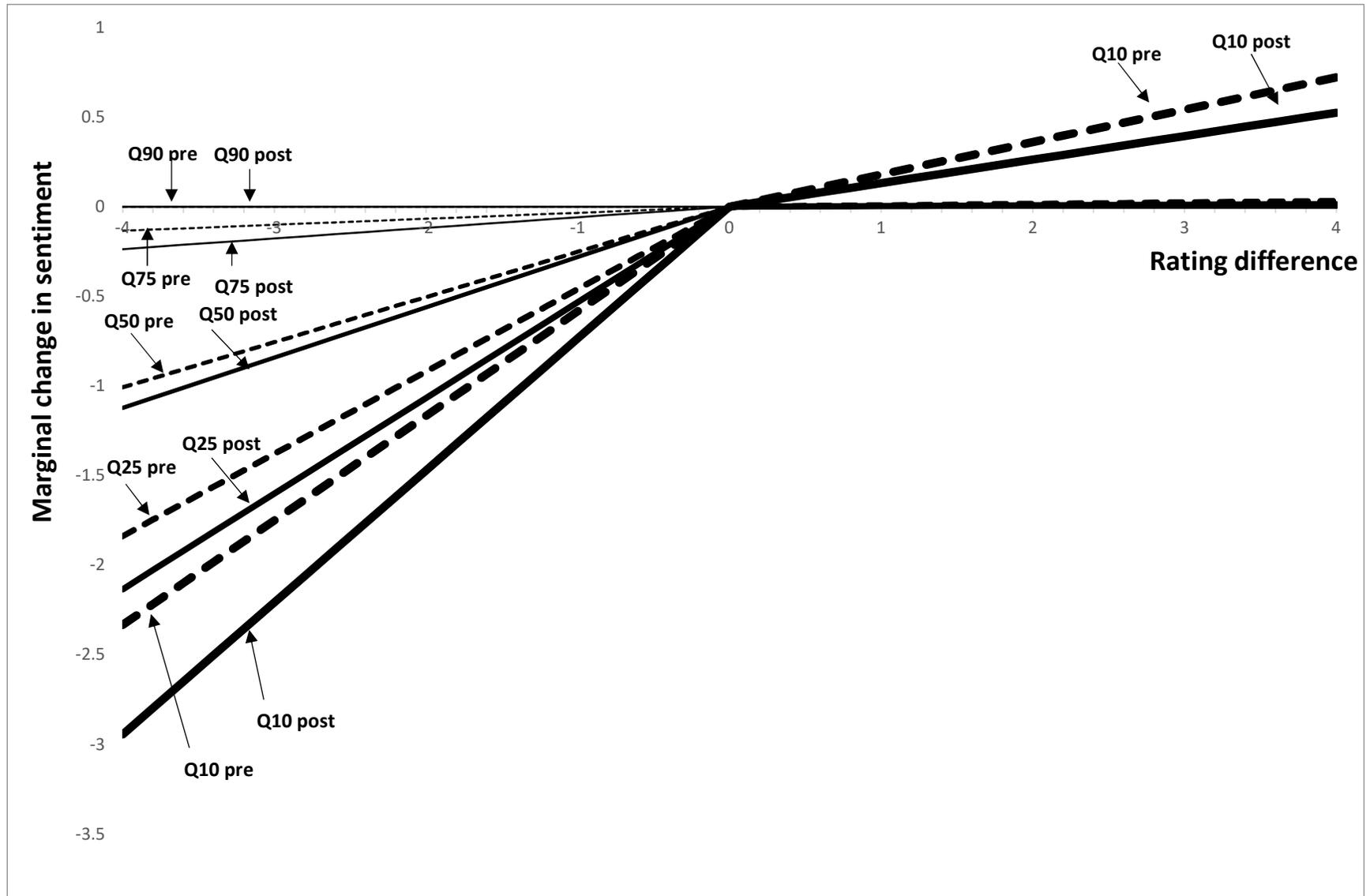
Variables	Quantiles				
	0.1	0.25	0.5	0.75	0.9
Gain	0.181a [0.006]	0.062a [0.003]	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
Loss	0.583a [0.004]	0.624a [0.003]	0.472a [0.002]	0.119a [0.002]	0.000 (0.001)
Gain*AfterCovid	-0.049c [0.023]	-0.034a [0.005]	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
Loss*AfterCovid	0.153a [0.018]	0.101a [0.009]	0.054a [0.005]	0.091a [0.013]	0.000 (0.001)

^a=p<0.01.

As for the city controls, we find that Paris (0.0685), Rome (0.0430), Lisbon (0.0422), Prague (0.0314), Barcelona (0.0278), Vienna (0.0234), Milan (0.0213) show sentiment scores that are significantly greater than Berlin (used as the baseline). Edinburgh (-0.0056), London (-0.0298), Madrid (-0.0309), Brussels (-0.0440), and Frankfurt (-0.0689) present sentiment scores that are

lower than Berlin. Dublin displays a non-significant parameter (0.0036), so its sentiment score is similar to that of Berlin. Therefore, there seems to be a disparity in the perceived service quality or sentiment expressed in hotel reviews across different cities.

Figure 1. Effect of loss aversion on change in sentiment across quantiles



6. Concluding Discussion

This research examined whether the two defining principles of Kahneman and Tversky's (1979) prospect theory—loss aversion and diminishing sensitivity—are revealed in online hotel review sentiment. The results show that, while both loss aversion and diminishing sensitivity occur in pre- as well as post-Covid-19 periods, both principles are significantly more accentuated in the post-Covid-19 period. However, it is noteworthy to observe that there is a gradual return to pre-pandemic norms.

Our findings are in line with broader discussions in the literature on how consumer behavior in the travel and hospitality industry evolved during and after the Covid-19 crisis (Gössling et al., 2020; Neuburger & Egger, 2021; Wang et al., 2024). Studies have highlighted shifts in perceived risk, changes in service expectations, and increased emphasis on safety and hygiene as key determinants of consumer decision-making post-pandemic (Pennington-Gray & Lee, 2024; Wen et al., 2021; Zhang et al., 2023). Our results contribute to this body of research by demonstrating that these behavioral shifts were not only present but also manifested in systematic cognitive biases, such as increased loss aversion and diminishing sensitivity in hotel review sentiment.

Important theoretical and managerial implications follow from our findings. From a theoretical perspective, first, this research extends the applications of prospect theory into a previously unexplored domain – that is, hotel review sentiment. The last two decades have witnessed a number of papers that test the tenets of prospect theory across a variety of areas, including other aspects of hotel reviews. However, to the best of the authors' knowledge this paper serves as one of the earliest – if not the earliest – attempt to demonstrate that the tenets of prospect theory hold in the context of hotel review sentiment. As such, we suggest that subsequent studies that seek to uncover other potential theoretical linkages between yet other independent variables and hotel review sentiment, not ignore potential distortions that may have resulted from the presence of loss aversion and diminishing sensitivity. Certainly, such distortions should not be dismissed as merely idiosyncratic inconsistencies in reviewer behavior. On the contrary, these and other asymmetries may be manifestations of actual preferences and must be scrutinized in more detail. Consequently, reference dependent variables should be included in this type of analysis.

Second, this research reaffirms the role of reference dependent thinking in shaping behavioral preferences when it comes to hotel reviews. This, and a growing number of other theoretical contributions across a range of disciplines now routinely observe that human beings tend not to make decisions based on absolute comparisons (see Hardie et al., 1993; Das & Dutta, 2022; Day et al., 2022; etc.). Our findings add to this growing body of evidence.

Third, the findings of this paper also add to the accumulating evidence that cognitive biases routinely skew human preferences. Therefore, in many ways, this research lends itself to the strand of literature that suggests that theoretical neoclassical economics assumption of rational decision-making may not be an accurate representation of real-world decision making. In this regard, we advocate that behavioral researchers avoid basing studies on the rational actor assumption, and instead support their arguments with alternative, more realistic models of human behavior. While prospect theory provides a powerful explanation of decision making and choice behavior under conditions of risk, additional explanations of behavioral conduct in other domains have also emerged in recent decades. Several of these may provide the basis for

more accurate modelling of real world preferences. Such alternative theoretical conceptualizations include, for instance, nudge theory (Thaler & Sunstein, 2009), sunk cost fallacy theorem (Arkes & Blumer, 1985), or fair wage hypothesis (Fehr & Gächter, 2002), among others.

Fourth, the results of this paper found that the Covid-19 pandemic had a noteworthy impact on loss aversion and diminishing sensitivity. The pandemic constituted an unprecedented type of global crisis in human history, and almost simultaneously impacted populations across the world in general and travel behaviors in particular (Park, Kim & Ho, 2022). The predictions of prospect theory were found to still hold up in the face of changes in risk levels. Yet, how the predictions are manifested in the real world under the theoretical framework of prospect theory were put to test in this research, and changes were observed. Upon integrating our results with research on consumer psychology during crisis periods, they are in line with existing studies that highlight how uncertainty influences decision-making biases (Kirk & Rifkin, 2020; Kim et al., 2021). The stronger loss aversion observed post-Covid-19 is consistent with findings that consumers become more risk-averse and prone to negativity bias following major disruptions (Jiang & Wen, 2020). These insights emphasize the importance of studying consumer behavior in evolving risk environments, as such biases may not persist indefinitely but rather follow an adjustment trajectory.

Importantly, our findings are in line with the idea that online reviews are a strong reflection of service satisfaction. Previous studies have demonstrated that the textual content of online reviews is closely linked to consumer satisfaction with service encounters (e.g., Xie et al., 2014). Text-based sentiment analysis provides a refined approach to consumer reactions than numerical ratings alone, as it captures the emotional intensity (Nicolau et al., 2024).

The findings of this research also have important managerial and practical implications.

The fact that loss aversion is detected in hotel reviews means that when hotels are able to exceed consumer expectations, they may also be shifting the customer's point of reference upward. Thus, the higher level of service may become an expectation during the future stays of the customer. This in turn means that upon achieving the higher level of service, hotels must maintain that level of service. Any reversion to previous service levels could lead to highly dissatisfied consumers – and specifically, it would lead to consumers who are now even more dissatisfied than they were before service levels were raised.

A second managerial implication emerges from this paper and pertains to the presence of diminishing sensitivity in consumer reviews of hotels. This means that hotels of high repute may enjoy a certain buffer when it comes to providing service – this means that a fall in hotel service from 5 to 4, will have a lower effect on customer satisfaction than a fall from 4 to 3. Conversely, for a low-end hotel, this also means that simply raising service from 1 to 2 can have a profound impact on consumer satisfaction, whereas, for a hotel to improve service from 4 to 5 is likely to induce a much smaller impact on satisfaction.

The third managerial implication resulting from this analysis has to do with how crises such as Covid-19 must be managed by service providers. We found that the pandemic might have altered customer reference points with regard to service levels. It is important for hotels to adapt to the changed reference points, or else customers could end up being dissatisfied or even lost. Adapting to the reference points means that managers should identify the specific aspects of service that could result in changes to expectations during crises as early as possible.

A fourth managerial implication derives from the different levels of loss aversion and diminishing sensitivity in the number of hotel stars. 5-star hotels have consumers with highest levels of both effects. This is relevant for these high-quality hotels because expectations matter more than in other lower categories. A final fifth managerial implication comes from the differentiated effect of ratings over the conditional distribution of sentiment found through quantile regression. Specifically, hotels with low levels of sentiment scores must be more alert to changes in the ratings posted by their consumers.

There are also certain limitations which must be considered when drawing conclusions from this paper. First, we acknowledge that we have retrieved reviews from only one hotel review platform. Although this concern is alleviated by the fact that our dataset is very large, we encourage other researchers to cross-validate our findings with data obtained from other review platforms like Google and Yelp. Second, in this analysis we have used the average rating for each month in the sample as a proxy for the hotel's rating (we also tested the rating of the previous month, but the results were not as accurate as those provided by the current month). Therefore, alternative proxies for these reference points could be considered to strengthen the results. In fact, the use of experimental methods would allow researchers to test different benchmarks in various pandemic-related scenarios.

Third, while our sentiment analysis approach provides robust evidence of behavioral shifts, future studies could complement this analysis with alternative methodologies, such as topic modeling or qualitative content analysis to explore the specific aspects of service evaluations that contributed to sentiment shifts. While our study focuses on sentiment analysis, such complementary methods could help disentangle whether negative evaluations were predominantly driven by service satisfaction, hygiene concerns, or broader travel-related anxieties. Fourth, while our study provides valuable insights into how prospect theory principles manifest in hotel review sentiment before and after the Covid-19 pandemic, it is important to acknowledge that our dataset spans reviews from 2000 to 2022, allowing us to capture the immediate post-pandemic reversion trend. However, as consumer attitudes and behaviors may continue to evolve over time, future research should investigate whether loss aversion and diminishing sensitivity fully return to pre-pandemic levels or if the pandemic has left a lasting behavioral imprint on travel reviews. Analyzing more recent review data would help determine whether these behavioral biases have stabilized at a new level, or revert completely to pre-pandemic levels. A final limitation arises from the sample. Note that the variations found in the effect of loss aversion should be regarded as minimum thresholds. Risk-averse individuals may not have traveled or may have delayed their travel plans, while non-risk-averse people were less likely to cancel. Consequently, our sample might include a greater proportion of the latter than the former, leading to a composition that could differ from the pre-pandemic period. Thus, if we were to go to the extreme and assume that only non-risk-averse individuals traveled, the results would represent the minimum threshold of potential variations in loss aversion and diminishing sensitivity (because the inclusion of risk-averse travelers would further affect the outcomes). Recall that Kahneman and Tversky (1979) demonstrated that as the stakes increase, levels of loss aversion increase. For instance, if our sample exclusively comprised non-risk-averse travelers, and loss aversion increased by 0.255 (in September 2020 (as reflected in Table 3)), it means that this increment would be even greater if risk-averse travelers were included in that hypothetical sample comprised only of non-risk-averse individual.

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Supplementary file

APPENDIX

Table 3. Effect of loss aversion and diminishing sensitivity on hotel review in pre- and post-pandemic scenarios

	Model 1	Model 2	Model 3	Model 4
<i>Loss aversion and diminishing sensitivity</i>				
Gain	0.056a (0.008)	0.018a (0.002)	0.004a (0.001)	0.058a (0.008)
Loss	0.484a (0.006)	0.076a (0.001)	0.03a (0.0001)	0.483a (0.006)
Gain ²	-0.027a (0.006)	-0.013a (0.001)	-0.003a (0.001)	-0.028a (0.006)
Loss ²	0.028a (0.002)	0.01a (0.0001)	0.002a (0.0001)	0.028a (0.002)
<i>Loss aversion and diminishing sensitivity after Covid-19</i>				
Year2020*Month6*Gain	-0.27 (0.319)	0.046 (0.088)	-0.002 (0.023)	-0.269 (0.318)
Year2020*Month6*Loss	0.449 (0.429)	-0.024 (0.02)	0.02 (0.024)	0.441 (0.425)
Year2020*Month6*Gain ²	0.164 (0.195)	-0.024 (0.048)	0.006 (0.014)	0.163 (0.194)
Year2020*Month6*Loss ²	0.052 (0.184)	-0.012 (0.008)	0.004 (0.011)	0.051 (0.182)
Year2020*Month7*Gain	0.001 (0.1)	0.007 (0.023)	0.007 (0.011)	0.021 (0.108)
Year2020*Month7*Loss	0.14 (0.124)	-0.011 (0.018)	-0.001 (0.007)	0.1 (0.127)
Year2020*Month7*Gain ²	-0.063 (0.087)	-0.014 (0.017)	-0.004 (0.009)	-0.08 5 (0.1)
Year2020*Month7*Loss ²	0.049 (0.042)	-0.001 (0.007)	0.003 (0.003)	0.037 (0.043)
Year2020*Month8*Gain	-0.065 (0.055)	0.001 (0.015)	0.004 (0.006)	-0.064 (0.058)
Year2020*Month8*Loss	0.137 (0.081)	0.008 (0.012)	0.002 (0.005)	0.124 (0.082)
Year2020*Month8*Gain ²	0.034 (0.041)	-0.002 (0.011)	-0.001 (0.004)	0.028 (0.043)
Year2020*Month8*Loss ²	0.041 (0.032)	-0.002 (0.005)	0.002 (0.002)	0.04 (0.032)
Year2020*Month9*Gain	-0.007 (0.049)	-0.001 (0.013)	0.008 (0.005)	-0.011 (0.05)
Year2020*Month9*Loss	0.255b (0.082)	0.026c (0.012)	0.001 (0.006)	0.232b (0.082)
Year2020*Month9*Gain ²	-0.001 (0.041)	-0.007 (0.009)	-0.006 (0.004)	0.0001 (0.042)
Year2020*Month9*Loss ²	<i>0.094b</i> (0.034)	0.008 (0.005)	0.0001 (0.002)	0.09b (0.034)
Year2020*Month10*Gain	0.062 (0.048)	-0.011 (0.017)	0.024b (0.008)	0.081 (0.051)
Year2020*Month10*Loss	0.092 (0.109)	0.01 (0.017)	-0.005 (0.009)	0.024 (0.112)
Year2020*Month10*Gain ²	-0.006 (0.032)	-0.004 (0.012)	-0.012b (0.005)	-0.025 (0.043)
Year2020*Month10*Loss ²	-0.006 (0.043)	0.005 (0.007)	-0.001 (0.003)	-0.026 (0.044)
Year2020*Month11*Gain	-0.206 (0.173)	-0.015 (0.046)	-0.014 (0.02)	-0.184 (0.173)
Year2020*Month11*Loss	0.014 (0.219)	0.047 (0.047)	0.002 (0.03)	-0.029 (0.238)

^a=p<0.01; ^b=p<0.05; ^c=p<0.05

Table 3. Cont.

	Model 1	Model 2	Model 3	Model 4
Year2020*Month11*Gain ²	0.124 (0.122)	0.002 (0.034)	0.005 (0.016)	0.09 (0.13)
Year2020*Month11*Loss ²	-0.039 (0.091)	0.008 (0.02)	-0.001 (0.013)	-0.053 (0.099)
Year2020*Month12*Gain	0.101 (0.113)	-0.028 (0.025)	0.021 (0.014)	0.103 (0.113)
Year2020*Month12*Loss	0.134 (0.139)	0.014 (0.02)	-0.006 (0.008)	0.118 (0.14)
Year2020*Month12*Gain ²	-0.133 (0.138)	0.025 (0.026)	-0.016 (0.013)	-0.136 (0.138)
Year2020*Month12*Loss ²	0.04 (0.045)	0.007 (0.007)	-0.001 (0.003)	0.035 (0.046)
Year2021*Month6*Gain	-0.044 (0.057)	0.008 (0.015)	0.015c (0.007)	-0.039 (0.058)
Year2021*Month6*Loss	0.230a (0.065)	0.044a (0.01)	-0.004 (0.004)	0.207b (0.066)
Year2021*Month6*Gain ²	0.029 (0.053)	-0.018 (0.014)	-0.011 (0.006)	0.026 (0.054)
Year2021*Month6*Loss ²	<i>0.077a</i> <i>(0.023)</i>	0.012b (0.004)	-0.002 (0.002)	0.07b (0.023)
Year2021*Month7*Gain	0.038 (0.038)	0.014 (0.011)	0.009 (0.005)	0.041 (0.039)
Year2021*Month7*Loss	0.113 (0.059)	0.028b (0.009)	0.008c (0.003)	0.085 (0.059)
Year2021*Month7*Gain ²	-0.029 (0.031)	-0.007 (0.009)	-0.005 (0.004)	-0.027 (0.031)
Year2021*Month7*Loss ²	0.036 (0.022)	0.008c (0.004)	0.003c (0.001)	0.027 (0.022)
Year2021*Month8*Gain	-0.009 (0.035)	0.017 (0.009)	0.008c (0.004)	-0.009 (0.036)
Year2021*Month8*Loss	0.206a (0.051)	0.032a (0.008)	0.006c (0.003)	0.197a (0.052)
Year2021*Month8*Gain ²	0.012 (0.03)	-0.014c (0.007)	-0.004 (0.003)	0.01 (0.031)
Year2021*Month8*Loss ²	<i>0.06b</i> <i>(0.02)</i>	0.007c (0.003)	0.002 (0.001)	0.057b (0.02)
Year2021*Month9*Gain	0.01 (0.033)	0.009 (0.01)	-0.001 (0.004)	0.007 (0.035)
Year2021*Month9*Loss	0.147b (0.05)	0.027b (0.008)	0.005 (0.003)	0.119c (0.051)
Year2021*Month9*Gain ²	0.001 (0.024)	-0.007 (0.007)	0.001 (0.003)	0.001 (0.025)
Year2021*Month9*Loss ²	0.033 (0.018)	0.006 (0.004)	0.001 (0.001)	0.025 (0.018)
Year2021*Month10*Gain	0.069c (0.032)	0.014 (0.01)	0.0001 (0.004)	0.073c (0.033)
Year2021*Month10*Loss	0.155b (0.054)	0.035a (0.009)	0.008c (0.003)	0.164b (0.054)
Year2021*Month10*Gain ²	-0.029 (0.025)	-0.005 (0.007)	0.0001 (0.002)	-0.032 (0.025)
Year2021*Month10*Loss ²	<i>0.046c</i> <i>(0.021)</i>	0.01b (0.004)	0.003c (0.001)	0.049c (0.021)
Year2021*Month11*Gain	0.06 (0.032)	0.025c (0.01)	0.0001 (0.004)	0.066c (0.032)
Year2021*Month11*Loss	0.118c (0.057)	0.028b (0.009)	0.006 (0.003)	0.11 (0.059)

^a=p<0.01; ^b=p<0.05; ^c=p<0.05

Table 3. Cont.

	Model 1	Model 2	Model 3	Model 4
Year2021*Month11*Gain ²	-0.021 (0.027)	-0.013 (0.008)	0.003 (0.004)	-0.027 (0.027)
Year2021*Month11*Loss ²	0.037 (0.023)	0.008c (0.004)	0.002 (0.001)	0.037 (0.024)
Year2021*Month12*Gain	0.074c (0.035)	0.004 (0.012)	0.005 (0.005)	0.088c (0.035)
Year2021*Month12*Loss	0.084 (0.062)	0.034b (0.01)	-0.001 (0.004)	0.048 (0.064)
Year2021*Month12*Gain ²	-0.017 (0.026)	0.009 (0.011)	-0.002 (0.004)	-0.028 (0.027)
Year2021*Month12*Loss ²	0.019 (0.024)	0.008 (0.004)	0.0001 (0.001)	0.007 (0.025)
Year2022*Month1*Gain	0.012 (0.047)	0.009 (0.016)	-0.003 (0.007)	0.017 (0.047)
Year2022*Month1*Loss	0.131 (0.075)	0.04b (0.013)	0.006 (0.005)	0.092 (0.077)
Year2022*Month1*Gain ²	-0.023 (0.038)	-0.011 (0.013)	0.004 (0.007)	-0.027 (0.038)
Year2022*Month1*Loss ²	0.049 (0.028)	0.011c (0.005)	0.002 (0.002)	0.038 (0.028)
Year2022*Month2*Gain	0.005 (0.044)	0.022 (0.013)	-0.011c (0.006)	0.014 (0.044)
Year2022*Month2*Loss	0.042 (0.063)	0.005 (0.01)	0.003 (0.004)	0.037 (0.065)
Year2022*Month2*Gain ²	-0.025 (0.044)	-0.022c (0.011)	0.011c (0.005)	-0.031 (0.044)
Year2022*Month2*Loss ²	0.003 (0.025)	-0.003 (0.004)	-0.001 (0.002)	0.0001 (0.026)
Year2022*Month3*Gain	-0.015 (0.043)	0.024 (0.014)	-0.006 (0.005)	-0.003 (0.043)
Year2022*Month3*Loss	0.129 (0.078)	0.017 (0.014)	0.012b (0.004)	0.094 (0.078)
Year2022*Month3*Gain ²	0.039 (0.032)	-0.007 (0.011)	0.003 (0.004)	0.032 (0.032)
Year2022*Month3*Loss ²	0.062c (0.03)	0.001 (0.006)	0.005b (0.002)	0.052 (0.03)
<i>Loss aversion and diminishing sensitivity by hotel stars</i>				
4 Stars	0.041a (0.003)	0.008a (0.001)	0.002a (0.0001)	0.042a (0.003)
3 Stars	-0.001 (0.004)	-0.002b (0.001)	-0.008a (0.0001)	-0.001 (0.004)
Gain* 4 Stars	-0.062a (0.011)	-0.01a (0.003)	-0.006a (0.001)	-0.063a (0.011)
Loss* 4 Stars	-0.118a (0.009)	-0.011a (0.002)	0.0001 (0.001)	-0.117a (0.009)
(Gain ²)* 4 Stars	0.039a (0.008)	0.006b (0.002)	0.002 (0.001)	0.04a (0.008)
(Loss ²)* 4 Stars	-0.045a (0.003)	-0.005a (0.001)	0.0001 (0.0001)	-0.045a (0.004)
Gain* 3 Stars	0.011 (0.012)	0.003 (0.003)	0.004a (0.001)	0.011 (0.013)
Loss* 3 Stars	-0.122a (0.011)	-0.03a (0.002)	-0.006a (0.001)	-0.121a (0.011)
(Gain ²)* 3 Stars	-0.012 (0.009)	-0.002 (0.002)	-0.005a (0.001)	-0.009 (0.009)
(Loss ²)* 3 Stars	-0.057a (0.004)	-0.008a (0.001)	-0.002a (0.0001)	-0.057a (0.004)

a=p<0.01; b=p<0.05; c=p<0.05

Table 3. Cont.

	Model 1	Model 2	Model 3	Model 4
Gain* 4 Stars*AfterCovid	0.081a (0.022)	0.004 (0.007)	-0.003 (0.003)	0.081a (0.022)
Loss* 4 Stars*AfterCovid	-0.007 (0.033)	0.005 (0.005)	-0.001 (0.002)	0.013 (0.034)
(Gain ²)* 4 Stars*AfterCovid	-0.059b (0.021)	0.003 (0.006)	0.003 (0.002)	-0.057b (0.021)
(Loss ²)* 4 Stars*AfterCovid	-0.002 (0.013)	0.002 (0.002)	0.0001 (0.001)	0.004 (0.013)
Gain* 3 Stars*AfterCovid	0.038 (0.025)	-0.015c (0.007)	-0.007c (0.003)	0.028 (0.026)
Loss* 3 Stars*AfterCovid	0.024 (0.04)	0.019b (0.007)	0.003 (0.002)	0.048 (0.041)
(Gain ²)* 3 Stars*AfterCovid	-0.017 (0.022)	0.021a (0.006)	0.006b (0.002)	-0.009 (0.023)
(Loss ²)* 3 Stars*AfterCovid	0.004 (0.016)	0.002 (0.003)	0.001 (0.001)	0.011 (0.017)
<i>Control variables - cities</i>				
Rome	0.043a (0.003)	0.007a (0.001)	0.015a (0.0001)	0.043a (0.003)
Brussels	-0.044a (0.004)	0.001 (0.001)	-0.004a (0.0001)	-0.045a (0.004)
Edinburgh	-0.006c (0.003)	0.006a (0.001)	0.003a (0.0001)	-0.008b (0.003)
London	-0.03a (0.003)	-0.004a (0.001)	0.001b (0.0001)	-0.032a (0.003)
Prague	0.031a (0.003)	0.009a (0.001)	0.002a (0.0001)	0.031a (0.003)
Madrid	-0.031a (0.004)	0.005a (0.001)	0.0001 (0.0001)	-0.033a (0.004)
Frankfurt	-0.069a (0.004)	-0.006a (0.001)	-0.01a (0.0001)	-0.069a (0.004)
Milan	0.021a (0.003)	0.013a (0.001)	0.003a (0.0001)	0.021a (0.003)
Dublin	0.004 (0.003)	0.005a (0.001)	0.002a (0.0001)	0.004 (0.003)
Lisbon	0.042a (0.003)	0.005a (0.001)	0.01a (0.0001)	0.042a (0.003)
Vienna	0.023a (0.003)	0.013a (0.001)	0.005a (0.0001)	0.024a (0.003)
Barcelona	0.028a (0.003)	0.008a (0.001)	0.009a (0.0001)	0.028a (0.003)
Paris	0.069a (0.003)	0.018a (0.001)	0.011a (0.0001)	0.069a (0.003)
<i>Control variables - years</i>				
Year2004	-0.05 (0.033)	-0.008 (0.006)	0.004 (0.003)	-0.041 (0.034)
Year2005	-0.035 (0.031)	-0.008 (0.005)	0.011a (0.002)	-0.032 (0.032)
Year2006	-0.048 (0.031)	-0.01c (0.005)	0.015a (0.002)	-0.045 (0.032)
Year2007	-0.011 (0.03)	-0.008 (0.005)	0.016a (0.002)	-0.005 (0.031)
Year2008	-0.009 (0.03)	-0.008 (0.005)	0.016a (0.002)	-0.009 (0.031)
Year2009	0.022 (0.03)	0.0001 (0.005)	0.014a (0.002)	0.026 (0.031)

a=p<0.01; b=p<0.05; c=p<0.05

Table 3. Cont.

	Model 1	Model 2	Model 3	Model 4
Year2010	0.049 (0.03)	0.005 (0.005)	0.011a (0.002)	0.05 (0.031)
Year2011	0.079b (0.029)	0.012c (0.005)	0.011a (0.002)	0.081b (0.03)
Year2012	0.092b (0.029)	0.012c (0.005)	0.012a (0.002)	0.093b (0.03)
Year2013	0.109a (0.029)	0.013b (0.005)	0.013a (0.002)	0.111a (0.03)
Year2014	0.129a (0.029)	0.02a (0.005)	0.012a (0.002)	0.132a (0.03)
Year2015	0.155a (0.029)	0.027a (0.005)	0.011a (0.002)	0.157a (0.03)
Year2016	0.168a (0.029)	0.032a (0.005)	0.009a (0.002)	0.17a (0.03)
Year2017	0.16a (0.029)	0.031a (0.005)	0.008a (0.002)	0.163a (0.03)
Year2018	0.159a (0.029)	0.031a (0.005)	0.008a (0.002)	0.161a (0.03)
Year2019	0.158a (0.029)	0.036a (0.005)	0.007b (0.002)	0.16a (0.03)
Year2020	0.162a (0.029)	0.039a (0.005)	0.008a (0.002)	0.165a (0.03)
Year2021	0.168a (0.03)	0.045a (0.005)	0.008a (0.002)	0.17a (0.03)
Year2022	0.186a (0.03)	0.054a (0.005)	0.009a (0.002)	0.188a (0.031)
<i>Control variables - months</i>				
Month2	0.007c (0.003)	0.003a (0.001)	0.0001 (0.0001)	0.007c (0.003)
Month3	0.008b (0.003)	0.003a (0.001)	0.0001 (0.0001)	0.009b (0.003)
Month4	0.007c (0.003)	0.002b (0.001)	0.0001 (0.0001)	0.007c (0.003)
Month5	-0.002 (0.003)	0.001 (0.001)	-0.001a (0.0001)	-0.002 (0.003)
Month6	-0.005 (0.003)	0.001 (0.001)	-0.002a (0.0001)	-0.005 (0.003)
Month7	-0.006c (0.003)	-0.001 (0.001)	-0.001a (0.0001)	-0.007c (0.003)
Month8	-0.001 (0.003)	0.0001 (0.001)	0.0001 (0.0001)	-0.001 (0.003)
Month9	-0.006c (0.003)	0.0001 (0.001)	-0.002a (0.0001)	-0.006c (0.003)
Month10	-0.009b (0.003)	0.001 (0.001)	-0.002a (0.0001)	-0.009b (0.003)
Month11	-0.002 (0.003)	0.003a (0.001)	-0.002a (0.0001)	-0.002 (0.003)
Month12	-0.006c (0.003)	0.003a (0.001)	-0.002a (0.0001)	-0.006c (0.003)
<i>Controlling for endogeneity - copulas</i>				
Copula Gain	0.002b (0.001)	0.0004b (0.0001)	0.0005a (0.0001)	0.003a (0.001)
Copula Loss	0.006a (0.001)	0.0009a (0.0001)	0.0007a (0.0001)	0.006a (0.001)
Constant	0.656a (0.029)	0.168a (0.005)	0.275a (0.002)	0.653a (0.03)
R-squared	0.3243	0.1605	0.1621	0.3240
Adjusted R-squared	0.3241	0.1602	0.1618	0.3237
F-statistic	1481.08a	589.84a	597.09a	1449.29a

^a=p<0.01; ^b=p<0.05; ^c=p<0.05

