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Room with a View – A Causal Analysis and Estimation of the Economic Benefit for Local Economies.

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Figure 1: The zone under study

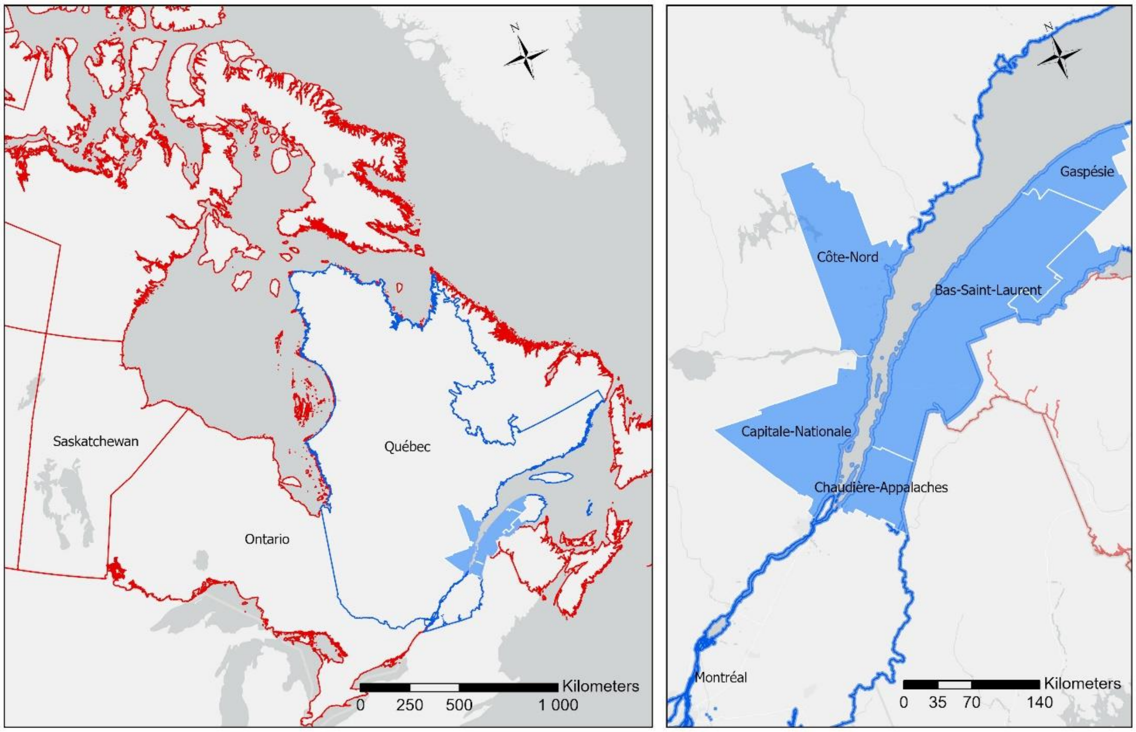
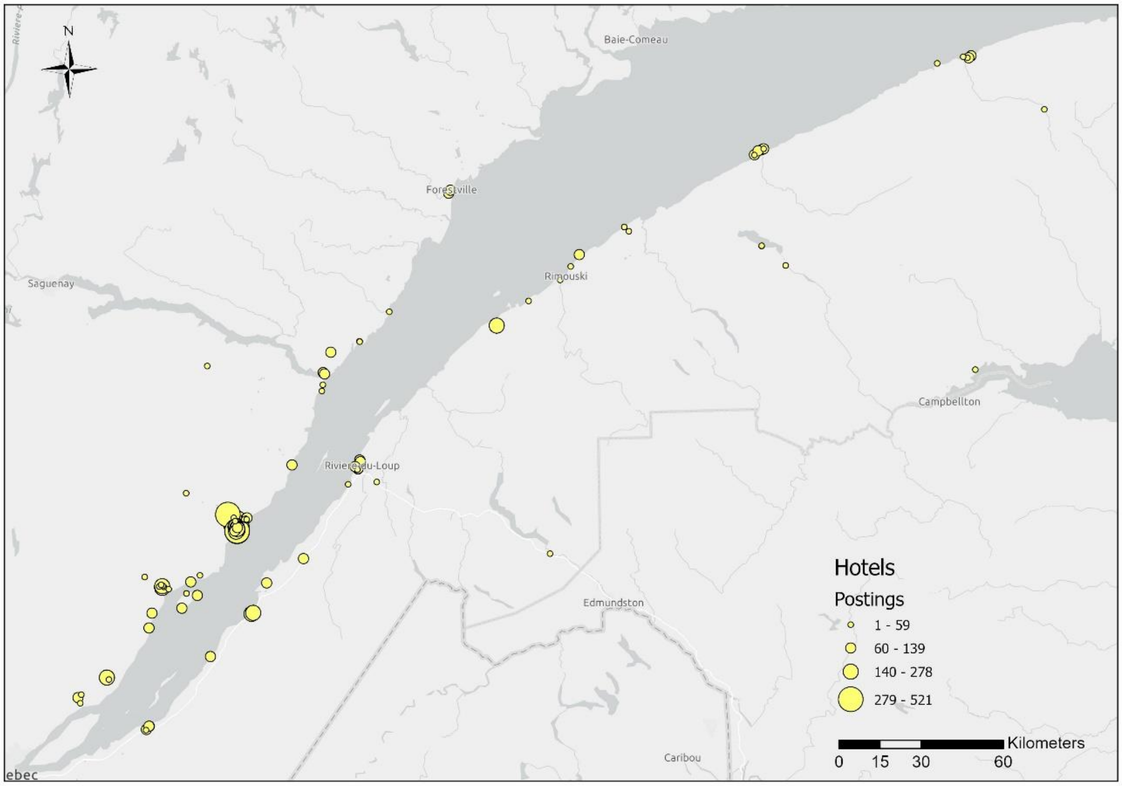
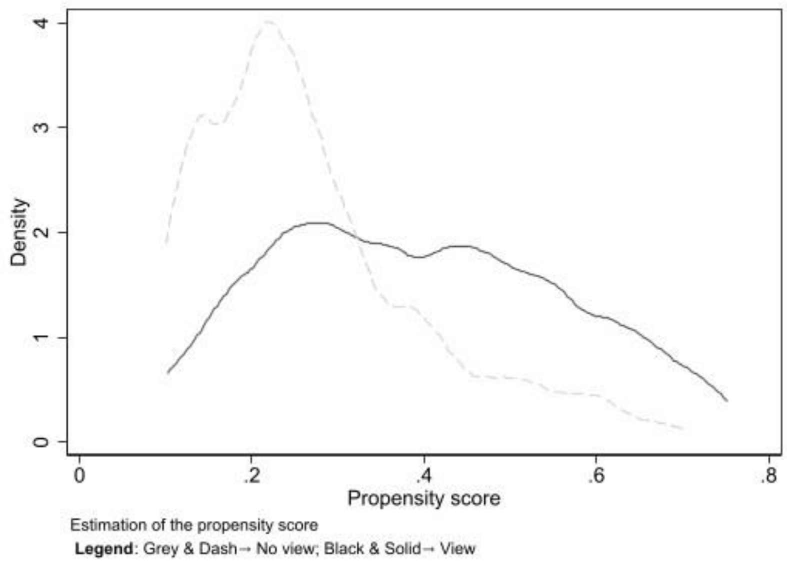


Figure 2: Spatial distribution of the hotels selected

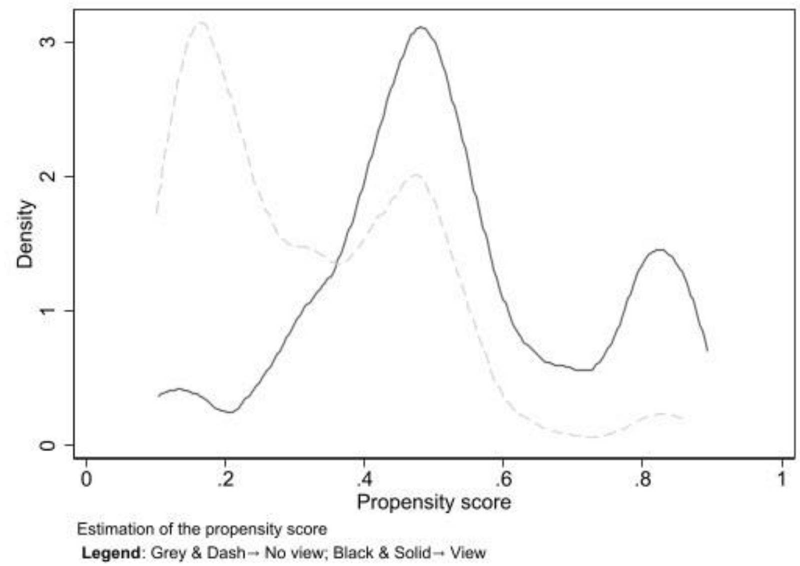


Note: The size of the points is relative to the number of rooms selected by hotels.

Figure 3: The common support zone for treatment and control areas

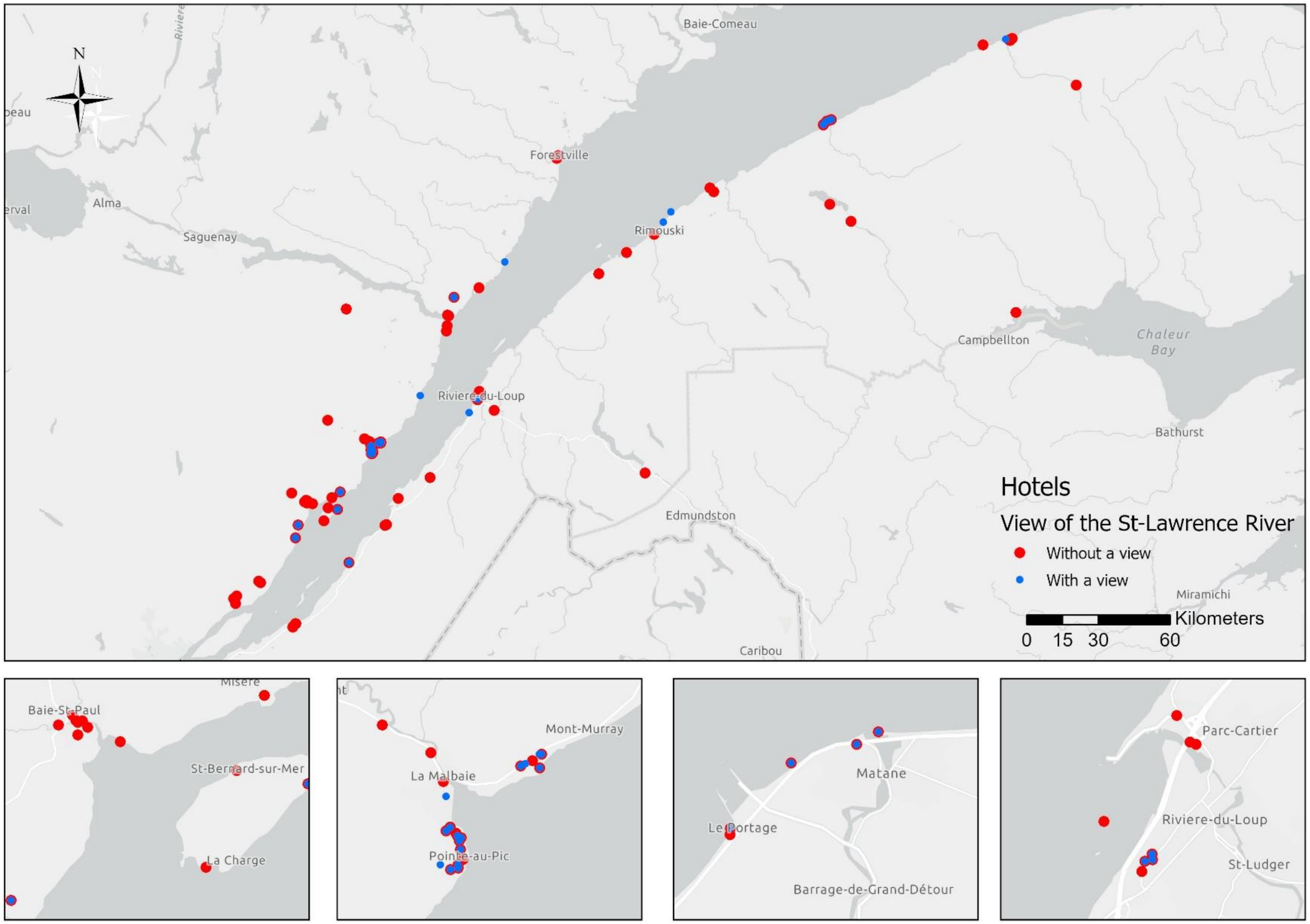


Summer



Winter

Figure 4: Selection of rooms with and without view in the same hotel



Highlights

- The view on the sea appears to have a seasonal and a geographical component.
- Propensity score matching approach is used to retrieve causal effect of the view.
- The view on the sea generates important local economic benefits.

Room with a View – A Causal Analysis and Estimation of the Economic Benefit for Local Economies.

Abstract

Many attempts have been made to measure the impact of the view of the sea on hotel room rates by using hedonic pricing models. While popular, this methodology fails to provide a causal interpretation. This study examines the causal impact of a specific view based on hotel room rates by using a propensity score matching approach. With the estimated location price premium, an evaluation of the potential economic benefit of the view of the St. Lawrence River is calculated for local economies. Results suggest that the price premium varies according to the season as well as to the shore where the hotel is located, with a price premium varying between 6.5% and 20%, which translates into a median economic benefit of about $42.4M/year.

Keywords:
Location Rent; Hedonic Pricing Model; Causal Analysis; Propensity Score Matching; Externalities; Economic Benefit.

Introduction

In real estate, an adage states that three things explain property value: location, location, location. The view of specific positive amenities is usually associated with a larger willingness-to-pay (Boyle & Kiel, 2001). For identical real estate goods, the difference in market value comes from the exposure to certain types of external characteristics (or amenities). The price premium is what economists refer to as the location rent. The presence/absence of public goods, i.e., goods that are non-rivals to consumption and for which it is impossible to exclude consumers, such as the view, is usually internalized by private real estate developers (Rigall-I-Torrent & Fluvia, 2011).

Hotel managers and real estate stakeholders are aware of the price premium benefit on hotel room rates. The location of accommodation complexes is not a random decision (Bull, 1994; Andersson, 2010; Yang et al., 2012). The same logic applies to residential properties (Jin et al., 2015). Location decision is an individual action that reflects an optimization process that maximizes profit or utility.

However, it is hard to put a price on the view, as no specific market exists for this characteristic alone. Price premium appears to vary over space (Soler et al., 2016; 2019; Latinopoulos, 2018) within seasons (Espinet et al., 2003; El-Namr et al., 2021), weekdays (Schamel, 2012) and even when the reservation is made (Yang & Leung, 2018). To isolate the impact of the view on hotel rooms rates, several methodologies have been proposed. One of those methods is based on individual travel cost (Blackwell, 2007). Another approach, which is far more popular, is based on the hedonic pricing model (Espinet et al., 2003; Fleischer, 2012).

While the impact of an ocean view has been demonstrated by many empirical applications based on hedonic pricing models (see Section 1), this approach suffers from important drawbacks. One of those weaknesses is that the estimated implicit, or hedonic, prices return a correlational interpretation (Antonakis et al., 2010; Kuminoff et al., 2010). Even with more sophisticated functional forms or models (Espinet et al., 2003; Fleischer, 2012; Latinopoulos, 2018; Bhattacharya & Nakamura, 2021), the results cannot be interpreted as being a causal effect.

The originality of the paper is threefold. First, the analysis proposes a causal approach to measure the impact of the view on room rates. The results are compared with those obtained with a two-way fixed effect (TWFE) panel specification (Wooldridge, 2001) of the hedonic pricing model. Second, while the impact on the view has been investigated for sunny touristic areas, not much has been said about the importance of such a view in the Nordic context (Hamilton, 2007). Third, the analysis proposes, based on the estimated price premium, to calculate the economic benefits of the view for local economies.

The empirical investigation is based on the St. Lawrence River in two touristic regions of the province of Quebec (Canada). One on the North Shore (Charlevoix) and the other on the South Shore (Bas-St-Laurent/Gaspésie). As opposed to sunny touristic places, where the presence of beaches is important, the St. Lawrence is rarely used for swimming and sunbathing activities. The temperature of the water in the estuary during summertime is about 5°C to 6°C. However, the impressive and massive natural amenity – the length of the river varies between 40 km to 60 km – represents an important environmental amenity. Consequently, the river represents important economic landscape amenities that might be internalized into hotel room rates since a lot of marketing is done worldwide to attract tourists.

The remainder of the paper is divided into six sections. Section 1 proposes a complete literature review regarding the study that aims to investigate the impact of a water view on hotel room rates. Section 2 presents the methodologies used to investigate the view price premium per room location. Section 3 presents the data used to investigate the relationship between the view of the river and the room rates. Section 4 presents the estimation results by season and by statistical approach. Section 5 presents an economic evaluation of the economic benefit of the exposition to the river on local economies based on the causal inference. The last section proposes a short conclusion.

1. Literature Review

Over the years, many attempts have been made to identify the impact of the proximity to rivers and seas on room rates (see Table 1). So far, most of the empirical analyses have focused on the view and proximity to beaches in sunny tourist coastal zone. Studies include analyses in Greece (Latinopouos, 2018), Spain (Espinet et al., 2003; Thrane, 2005; Rigall-I-Torrent & Fluvia, 2011; Rigall-I-Torrent et al., 2011; Alegere et al., 2013; Alegre et Sard, 2015), Portugal (Solder et al., 2019), Mexico (Mendoza-Gonzalez et al., 2018), Thailand (Somphong et al., 2022), Taiwan (Chen & Rothschild, 2010) and the Mediterranean coast (Fleischer, 2012). A few studies have looked at other touristic coastal places such as Japan (Bhattacharya & Nakamura, 2021) and Beirut (El-Nemr et al., 2021), while only one study investigates the impact of the view for northern locations in Germany (Hamilton, 2007).

Most of the results suggest a positive price premium for rooms having a view (Mendoza-Gonzalez et al., 2018; Latinopoulos, 2018; Bhattacharya & Nakamura, 2021) or an access to the beach (Espinet et al., 2003; Thrane, 2005; Rigall-I-Torrent & Fluvia, 2011; Soler et al., 2019, Somphong et al., 2022). In the worst-case scenario, a non-statistically significant relation between the distance to the sea and the room rate is reported (Chen & Rothschild, 2010; El-Nemr et al., 2021).

The vast majority of empirical applications are based on hedonic pricing model to explore the relationship between room rates and locational amenities. Empirical investigation before 2015 was mainly based on the collection of data from tourism company packages (Espinet et al., 2003; Thrane, 2005; Hamilton, 2007; Rigall-I-Torrent, 2011; Rigall-I-Torrent et al., 2011; Algere et al., 2013;). Other studies have used information from travel agencies (Chen & Rothschild, 2010) or surveys with hotel personnel (Mendoza-Gonzalez, 2018). More recently, the analysis has begun to use information from web location platforms such as Booking, (Fleischer, 2012; Latinopoulos, 2018; Somphong et al., 2022), TripAdvisor (Soler et Gémar, 2017; Soler et al., 2019; El-Nemr et al., 2021), Trivago.com (Schamel, 2012), hotels.com (Bhattacharya & Nakamura, 2021), or hoteltravel.com

(Andersson, 2010). The use of web scrapping techniques makes it easier to collect uniform data and implement statistical techniques, such as multiple linear regression (MLR).

INSERT TABLE 1 HERE

Statistical analyses are mainly based on ordinary least squares (OLS) or robust estimation, to correct for the presence of heteroskedasticity. Fleischer (2012) shows that not correcting for heterogeneity of the variance can lead to erroneous conclusions regarding the significance of the coefficients and thus to misleading conclusions. While the possible problem of spatial autocorrelation among residuals (Moran, 1950; Anselin, 1995) has been raised in real estate literature over the years (Dubin & Song, 1987; Can, 1992; Can & Megbbolugbe, 1997; Dubin, 1998a, 1998b), none of the studies formally proposed spatial econometrics models (Anselin, 1988; LeSage and Pace, 2009). However, some authors used geographically weighted regression (GWR) to explore the spatial variation of the value of a room view (Latinopoulos, 2018; Bhattacharya & Nakamura, 2021; Samphong et al., 2022).

A more sophisticated econometric specification has been proposed. Espinet et al. (2003) used a multilevel, or mixed, panel model by introducing random effect on some coefficients. Gopalakrishnan et al. (2011) proposed a two-stage least squares (2SLS) estimation method to deal with the endogeneity issue of beach characteristics (see also Thrane, 2005). Except for Gopalakrishnan et al. (2011) who used an instrumental variables (IV) method, the applications of the hedonic pricing suggest that room view is statistically related to the rates. However, this link cannot be interpreted as a causal interpretation (Kuminoff, 2010). For a causal interpretation of the coefficients, specific estimation methods need to be selected.

2. Methodology

2.1 A Correlational Approach: Hedonic Pricing Model

Hedonic pricing theory has been formally developed by Rosen (1974). The hedonic pricing approach is based on revealed preference (Lancaster, 1966), where the equilibrium of the market is defined by the multitude of transactions occurring, i.e., when a buyer and a seller agree on the final sale price. The hedonic theory assumes that complex good can be seen as a bundle of individual characteristics. The goods, or bundle, are heterogenous because of the different combinations of individual homogenous characteristics.

The hedonic applications are based on a two-step procedure. The first one expresses the final sale price of the complex goods on the complete set of individual characteristics forming the bundle. This first step corresponds to the hedonic pricing equation. The second step consists of using the estimated coefficients from the first step to retrieve the shape of the supply and the demand of the market. This second step has been less involved within empirical investigation.

More specifically, hedonic pricing equation expresses the statistical (linear) relation between the sale price, p_{it}, usually log-transformed, and different components: i) individual (fixed) characteristics of the good, S_i; ii) time-invariant, observable or unobservable, neighborhood characteristics, L_i; and iii) time-variant characteristics, L_{it}. As usual, an error term, ε_{it}, completes the statistical relation and contains the unknown components (equation 1).[1]

$$\ln(p_{it}) = \alpha + \sum_{k=1}^{K} S_i\beta_k + \sum_{l=1}^{L} L_i\delta_l + \sum_{m=1}^{M} L_{it}\gamma_m + \varepsilon_{it} \tag{1}$$

The theory suggests that regression allows to recover the implicit, or hedonic, prices of all individual observed characteristics through the estimated coefficients β_k, δ_l and γ_m.

While the theoretical foundations of the hedonic pricing model are well known, nothing is explicit about the functional form that the price equation must take. Attempts have been made to select the more interesting choice between a set of different specifications (Halvorsen & Pollakowsky, 1981) as well as the adequate transformation of the dependent variable (Box & Cox, 1964; Sakia, 1992). Nevertheless, the interpretation of the results is highly linked to such choices made by the researchers.

The interpretation is also subject to some other important assumptions. One critical assumption behind the application of the hedonic pricing model is that the set of all important characteristics might be observed and included in the regression analysis. Otherwise, the results face omission variable bias (OVB), which invalidates the results. A practical way to account for omitted variables is to introduce some specific fixed effects, such as temporal fixed effect, D_t, and individual, or group, fixed effects, D_i (equation 2). This decomposition corresponds to a two-way fixed effect (TWFE) specification (see also Fleischer, 2012).

$$\varepsilon_{it} = \sum_{t=2}^{T} D_t\theta_t + \sum_{i=1}^{N} D_i\varphi_l + \mu_{it} \tag{2}$$

Where μ_{it} is an error term assumed to be independent, identically distributed, of mean zero with a homogenous variance.

Another important assumption is that the error terms are not (spatially) correlated (Kochinsky, 2009). Since the end of the 1980s, it is well recognized that the residuals of the hedonic equation are spatially correlated. Spatial autocorrelation among residuals can bias the estimated coefficients and/or bias the estimated variance, which can lead to erroneous interpretation and conclusions (LeSage & Pace, 2009).

[1] The error term can also include individual or neighborhood fixed effects to control for unobserved characteristics.

Finally, the interpretation of the coefficients in a cross-sectional estimation cannot be interpreted as a causal effect on the dependent variable (Kuminoff et al., 2010; Kuminoff & Pope, 2014). A causal interpretation lies on some specific approaches (Imbens & Wooldridge, 2009; Antonakis et al., 2010) that go beyond the estimation of the hedonic price equation.

2.2 A Causal Approach: Propensity Score Matching

There exist a few methods that allow causal interpretation. One popular method is the difference-in-differences (DID) approach, which is a simple extension of the hedonic pricing model introducing additional explanatory variables to the model (Banzhaf, 2021; Dubé et al., 2014). However, this approach requires that a change in a specific characteristic (individual or spatial) be observed over time. This approach is impossible when trying to investigate the impact of time-invariant natural amenities such as the presence/view of specific characteristics.

Another approach is based on matching (Rubin, 1974; Rosenbaum & Rubin, 1983; Abadie et al., 2004; Abadie & Imbens, 2006, 2012; Caliendo & Kopeinig, 2008;). Matching analysis aims to compare the difference of outcome, room rates, for a good that is exposed to a specific amenity, mathematically expressed as $C_i=1$, to the same good non-exposed, $C_i = 0$.[2] The difference in price, called the average treatment effect (ATE), reflects the causal impact of the specific amenity on price (equation 3).

$$\mathrm{ATE} = \mathrm{E}\left[p_{it|C_i=1} - p_{it|C_i=0}\right] \tag{3}$$

However, it is impossible to observe a good in both statuses simultaneously, i.e., exposed and non-exposed to a specific amenity. This is the fundamental problem of the causal inference analysis (Holland, 1976). As such, it is necessary to identify proxies for the inverse status. The idea is to find counterfactual observations, i.e., similar observations (good with similar characteristics) with a different status, to proxies that could have been observed as outcomes for the opposite status. There exist many ways to define "similar" observations, but one of the most famous is based on the propensity score analysis.

The propensity score analysis is based on a discrete choice model (logit or probit) where the dependent variable is the exposition status ($C_i = \{0,1\}$). The independent variables are the list of all the observed characteristics (S_i, L_i, L_{it}), just as the hedonic pricing model (equation 4).

$$\Pr(C_i = 1) = f(S_i, L_i, L_{it}; \lambda) \tag{4}$$

The estimated coefficients of the discrete choice model, $\hat{\lambda}$, do not have a specific interpretation. It only helps to construct the predicted probability of being in a specific status and summarizes the information of the observed characteristics into a single metric.

[2] Where, for the analysis, the variable C_i is a subset of the vector of characteristics L_i, i.e., a specific time-invariant characteristic

The predicted probability, i.e., the propensity score, $\hat{\mathrm{C}}_{\mathrm{i}} = f(S_i, L_i, L_{it}; \hat{\lambda})$, is used to identify counterfactuals.

For the observation with the exposed status, $\mathrm{C_i} = 1$, the counterfactual price is defined as the mean price of the observations with the non-exposed status, $\mathrm{C_j} = 0$, of similar propensity score ($\hat{\mathrm{C}}_{\mathrm{i}} \approx \hat{\mathrm{C}}_{\mathrm{j}}$). And conversely for the non-exposed status (equation 5).

$$\hat{p}_{it|C=s} = \frac{1}{n_j}\sum_{j=1}^{J} p_{jt|C_j=1-s;|\hat{C}_i - C_j| \leq \kappa} \quad (5)$$

Where $\mathrm{n_j}$ is the number of observations, i.e., neighbors, used to build the counterfactual prices for observations i, j identifies the potential counterfactual observations (inverse status) and κ, called the caliper, limit the maximum difference allowed between the estimated propensity scores ($|\hat{\mathrm{C}}_{\mathrm{i}} - \hat{\mathrm{C}}_{\mathrm{j}}|$).

The exercise is straightforward but lies on certain assumptions. The first is about the exogeneity of the status, and more specifically the fact that the status of an observation (exposed or non-exposed) is conditionally independent on the observable characteristics. The second is that similar observations, in terms of observable characteristics, should respond in the same way to the status. The exposure is therefore independent of the potential outcome. The third is that there is at least one counterfactual for each of the observations, regardless of status. This assumption ensures that comparisons are made on observations that are similar enough to have confidence in the calculation of the ATE. This is also referred to as the common support zone. In practice, the common support domain must be limited to avoid the pitfall of the extreme values (Imbens & Wooldridge, 2009).

3. Data

3.1 The region

The empirical analysis is based on two touristic regions in the province of Quebec (Canada). The regions are located along the St. Lawrence River on both sides, north and south. Both regions are in the estuary part of the river. Between the selected regions, the length of the river varies between 40 and 60 kilometers (Figure 1). Both regions are sparsely populated, but even less populated on the North Shore. The largest city on the North Shore is La Malbaie, with fewer than 9,000 inhabitants. On the south, the largest city is Rimouski, with around 50,000 inhabitants, while there are other important local centers such as Rivière-du-Loup, with about 20,000 inhabitants.

INSERT FIGURE 1 HERE

The northern part is famously known for the mountainous landscape, shaped by the Laurentians, and the magnificent view it offers over the river, especially for sunrise and sunset. It is also recognized for its bucolic rural landscape and villages. The economy is largely based on tourism activities, while not necessarily all hotels are exposed to the river view. It is highly frequented by tourists during the summer, but also during the winter. The Massif de la Petite-Rivière-St-François, a major ski resort, is the first winter Club Med resort and brings many tourists. The autumn season is also particularly attractive with the trees changing to fall colors.

The southern part also relies on tourism activity, especially during summertime, but is more diversified. Some important cities are the hub of administrative activities for the eastern part of the province (Rimouski). It also hosts some important manufacturing centers (Rivière-du-Loup, Mont-Joli). Another important mountain chain crosses the region, the Apalaches. However, it has a lower gradient than on the north shore and is further away from the shore, especially on the western part. The regions have two parallel valleys along the mountain chain, introducing more diverse landscape along the coast.

3.2 Hotel room rates and characteristics

To explore the relationship between hotel room rates and the view of the river, data was extracted from the internet web site Expedia.ca. The site was selected for two reasons. First, Expedia provides the information about the view from the rooms, which is essential to the analysis. Second, Expedia has more results regarding the number of rooms than the alternative site for the regions under study.

The web scrapings search has been made for room accommodation for two nights in two distinct time periods.[3] An initial collection was launched in the beginning of December 2022 for rooms available between December 21 and January 10, 2023. A total of 7,017 observations were collected: 2,452 rooms on the north shore and 4,565 rooms on the south shore. The second collection was launched in March of 2023 for two nights in hotel rooms available between July 23 and August 3. Those dates were selected because it represents the peak tourist season in the province. A total of 5,890 rooms were identified: 1,939 on the North Shore and 3,951 on the south shore.

Two distinct datasets are compiled and contain information about the characteristics of the room (check-in/check-out date, rate (in $CAN), number of beds, type of room, view, services) and the hotels (services, stars, proximity to local services and attractions, etc.) (Table 2). The number of rooms compiled in individual hotels can be multiple. For the same hotel, some rooms do have a view of the river, while others don't. To simplify the analysis and reduce the potential of omission variable bias, hotel services are resumed into a set of hotel fixed effect (dummy) variables, as all the rooms in the same hotel benefit from the same services. It should be noted that some hotels are not exposed at all to any view of the river.

INSERT TABLE 2 HERE

[3] Searching for two consecutive nights returns a higher number of rooms than when looking only for one night. This is why this choice has been made.

The rooms were selected for analysis if they were located within the two regions identified,[4] the night rate was available, and the complete postal address was available. In the end, the total number of observations by season was 4,670 during winter and 3,161 during summer (Figure 2). The mean night rate was about $70 more expensive in summer ($251) than in winter ($178) (Table 3). The median room rate was lower than the mean rate, suggesting a log-normal distribution of the dependent variable.

INSERT FIGURE 2 HERE

The characteristics of the rooms are globally similar within the seasons (Table 3). The hotels have a better quality in summer while the rooms offer a smaller number of places during the summer, both indicators suggesting that some good hotels are closed during the winter. The type of rooms available by seasons are relatively similar, with the type “Standard,” “Classic” or “Superior” being the more predominant style.

INSERT TABLE 3 HERE

A manual and visual search was made with all the rooms in hotels that mentioned having a view of the “River,” “Sea,” “Ocean” or “Lake.” In the end, those mentions point to similar characteristic: a view of the St. Lawrence River. For this reason, those variables are aggregated in a single variable and represent the variable of interest. About one quarter of the rooms have a view of the St. Lawrence River. While the view of the mountain appears more often in summer, the frequency of the characteristics remains relatively sparse, with 4% to 2% of rooms having such a view, depending on the season.

4. Results

4.1 The Hedonic Pricing Model

The hedonic pricing equations have been estimated using the usual two specifications: i) one that only accounts for the individual characteristics of the rooms; and ii) one based on a two-way fixed effect (TWFE) specification. The TWFE introduces: i) a set of time fixed effect variables, using information on the check-in day; and ii) a set of spatial fixed effect variables, using the information on the hotel. The TWFE procedure allows to control for unobservable information that could influence the price determination process and is more efficient than ordinary least squares (OLS) estimation methods. The variance-covariance matrix is also specified to include groupwise heteroskedasticity pattern within hotels. The price equation is estimated for both seasons.

In both specifications and seasons, the Moran’s I index (Moran, 1950) has been calculated to check if spatial autocorrelation is detected among residuals of the models. The spatial weights matrix limits the spatial relations within the same hotel. The weights are set to zero otherwise. The spatial weights are row-standardized and all observations have at least one spatial relation.

[4] Some hotels were located in New Brunswick and were discarded from the analysis.

The global performance of the first specification for both seasons is higher in winter (R^2 = 0.4079 – Table 4) than in summer (R^2 = 0.2424 – Table 5). The correlation between the independent variable remains well under control with a maximum variance inflation factor (VIF) of 1.3. While the explanatory power of the model is relatively low, the results are generally coherent with theoretical expectations: prices are higher for rooms of better quality. However, the price premium for the view of the river suggests a positive and significant price premium in winter (about 11.2%), while it is not statistically significant in summer. Both specifications return a highly positive and highly significant spatial autocorrelation among residuals of the models (0.7840 in winter and 0.6056 in summer), suggesting that conclusions from those specifications might not be adequate.

INSERT TABLE 4 HERE

INSERT TABLE 5 HERE

Adding the temporal and spatial fixed effect provides a more interesting global performance for both models. The respective R^2 statistics rise to 0.9225 in winter and 0.7850 in summer. The higher R^2 in winter suggests that variation is more difficult to explain in summertime. The high season shows a less flattened distribution of the room rates. With the TWFE specification, the results are more in line with theoretical expectations, with both price premiums for view of the river positive significant. No spatial autocorrelation is detected among the residuals, the specifications suffer from heteroskedasticity.

The model is re-estimated using a grouped variance-covariance matrix based on the hotels to correctly interpret the t-test statistics associated with the significance of the individual estimated parameters. With the correction for heteroskedasticity (column 3), some coefficients turn out to be not statistically significant. This is the case for the mean price premium for the view of the river in winter (6.12% - Table 4).[5] The price premium for the view in summer is estimated at 13.25% and is statistically significant (Table 5).

4.2 The Propensity Score Matching Approach

For the matching analysis, the estimation is limited to rooms located in the same hotels but exposed to a different view. This choice is made to make sure that the counterfactuals are highly similar and benefit from the same services. For both seasons, the number of observations used for estimating the propensity score is reduced. About 84% of the total sample is used in winter, while this proportion drops to 77% in summer.

The propensity score is estimated using the type of rooms, the number of places available and the moment when the check-in is proposed. Many variables appear to be statistically significant and related to the exposition status (Table 6). The pseudo-R^2 is higher in winter (0.2602) than in summer (0.1208), but the common support zone assumption, i.e. the fact

[5] Focusing only on the northern part of the province, the price premium appears positive and significant (8.14% with p-value = 0.0200).

that treated observations have a predicted probability similar to the control observations (and vice-versa), holds for both models (see Figure 3).

INSERT TABLE 6 HERE

INSERT FIGURE 3 HERE

For calculating the ATE, the caliper has been set at 0.05. The number of neighbors used for the counterfactual is set between 1 and 3. Observations with a propensity score higher than 0.9 or lower than 0.1 are not selected (Imbens & Wooldridge, 2009). It should be noted that the counterfactual selection is limited to the same season. According to those additional constraints, the number of observations for the analysis is reduced. The total number of observations in winter is 595 (354 exposed to view; 241 not exposed), while the total number of observations in summer is 567 (241 exposed to view; 326 not exposed).

As for the hedonic pricing equation, the difference between the room rates according to the exposition status varies by season, with a higher price premium during the summer ($40) than the winter ($22) (Table 7). Translated into a percentage price premium using the mean room rate by season, the mean premium during the winter is about 10%, and about 15% in summer. Both premiums are highly statistically significant and robust to the number of neighbors used to build the counterfactual. The causal price premiums appear to be higher than those obtained with the hedonic pricing model, especially during winter.

INSERT TABLE 7 HERE

The impact can also be decomposed by the north/south shore and by seasons (Table 8). For the South Shore, the number of observations available for the analysis is 81 in winter (55 exposed to view; 26 not exposed) and 162 in summer (79 exposed to view; 83 not exposed). For the North Shore, the number of observations used for the analysis is 514 in winter (299 exposed to view; 215 not exposed) and 405 in summer (162 exposed to view; 243 not exposed) (Figure 4).

INSERT FIGURE 4 HERE

The mean price premium for the view in winter on the South Shore is about $8, while it is about $25 on the North Shore of the river. Both price premiums are statistically significant. Translated into a percentage using the mean room rate from both shores, the mean price premium varies between 6.5% on the South Shore to 10% on the North Shore. Regarding the summer price premium, it is estimated to be about $50 on the South Shore, while it varies between $30 and $45, according to the number of neighbors used, on the North Shore. In percentage point, it corresponds to 20% for the south and about 11% to 15% on the north.

INSERT TABLE 8 HERE

In the end, the price premium according to the season and the shore varies between 6.5% and 20%. The causal impact of a sea view on hotel room rates appears to be higher and more significant as compared to the hedonic analysis. It suggests that classical empirical analysis underestimates the causal impact.

5. The Economic (partial) Benefit

Using the causal estimates, a benefit analysis is conducted to evaluate the (partial) economic impact of having a view of the St. Lawrence River for the two selected regions. The calculation of the economic benefits is based on a Monte Carlo simulation (Elariane & Dubé, 2018). The parameters vary according to the extreme, maximum and minimum values (Table 9). For each simulation, individual parameters are selected according to a random uniform distribution between the two extremes. Each simulation provides an estimation of the annual benefit.[6] The exercise is repeated 5,000 times, using different values of the parameters each time. The procedure allows to obtain a distribution of the benefit for the first year, but also a distribution of the total economic values over total time periods (T = 1,000).

An exhaustive search based on the valuation roll, an administrative dataset returning the location of all the parcels recorded in the province with the main vocation of each parcel, a total number of 537 accommodation establishments located within 350 meters from the river on both shores. As this total may include some hotels that are closed and/or exclude hotels that do have a view of the river while being located further away, the minimum and maximum values for the number of hotels was set between 450 and 700. Moreover, as the hotels usually have one side exposed to the river, it is assumed that the number of rooms exposed can vary between 5 and 20 units by hotel. This exposition rate is reduced by considering a vacancy rate. Based on the official statistics of the provincial government, the vacancy rate can be as high as 50% in winter, and around 25% in summer (Table 9).

INSERT TABLE 9 HERE

The economic annual benefit is defined by the gain that can be obtained from renting individual rooms (N) in all hotels/motels (M) taking into account a vacancy rate (τ) to the mean price premium (δ) multiplied by the mean price of individual rooms ($\bar{p}$) (equation 6).

$$B_t = 365 \times MN\tau(\delta\bar{p}) \qquad (6)$$

The annual gain is actualized at a nominal discount rate (r) of 10% with a mean inflation rate (π) of 3%. The analysis also assumed that the mean room rate increases at a rate equal to the inflation rate over the years (equation 7).

[6] The value per simulation is calculated based on the following transformation: $b_t = b_{min} + \theta(b_{max} - b_{min})$, where θ is a random number taking a value between 0 and 1, and b_t is the individual benefit parameter (see Table 10).

$$B = \sum_{t=0}^{T} \frac{B_t(1+\pi)^t}{\left({(1+r)}/{(1+\pi)}\right)^t} \tag{7}$$

Simulation suggests a mean annual benefit of the exposition to the St. Lawrence River of about \$63.2M and a median benefit of \$42.4M. The estimated benefit varies between \$4M and \$205.3M (Table 10). Translating the impact on the long run, i.e., for a thousand years, returns a mean actualized value of \$1,779M and median value of \$1,192M. The distribution varies between \$112.7M and \$5,775M.

INSERT TABLE 10 HERE

The exercise clearly demonstrates that the presence of the St. Lawrence River has an important economic impact for the two regions of the province. The economic benefit of having a view of important environmental amenities and public goods reveals to be important for small local economies, even if the regions are not typical sunny touristic areas.

Conclusion

The paper proposes to investigate the relation between the exposition (view) of the St. Lawrence River on the eastern part of the province of Quebec on hotel room rates. Using information from hotel rates available on Expedia.ca in two distinct periods, winter and summer, causal statistical analysis aims at retrieving the implicit value of the view on the final rate. The results suggest that the price premium is higher in summer than in winter, especially for the south shore. The mean price premium of having a view from the room is about 10% in winter and about 15% in summer. While the estimated price premium is relatively similar with the hedonic pricing model in summer (13.25%), it clearly differs for the winter period since the price premium appears to be not statistically significant.

The analysis suggests that the results are heterogenous within regions and seasons. While price premium varies little within the seasons on the North Shore (10% in winter vs. 11% to 15% in summer), a region that is highly based on tourism activities, the variation of the price premium is more important on the south shore. During the winter, the price premium for the view of the St. Lawrence River appears to be as low as 6%. However, during summer, the price premium is estimated to be about 20%. These results clearly underline the importance of the view for hotel owners' revenues.

The results have important implication for future research. It shows that using the ordinary least squares (OLS) approach to isolate the impact of the view leads to some problems. First, a heteroskedasticity problem can bias the significance of some key coefficients, such as the one of interest. The estimation using a grouped variance-covariance matrix shows that significant results can in fact be non-statistically significant. Second, it shows that the correlational interpretation of the hedonic pricing model differs from the estimation obtained using a causal approach. A hedonic pricing model appears to return a lower price premium than its causal counterpart. Specifically, the non-significant results obtained for the winter season with a two-way fixed effect (TWFE) price equation turns out to be positive and highly significant with the propensity score matching approach.

The results also have important implications for tourism development policies. The analysis clearly underlines that the natural amenity of the St. Lawrence River helps in returning many millions of dollars into the local and global economies each year. While benefits are concentrated on private promoters, taxes and duty paid by stakeholders contribute to the collective well-being. Exposition to environmental amenities, such as a bucolic view of the river, translate into economic benefits.

From an environmental perspective, the economic benefit of the exposition to the St. Lawrence River points in favor of global policies aiming at reducing the negative externalities that can badly affect its attractivity. There is a need to ensure that actions that alter the attractivity of the river can be controlled, as many small local economies might be hardly affected. As management of negative externalities cannot be controlled at the local level, a global perspective is needed to preserve positive externalities.

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Table 1: Synthesis of the results in the literature.

Authors	Place	Data	Conclusions
Espinet, Saez, Coenders & Fluvia (2003)	Northern Catalonia (Spain) Southern Costa Brava	Hotels in the sun-and-beach segment from tour operator 82,000 prices between 1991 and 1998	"Hotels located in front of the beach appear to be more expensive (by 19.4%) […] (p. 173)" "[…] hotels in front of the beach have greater expected revenues. (p. 175)"
Thrane (2005)	Canary Islands Norwegians tourist in winter	252 package tours First week of November 2003	"[…] an apartment-hotel located 3 kilometers from the beach is about 11% less expensive than a hotel located by the beach […] (p. 306)" "The latter variable (distance to the beach) had a negative effect on package tour prices […] (p. 307)"
Chen & Rothschild (2010)	Taipei (Taiwan)	Internet travel agent (eztravel.com) 73 hotels (July 2007)	"[…] rates in hotels located in the city centre are typically about 38.0% lower than those of hotels lying outside of the city centre […] (p. 691)" "[…] hotels outside of the city are associated with resorts. (p. 692)"
Rigall-I-Torrent & Fluvia (2011)	Coastal area of Catalonia	Operator brochures 279 coastal hotels for six months in 2000 3208 observations	"[…] coefficient associated to the variable 'beach' says that a hotel located in front of the beach can set (on average) prices 8.7% higher […] (p. 251)"
Rigall-I-Torrent, Fluvia, Ballester, Salo, Ariza & Espinet (2011)	Coastal Catalonia	Operator brochures, official hotel guides, local tourism offices 197 hotels for six months in 2002 4934 prices	"Location in front of the beach matters a lot (p. 1152)" "[…] location in front of a beach increases hotels' prices by average 13-17%. (p. 1158)"

Table 1 (continued): Synthesis of the results in the literature.

Authors	Place	Data	Conclusions
Fleischer (2012)	Mediterranean Sea (North Shore) Costa del Sol, Costa Brava, Balearic Islands, French Riviera, Italian Riviera, Sardinia, Sicily, Greek Islands, Cyprus and Antalya	Night available on Booking.com June 20, 2011 and October 24, 2011 (on January 5, 2011); 589 hotels and 2819 rooms for June and 487 hotels and 2406 rooms in October	"[…] price of a room with a view is higher by 11% in the high season (and by 10% in the low season) than that of a room without a view in the reference region Cyprus. (p. 601)" "[…] there is no significant additional value to the sea view in Cyprus in any other region. […] Mediterranean Sea view has the same value in terms of price percentage […] (p. 601)" "Other views from the hotel rooms, such as a city or a garden view, are considered inferior in these regions and are valued significantly less than rooms with no specifications of view. (p.602)"
Algere, Cladera & Sard (2013)	Majorca (Balearic Islands)	(11) German and (9) British packages from tour operators Summer of 2008 (first week of August) with 3636 prices (3101 German; 535 British)	"Having a room with a sea view pushed up the price by 8.84% for German package holidays and by just 6.85% for British ones. (p. 138)" "When the price of beachfront hotel and motel with a near-beachfront location (10 m away) is compared, the plot shows a huge drop in price of 22.28% for German tourists and 29.93% for British ones. (p. 138)"
Latinopoulos (2018)	Halkidiki (Greece) Coastal zone	Booking.com for reservation Saturday, September 5, 2015 Search was made between August 17 and August 20 557 rooms (summer tourism season)	"[…] increasing the hotel's distance: (a) from the nearest beach, […] is likely to decrease hotel prices. (p. 93)" "[…] the effect of Seaview on room prices seems to correspond on average to 4.85% of room rate […] (p. 96)" "According to the semi-parametric GWR model, the positive relationship of Seaview and room prices is statistically significant in 46.3% of the study area. […] local coefficients range from 0.073 to 0.178, with a mean value equal to 0.124. (p. 96)"

Table 1 (continued): Synthesis of the results in the literature.

Authors	**Place**	**Data**	**Conclusions**
Mendoza-Gonzalez, Martinez, Guevara, Perez-Maqueo, Garza-Lagler & Howard (2018)	Veracruz (Gulf of Mexico)	Interview with hotel personnel (questionnaires) High season of July 2007 - 92 hotels	"[…] hotel prices were higher when rooms had an ocean view and were near the beach, which resulted in an increment of non-ecosystem amenity of $17.6USD/2016 […] (p. 8)" "[…] hotels with access to an ocean view had higher prices than those that did not have the benefit of this ecosystem service; […] (p. 9)" "[…] the approximate extra annual income in Boca del Rico, Costa Esmeralda, and Chachalacas would be $36,377, $43,652, and $8148 USD for proximity to the beach and $208,927, $77,373, and $45,184 USD for ocean view, respectively. (p. 9)"
Soler, Gemar, Correia & Serra (2019)	Algarve region Southern Atlantic coast of Portugal	Rooms available on TripAdvisor (UK) Collected from 9 to 29 August 2016 (double room); 9,992 prices	"The presence of a beach has an average impact of the price of rooms in the region of €13.61, which is similar with that found by other studies […] (p. 318)" "[…] positive impact of a location in Falesia Beach […] (p. 31)" "Only the Falesia Beach label has a significant positive effect […] (p. 318)"
El-Nemr, Canel-Depitre & Taghipour (2021)	City of Lebanon Beirut region	TripAdvisor.com in March 2019 (20-26) - 89 hotels	"[…] in our study, sea distance has no significant effect on room rates. (p. 38)" "[…] new entries in the market are advised to find more attractive locations than city center that appeared to not offer an advantage to hotels […] (p. 38)"
Bhattacharya & Nakamura (2021)	Pacific coastal zone of Japan (9 prefectures)	Hotels.com with rurubu.travel and ikyu.com Extractions on 21 December 2019 for 21 January 2020 478 rooms from 382 hotels	"Rooms that offered seaview as opposed to any other view types were priced 11.4% higher […] (p. 6)" "[…] the 'view of the sea', approximated a 9.7% of the average room price in the area of study regardless of the location; […] (p. 12)"

Table 1 (continued): Synthesis of the results in the literature.

Authors	Place	Data	Conclusions
Somphong, Udo, Ritphring & Shirakawa (2022)	Thailand coastal beaches	Booking.com in November 2018 Search for rooms available on 11-18 August 2019 3319 hotel room prices	"A room with a beachfront location or beach access has a 23% higher price than a room not placed in front of the beach. (p. 6)" "[…] annual beach tourism benefit is approximately $841M. (p. 9)" "The statistically significant effects of beachfront location obtained from the spatial hedonic model ranged from 13% to 41% increase in the hotel room prices. (p. 11)"

Table 2: List of the individual characteristics of the rooms

Variable	**Description**
Price	Rate for one night (in $CAN)
Star	Number of stars for the hotel
Check In	Check in date
Check Out	Check out date
Suite	The room is a Suite (Yes/No)
Penthouse	The room is a Penthouse (Yes/No)
House	The room is in a House (Yes/No)
Condo	The room is in a Condo (Yes/No)
Loft	The room is in a Loft (Yes/No)
Apartment	The room is in an apartment (Yes/No)
Studio	The room is a Studio (Yes/No)
Classic	The room is a classic style (Yes/No)
Deluxe	The room is a Deluxe style (Yes/No)
Superior	The room is classified as Superior (Yes/No)
Signature	The room is classified as Signature (Yes/No)
Standard	The room is Standard (Yes/No)
Business	The room is a Business suite (Yes/No)
Family	The room is for Family (Yes/No)
Economy	The room is classified as Economy (Yes/No)
Basic	The room is classified as Basic (Yes/No)
Romantic	The room is classified as Romantic (Yes/No)
Dormitory	The room is in a Dormitory (Yes/No)
King Bed	The room has a King size bed (Yes/No)
Queen Bed	The room has a Queen size bed (Yes/No)
Double Bed	The room has a Double bed (Yes/No)
Sofa Bed	The room has a Sofa bed (Yes/No)
Twin Bed	The room has a Twin bed (Yes/No)
RiverView	The room has a view of the St. Lawrence River (Yes/No)
Sea View	The room has a view of the St. Lawrence River (Yes/No)
Ocean View	The room has a view of the St. Lawrence River (Yes/No)
Lake View	The room has a view of the Lake (Yes/No)
Courtyard View	The room has a view of the Courtyard (Yes/No)
Garden View	The room has a view of the Garden (Yes/No)
Mountain View	The room has a view of the Mountain (Yes/No)
Breakfast	Breakfast is included in the price (Yes/No)
Kitchen	The room has a Kitchen (Yes/No)
Fireplace	The room has a Fireplace (Yes/No)
Balcony	The room has a Balcony (Yes/No)
Fridge	The room has a private refrigerator (Yes/No)
Animals	The hotel allows pets (Yes/No)
Wi-Fi	The room has Wi-Fi service (Yes/No)
Places	Maximum number of persons allowed in the room

Note: River View, Sea View, Ocean View and Lake View are aggregated for analysis
Courtyard View and Garden View are aggregated for analysis

Table 3: Descriptive statistics of the individual characteristics

	Summer			Winter				
Variable	Mean	Min	Max	Mean	Min	Max	Difference	sign.
Price	251.19	50	2261	178.56	45	949	72.62	***
Star	3.03	2	4.5	2.88	2	4.5	0.15	***
Suite	0.13	0	1	0.09	0	1	0.04	**
Penthouse	0.00	0	0	0.01	0	1	-0.01	
House	0.04	0	1	0.04	0	1	0.00	
Condo	0.02	0	1	0.02	0	1	0.00	
Loft	0.01	0	1	0.01	0	1	0.00	
Apartment	0.01	0	1	0.01	0	1	0.00	
Studio	0.06	0	1	0.05	0	1	0.00	
Classic	0.12	0	1	0.10	0	1	0.02	
Deluxe	0.05	0	1	0.06	0	1	-0.01	
Superior	0.12	0	1	0.10	0	1	0.02	
Signature	0.02	0	1	0.01	0	1	0.01	
Standard	0.23	0	1	0.25	0	1	-0.02	
Business	0.00	0	0	0.00	0	0	0.00	
Family	0.03	0	1	0.03	0	1	0.00	
Economy	0.03	0	1	0.05	0	1	-0.02	*
Basic	0.00	0	1	0.01	0	1	0.00	
Romantic	0.01	0	1	0.00	0	1	0.01	
Dormitory	0.00	0	1	0.00	0	1	0.00	
King Bed	0.95	0	1	1.00	0	1	-0.05	***
Queen Bed	0.57	0	1	0.58	0	1	-0.01	
Double Bed	0.38	0	1	0.44	0	1	-0.05	***
Sofa Bed	0.07	0	1	0.07	0	1	0.00	
Twin Bed	0.07	0	1	0.06	0	1	0.00	
River View	0.11	0	1	0.15	0	1	-0.04	**
Sea View	0.08	0	1	0.04	0	1	0.05	***
Ocean View	0.02	0	1	0.03	0	1	-0.01	
Lake View	0.01	0	1	0.03	0	1	-0.02	*
Courtyard View	0.01	0	1	0.03	0	1	-0.02	
Garden View	0.01	0	1	0.00	0	1	0.00	
Mountain View	0.04	0	1	0.02	0	1	0.02	*
Breakfast	0.26	0	1	0.26	0	1	0.00	
Kitchen	0.03	0	1	0.04	0	1	-0.01	
Fireplace	0.00	0	1	0.01	0	1	0.00	
Balcony	0.02	0	1	0.01	0	1	0.02	
Fridge	0.01	0	1	0.02	0	1	0.00	
Animals	0.00	0	1	0.01	0	1	-0.01	
Wi-Fi	0.95	0	1	0.96	0	1	-0.01	
Places	2.93	2	7	3.04	2	7	-0.11	***

Note: Total number of observations is 4,670 in Winter and 3,161 in Summer

Table 4: Estimation results for Winter – Hedonic pricing model

Variables	Coefficient	sign.	Coefficient	sign.	Coefficient	sign.
Hotel fixed effects	No		Yes		Yes	
Check In day fixed effects	No		Yes		Yes	
Number of places fixed effects	Yes		Yes		Yes	
View of St. Lawrence River	0.1059	***	0.0594	***	0.0594	
View of the garden	0.2339	***	0.0133		0.0133	
View of the mountain	-0.3553	***	-0.1886	***	-0.1886	*
Kitchen (Yes/No)	0.4948	***	0.3321	***	0.3321	***
Fireplace (Yes/No)	0.0263		0.0285		0.0285	*
Classic	-0.0898	***	-0.0568	***	-0.0568	
Luxury	0.1277	***	0.0176		0.0176	
Superior	-0.0183		0.0467	***	0.0467	
Standard	-0.2507	***	-0.0872	***	-0.0872	**
Family	-0.0381		-0.0107		-0.0107	
Economy	-0.4019	***	-0.2411	***	-0.2411	***
Dormitory	0.7630	***	-0.0701		-0.0701	
Other	Reference		Reference		Reference	
Number of observations	4,670		4,670		4,670	
R2	0.4079		0.9225		0.9225	
RMSE	0.3390		0.1239		0.1239	
F-stat	188.4894		484.3799		.	
Moran's I index†	0.7840	***	0.0000		0.0000	
AIC	3,167.24		-6,139.60		-6,295.60	

Legend: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Note: Last model correction for heteroskedasticity with a grouped variance-covariance matrix by hotels

† Spatial weights matrix is based on hotels sharing the same postal code or the same establishments (when n>50)

Table 5: Estimation results for Summer – Hedonic pricing model

Variables	Coefficient	sign.	Coefficient	sign.	Coefficient	sign.
Hotel fixed effects	No		Yes		Yes	
Check In day fixed effects	No		Yes		Yes	
Number of places fixed effects	Yes		Yes		Yes	
View of St. Lawrence River	-0.0021		0.1244	***	0.1244	***
View of the garden	0.0942		-0.0071		-0.0071	
View of the mountain	-0.2258	***	0.1015	**	0.1015	*
Kitchen (Yes/No)	0.1795	***	0.1197	***	0.1197	
Fireplace (Yes/No)	0.1620		0.0761		0.0761	
Classic	-0.0256		-0.0538	**	-0.0538	
Luxury	0.0387		0.0114		0.0114	
Superior	-0.0666	**	0.0128		0.0128	
Standard	-0.2941	***	-0.1056	***	-0.1056	**
Family	-0.1702	***	-0.0498		-0.0498	
Economy	-0.3585	***	-0.1643	***	-0.1643	***
Dormitory	0.3164	**	-0.0859		-0.0859	*
Other	Reference		Reference		Reference	
Number of observations	3,161		3,161		3,161	
R2	0.2424		0.7850		0.7850	
RMSE	0.3968		0.2148		0.2148	
F-stat	59.1675		95.7986		.	
Moran’s I index†	0.6056	***	0.0000		0.0000	
AIC	3,144.14		-638.69		-820.69	

Legend: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Note: Last model correction for heteroskedasticity with a grouped variance-covariance matrix by hotels

† Spatial weights matrix is based on hotels sharing the same postal code or the same establishments (when n>50)

Table 6: Estimation of the discrete choice model (propensity score)

	Winter		Summer	
Variables	Coefficient	sign.	Coefficient	sign.
Hotel fixed effects	Yes		Yes	
Check In day fixed effects	Yes		Yes	
Number of places fixed effects	Yes		Yes	
Kitchen (Yes/No)	1.9677	***	0.3495	
Classic	0.1040		-0.1914	
Luxury	-0.1379		0.5504	*
Superior	1.6826	***	0.8584	***
Standard	-0.6391	***	0.3790	**
Family	1.4909	***	0.7058	*
Economy	-2.2113	***	-0.4353	
N. observation	3,934		2,442	
Pseudo-R^2	0.2602		0.1208	
AIC	3,522.44		2,632.15	
BIC	3,760.98		2,823.56	

Legend: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Note: The number of observations is reduced to make sure counterfactual are in the same hotel

Table 7: Estimation of the price premiums by season

	Winter		Summer	
Number of neighbors	ATE	sign.	ATE	sign.
1	22.35	***	37.14	***
2	22.92	***	38.78	***
3	23.44	***	46.63	***
N. of observations	595		567	
Mean room rate	216.22		270.11	

Legend: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Table 8: Estimation of the price premiums by season and shore

	Winter				Summer			
	North Shore		South shore		North Shore		South shore	
Number of neighbors	ATE	sign.	ATE	sign.	ATE	sign.	ATE	sign.
1	24.56	***	8.30	***	32.17	***	49.56	***
2	25.24	***	8.24	***	35.34	***	47.36	***
3	25.86	***	8.10	***	44.51	***	51.93	***
N. of observations	514		81		405		162	
Mean room rate	231.10		121.74		284.21		234.86	

Legend: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Table 9: List of the parameters (and values) for calculating the economic benefit

Parameters	**Min**	**Max**
Price premium	0.065	0.20
Rate (per night)	175	250
Vacancy rate	0.25	0.5
Units/hotel	5	20
# Hotels	450	750
Inflation rate	0.03	0.03
Interest rate	0.1	0.1

The values of the parameters for simulation are randomly fixed.

Table 10: Distribution of the estimated benefits

Benefits (in M$)	**Annual**	**Perpetual**
Min	4,009	112,773
1%	4,322	121,585
5%	5,422	152,549
25%	15,919	447,860
50%	42,376	1,192,165
75%	100,029	2,814,104
95%	179,809	5,058,564
99%	200,152	5,630,872
Max	205,300	5,775,706
Mean	63,235	1,779,001

Note: Results obtained with 5,000 simulations