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The Timing of Spatial Competition:
Price Interdependence Across Booking Horizons

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Abstract:

This paper examines the interplay between spatial and temporal dimensions of price competition in the hotel industry, where services are non-storable and consumers must book in advance. We study how spatial price competition among hotels evolves across different booking horizons. Using a panel dataset of hotels in Venice covering daily asking prices, we estimate spatial price reaction functions for multiple booking lead times using Spatial Durbin Models. We find heterogeneous spatial price mimicking across booking horizons, with spatial dependence peaking at mid-range lead times and weakening at short lead times. Furthermore, hotels with greater room variety are able to charge higher prices, while greater variety among nearby rivals exerts downward pressure on prices. These findings reveal that the strength of spatial competition is not constant but jointly shaped by timing of booking and seasonal demand, offering new insights into intertemporal pricing and strategic interactions in perishable service markets.

Keywords: spatial price dependence; booking horizon; product variety; Spatial Durbin; hotel industry; monopolistic competition

JEL codes: L83; D22; L11; R32; C23; D40.

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Non-Technical Summary

This paper explores the interaction between timing and location when setting hotel prices, with a focus on Venice city (Italy), a top-tier tourism destination. Hotel rooms are perishable services: unsold rooms nights generate no revenue. At the same time, to secure availability, prospective guests must book in advance with respect to the check-in date, making the timing of purchase a key factor in pricing and competition.

We study how hotels react to the prices of nearby competitors across different booking horizons (time of purchase), from a few days to several months in advance the consumption time (check-in date). Using data on daily asking prices for 151 Venetian hotels over a full year, we estimate how local price interdependence changes depending on both time to check-in and seasonality. Our approach accounts for each hotel's own offerings and those of its neighbours, allowing a detailed view of strategic pricing behaviour.

Our findings reveal three main patterns. First, hotels tend to mimic the prices of nearby rivals, but this spatial dependence is not constant: it is weakest for very short or very long booking horizons and peaks at mid-range horizons, when most reservations occur. Second, hotels with a greater variety of rooms can charge higher prices, while a richer variety among competitors exerts downward pressure. Third, these relationships vary across seasons: in low-demand periods, hotels react more strongly to nearby competitors, whereas in high-demand periods, they enjoy more pricing autonomy.

These results show that spatial competition in service markets is dynamic, shaped by both the timing of bookings and seasonal demand fluctuations. For hotel managers, the study suggests that revenue strategies should explicitly consider the interaction between booking horizons and seasonality. Mid-range booking windows, when competition is most intense, deserve particular attention in pricing and inventory decisions. Beyond hotels, the insights are relevant for any market where services are perishable, and timing and location jointly affect demand, such as ride-sharing, air travel, or ticketed events.

1. INTRODUCTION

In many service markets, such as ridesharing, air travel, lodging, or tickets for concerts, movies, or sports, supply is perishable and cannot be stored. In these settings, timing is a central dimension of consumer choice (Li et al., 2014), as demand fluctuates significantly across weekdays, weekends, and seasons. Due to high sunk costs, supply is less flexible than demand, which often compels consumers to book in advance to secure availability, especially during peak periods (Escobari et al., 2019; Williams, 2022). The decision of when to book thus becomes strategic, reflecting an intertemporal trade-off between willingness to pay at different time-to-consumption intervals and the willingness to wait while facing the risk of a stock-out (e.g., Garcia et al., 2022; Lacetera et al., 2025).

From the provider's perspective, the consumption date acts as a fixed deadline: unsold units represent irrecoverable losses (Butters, 2020). To maximize revenue within this finite horizon, firms typically adopt intertemporal price discrimination strategies, also known as yield management (Escobari et al., 2019; Gallego and van Ryzin, 1994; Soysal and Krishnamurthi, 2012; Su, 2012; Sweeting, 2012; Williams, 2022). This implies that two consumers purchasing the same service for the same date may face very different prices depending on their booking lead time. Accordingly, some service markets exhibit a dual form of time-based differentiation: the time of consumption, and the time of purchase.

Beyond timing, location plays a crucial role in many service industries. Consumers often have strong preferences for specific locations, driven by personal tastes and accessibility (Salop, 1979). A growing body of literature shows that firms engage in spatial price competition (Ellickson et al., 2020; Pinkse et al., 2002; Pennerstorfer, 2009), particularly against nearby competitors offering comparable quality.

This article studies the joint spatial and temporal dimensions of price competition in differentiated-good markets. Specifically, we examine how the well-established concept of spatial price dependence varies across the temporal distance between booking and consumption, a dimension we refer to as the 'booking horizon'. While prior research has extensively studied intertemporal price discrimination (e.g., Su, 2012; Sweeting, 2012) and spatial price competition (e.g., Li et al., 2018; Pinkse et al., 2002), the interaction between them remains largely underexplored. This constitutes a research gap the article aims to fill.

Our study is carried out for the hotel industry, which represents a relevant setting for our research purposes. On the one hand, proximity to popular sightseeing spots or key business hubs is a key dimension for hotel guests (Masiero et al., 2019; Yang and Mao, 2020; Yang et al., 2018). Nonetheless, the high degree of substitutability among hotel firms compels them to engage in spatial price competition (Kim et al., 2018; Park et al., 2022), particularly with their nearest neighbours (Abrate and Vigilia, 2016; Balaguer and Pernías, 2013; Lee, 2015; Lee and Jang, 2013; Park et al., 2020; Rezvani and Rojas, 2019). On the other hand, hotels practice intertemporal price discrimination, both across calendar check-in periods and booking horizons (Abrate et al., 2012; Bigne et al., 2021; Guizzardi et al., 2022; Tian et al., 2024; Vives and Jacob, 2021).

We conduct an empirical analysis using a daily panel dataset involving 151 hotels in Venice over 365 check-in dates. Venice constitutes a relevant case study as it stands as one of the most visited cities in the world, annually receiving more than 5 million tourists (ISTAT, 2024). For each check-in day t in our sample, we observe hotels' asking prices and the number of room varieties available at several lead times: 7, 14, 28, 56, 84, 140 and 224 days before check-in. This structure provides a rich panel of asking prices across multiple booking horizons. We estimate spatial pricing reaction functions at each horizon using Spatial Durbin Models (SDM) (LeSage and Pace, 2009) with hotel and period fixed effects. By controlling for location and seasonal variation, our empirical strategy leverages within-hotel price variation across booking horizons, enabling us to assess how spatial price competition evolves as check-in approaches.

Our results show that hotel prices are positively related to those of nearby competitors, confirming the presence of spatial price mimicking in the hotel industry. This interdependence follows a nonlinear pattern across booking horizons: it is weakest at very short and very long leads, but peaks at mid-range horizons (28–140 days), when most reservations are made (Bigne et al., 2021). We also find strong seasonal heterogeneity. In low-demand quarters, spatial competition intensifies and hotels respond more strongly to neighbouring prices, whereas in high-demand quarters, hotels set prices more independently. Finally, own room variety allows hotels to set higher prices, while competitors' variety generally exerts downward pressure on prices, especially at short booking horizons.

The article fills a research gap at the intersection of two strands of literature. On the one hand, we contribute to the growing body of research on pricing behaviour and spatial price competition in the services sector (Ellickson et al., 2020; Pinkse et al., 2002; Pennerstorfer, 2009), and in the hotel industry in particular (e.g., Guizzardi et al., 2019; Kim et al., 2018; Rezvani and Rojas, 2020). On the other hand, we add to the literature on intertemporal and dynamic pricing strategies (Guizzardi et al., 2022; Li et al., 2018; Su, 2012; Sweeting, 2012). The distinctive feature of this study is that it examines how spatial price competition among hotel firms varies across lead times to check-in dates (booking horizons). Most previous studies have primarily estimated Spatial Autoregressive Models (SAR) that relate average hotel prices with the corresponding average prices charged by their spatial neighbours (Abrate and Viglia, 2016; Lee and Jang, 2013; Mohammed et al., 2019a). However, the use of average transaction prices may mask substantial heterogeneity depending on the booking lead time of each guest. We go a step forward and evaluate how the spatial price dependence in asking prices varies depending on the time-to-check-in. This provides relevant insights about the dynamics of spatial competition across booking horizons rather than calendar periods.

Another original aspect of the article is that we study seasonal differences in spatial price competition across booking lead times. Because both the level and composition of demand vary significantly during the year (and thus the price elasticity of each firm's residual demand), the intensity of spatial price competition is likely to change across seasons. To capture these dynamics, we estimate separate spatial Durbin models for each calendar quarter. This approach allows us to identify whether and how spatial price dependencies evolve not only across booking horizons but also across seasons. Our findings shed light on the temporal granularity of spatial competition and highlight the importance of accounting for seasonality when studying pricing behaviour in perishable service markets.

A further contribution is that our spatial price equation considers not only the influence of a hotel's own room variety, but also the one of neighbouring hotels at each period and booking horizon. Theoretical models on dynamic pricing strategies predict that firms adjust their asking prices based on their available inventory to maximize revenue (Gallego and van Ryzin, 1994; Sweeting, 2012). The available supply and its variety by close competitors at each booking horizon likely affects hotels' own residual demand and, in turn, their asking prices (Abrate et al., 2012). Therefore, apart from spatial price dependence, our analysis assesses the influence of competitors' variety on asking prices at each booking horizon, offering a more nuanced understanding of pricing strategies in the hotel industry.

It is important to acknowledge that there are two closely connected studies to ours by Angelini et al. (2025) and Armillotta et al. (2024), also using data for hotels in Venice. Angelini et al. (2025) use a Structural Vector Autoregressive (SVAR) model to evaluate hotel pricing strategies across three booking windows (0, 7 and 28 days in advance). Their analyses reveal a U-shaped pattern of negative competition effects across the booking window. They also find that factors like strategic location convey significant price premiums for reservations made close to the check-in date. Armillotta et al. (2024) similarly evaluate hotels' intertemporal pricing across various booking windows (up to 13 days), focusing on differential patterns between leaders and followers. However, these studies do not consider the spatial dependence dimension in price setting nor how it varies across lead times. Moreover, our study considers wider lead times, allowing a more comprehensive characterization of spatial price dynamics over the full booking horizon.

The remainder of the article is structured as follows. Section 2 provides a theoretical background for the analysis. Section 3 presents the data and some descriptive statistics. Section 4 outlines the empirical strategy. Section 5 presents and discusses the estimation results. Finally, Section 6 concludes with a summary of the findings and some implications.

2. THEORETICAL FRAMEWORK

2.1. Hotels pricing behaviours under non-constant elasticities of substitution

Let us assume that hotels operate under monopolistic competition à la Dixit and Stiglitz (1977), where each hotel enjoys some degree of market power due to differentiation based on its location, amenities, and services. Assuming consumers preferences over hotel varieties can be characterized by a CES (constant elasticity of substitution) utility function, Dixit and Stiglitz (1977) show that profit maximization leads hotels to set prices according to the following rule:

$$p_j^* = \frac{c}{\rho} = c\left(\frac{\sigma}{\sigma-1}\right), \tag{1}$$

where c denotes the marginal cost of providing one night of accommodation (which we assume to be constant across hotel firms), σ is the elasticity if substitution between hotel varieties, and $\rho = \frac{\sigma-1}{\sigma}$ is the inverse mark-up. A higher value of σ implies greater substitutability among hotels, resulting in lower markups and intensified price competition. For the CES utility function to be concave and capable of supporting corner solutions ($q_j = 0$ for non-chosen hotels), it is necessary that $0 < \rho < 1$. This condition ensures that hotels are neither perfect substitutes nor perfect complements (Dixit and Stiglitz, 1977). Under this framework, equilibrium prices reflect a constant and symmetric markup over marginal cost. The reader is referred to the Appendix for a formal characterization of this equilibrium.

Although the assumption of a constant elasticity of substitution facilitates analytical tractability, it is arguably unrealistic in the context of hotel markets. In practice, each hotel likely faces a residual demand curve with a different slope, reflecting heterogeneous consumer preferences for specific varieties. In the spirit of Lancaster (1966), these references depend not only on their observable amenities, but specially on strategic location.[1] For instance, the lower the transportation cost to a consumer's destination (e.g., tourist attractions or business centres), the higher the utility derived from staying at that hotel (Masiero et al., 2019; Yang et al., 2018), and hence the lower its substitutability. This perspective aligns with Salop's model of spatial competition (Salop, 1979), in which each consumer has a 'most-preferred' hotel based on their characteristics and location, leading to a higher willingness to pay relative to other alternatives. In such settings, substitutability varies across hotels, and price competition is more local than global.

To account for this heterogeneity in consumer preferences for hotel characteristics, we adopt the model proposed by Zhelobodko et al. (2012), which allows for firm-specific elasticities of substitution (σ_j). These authors move away from a CES utility function and assume instead a general utility function that is thrice continuously differentiable, strictly increasing and concave. These authors define a relative-love-for-variety (hereafter RLV) parameter that, unlike in the standard CES case, varies with the level of consumption. For a given pair of varieties with a symmetric consumption pattern, it holds that RLV=$\frac{1}{\sigma_j}$=$-\frac{1}{\varepsilon_j}$. As they argue, "the relative

[1] While there are information asymmetries between sellers and consumers (e.g., Lewis, 2011), let us assume that digital platforms allow consumers to gauge accurate information about expected quality based on previous experiences by other users (Acemoglu et al., 2022).

love for variety, the elasticity of substitution, and the price elasticity of a variety's demand can be used interchangeably" (Zhelobodko et al., 2012, p. 2770).

Following Zhelobodko et al. (2012)'s framework, each hotel maximizes profits by setting prices according to the following rule:

$$p_j{}^* = c_j\left(\frac{1}{1-\frac{1}{\sigma_j}}\right) = c_j\left(\frac{1}{1+\frac{1}{\varepsilon_j}}\right), \tag{2}$$

where c_j is the hotel-specific marginal cost of providing one night of accommodation, σ_j is the elasticity of substitution between hotel j and other hotel varieties, and ε_j is the price elasticity of demand of hotel j. Accordingly, prices increase with marginal costs, and decrease with σ_j. The more elastic the individual demand curve, the lower the markup, reflecting greater substitutability.

Consumers' hotel choice can be described using a Random Utility Model, where each consumer selects the hotel that provides the highest utility (Perloff and Salop, 1985). Microeconomic theory predicts that when the price of a consumer's preferred hotel rises, *ceteris paribus*, consumers switch to their next-best option. Conversely, if competitors increase their prices, everything else being equal, hotel j becomes relatively more attractive, decreasing its substitutability (Anderson et al., 1992). From this viewpoint, we expect σ_j to be decreasing with competitors' prices: the more expensive a night stay in other hotels, the less substitutable hotel j becomes, everything else being equal.

Importantly, location plays a central role in shaping these substitution patterns. Since consumers often have strong location preferences, the substitutability between hotels decreases with geographic distance (Kim et al., 2020). While consumers exhibit a preference for variety, they are less willing to pay for options farther from their preferred location, which we assume to be given for each consumer.[2] This implies that the competitive pressure a hotel faces decays with the spatial distance to its rivals (Anderson et al., 1989). Consistent with Ushchev and

[2] There is the possibility that consumers are indifferent with respect to location. However, it seems reasonable that in most cases, either for business or for leisure purposes, individuals have pre-defined preferences for locating close to their points of interest.

Zenou (2018), consumers' willingness to pay falls as the geodesic distance between a hotel and their ideal location increases.

In addition to spatial factors, product variety also affects substitutability. When a hotel offers a broader range of room types (e.g., single, double, triple, balcony rooms, breakfast-inclusive), it becomes less substitutable for a randomly drawn consumer, *ceteris paribus*, because a wider variety increases the likelihood that at least one option matches heterogeneous consumer needs. This lower substitutability allows the hotel to sustain higher markups (Zhelobodko et al., 2012). From this perspective, σ_j is decreasing with product variety offered by the hotel. Conversely, when close substitutes provide a wide range of room types, competition intensifies, and residual demand for a given hotel becomes more elastic. Altogether, we expect σ_j to be:

i) Decreasing with the prices set by competitors ($\tilde{P}$)
ii) Decreasing with the room varieties offered by hotel j (Z_j)
iii) Increasing with the room varieties offered by competitors ($\tilde{Z}$)

The above characterization is static. However, hotel demand is highly seasonal. The pool of consumers varies in each calendar period depending on factors like weather, holidays, or the celebration of special events (Butters, 2020). For instance, the demand for hotels next to the beach is likely to be more inelastic in the summer than during the winter. On the contrary, the price premium of being located next to the business district may be larger during the low season, when business travellers represent a larger share of the pool of consumers. Therefore, consumers' preferences for hotel characteristics and their corresponding degree of substitutability are expected to vary over time due to seasonality. When adding the temporal dimension to the problem, the pricing rule incorporates subindex *t*:

$$p_{jt}{}^{*} = c_j\left(\frac{1}{1-\frac{1}{\sigma_{jt}}}\right) = c_j\left(\frac{1}{1+\frac{1}{\varepsilon_{jt}}}\right), \tag{3}$$

where now each hotel's elasticity of substitution varies over time (σ_{jt}). Again, the elasticity of substitution is expected to be decreasing with competitors' prices and own variety supplied but increasing with competitors' variety. Accordingly, because σ_{jt} changes across hotels and calendar check-in periods t, we expect different prices for each hotel-period combination.

2.2. Intertemporal price discrimination

Aside from the observed variation in hotel prices across different calendar check-in dates t, driven by changes in consumers' elasticity of substitution for each hotel j over time, hotel managers also engage in intertemporal price discrimination by adjusting prices for the *same* check-in date t depending on the booking horizon (i.e., the time remaining until check-in) (Abrate et al., 2019; Guizzardi et al., 2022; Mohammed et al., 2019b). This strategy, rooted in yield management, leverages the fact that consumers enter the market at different booking windows and display varying price elasticities depending on the time to check-in (Gallego and van Ryzin, 1994; Su, 2007). As shown by Abrate et al. (2019), higher dynamic price variability leads to higher hotel revenues.

Consider a given check-in date t (for instance, July 15). Hotels offer a discrete number of room varieties (e.g., single room, double room, single room with breakfast, double room with balcony, etc.), denoted by $Z_{itk} \leq Z_{itk}{}^{*}$, for sale K periods ahead of t (e.g., 365 days in advance) at a price p_{itk}, where k indicates a specific booking window and $Z_{itk}{}^{*}$ is the maximum number of room varieties the hotel can offer. As abovementioned, we expect that the greater the variety of rooms available at each period K (for a given check-in period t), the higher the asking price (i.e., variety confers market power).

Let us assume that potential buyers are forward-looking and behave strategically by monitoring asking prices on digital platforms (Board and Skrzypacz, 2016; Li et al., 2014; Su, 2007). Consumers searching for a hotel room for calendar date t, and for whom a given hotel maximizes utility, must decide whether to book at price p_{itk} k periods in advance to avoid the risk of a stockout, or wait in anticipation of a better deal (e.g., Dilmé and Li, 2019; Soysal and Krishnamurthi, 2012). [3] This decision depends on their preference for the hotel on that date (as reflected in σ_{jt}), their patience (i.e., waiting costs), and their risk aversion (Masiero et al., 2020), among others.[4]

[3] Some evidence points to significant economic savings from last-minute reservations, particularly in low and middle quality hotels (Abrate et al., 2012).
[4] Evidence by Su (2007) shows that business travellers exhibit less patience in searching for a better deal than leisure travellers, because of their higher value of time and lower dependence on own funds.

Consumers sort themselves endogenously: those with the lowest willingness to pay tend to purchase earlier (Deneckere and Peck, 2012). As the check-in date approaches, bookings accumulate, and the number of available room varieties Z_{itk} typically decreases—although not necessarily, as cancellations may occur (Lacetera et al., 2025). Hotels that no longer have rooms available of a specific variety face zero demand from consumers with strong preferences for that variety. As a result, the composition of demand and the degree of substitutability faced by each hotel evolve systematically as the check-in date approaches.

Since capacity adjustments are costly and unsold rooms represent lost revenue (Butters, 2020), hotel managers implement revenue management by strategically setting prices for each booking window k given a check-in date t (see Badinelli, 2000 for a theoretical treatment). Managers must choose between: (i) setting a low price to ensure early bookings (reservation prices), or (ii) maintaining a high price in anticipation that a consumer with a higher willingness to pay will arrive later. This decision depends heavily on expected demand in future booking windows. Automated pricing tools and advanced algorithms assist managers with these complex decisions using demand forecasts from multiple data sources (Calvano et al., 2020).[5]

3. DATA

3.1. Case study

Our empirical analysis is conducted using data for 151 hotel located in Venice's historic city centre (Italy). As a top-tier tourism destination, Venice welcomed around 5 million arrivals and 13.3 million overnight stays in 2024 (ISTAT, 2024). Approximately 67% of arrivals and 70% of overnight stays are attributed to the historic city centre. In terms of seasonality, 62% of tourist flows in Venice are concentrated between May and October, with an average length of stay of 2.7 days. International arrivals accounts for 87% of the total. Additionally, 60% of tourist stays occur in hotel accommodations. Regarding lodging facilities, the entire municipality of Venice has 414 hotels, ranging from two to five stars.

[5] Hotels hire the services of revenue-management companies that maximize their clients' revenues through optimized pricing. Revenue-managing companies use information on all bookings from a hotel together with local variation in weather conditions, events, hotel reputation and competitor prices to make a recommendation of the best price for a given check-in date. Evidence by Melis and Piga (2017) suggest that dynamic pricing is comparatively more prevalent among high-starred hotels.

Figure 1 presents the spatial distribution of hotels in the Venice city centre, where each point represents the location of a hotel included in the sample.

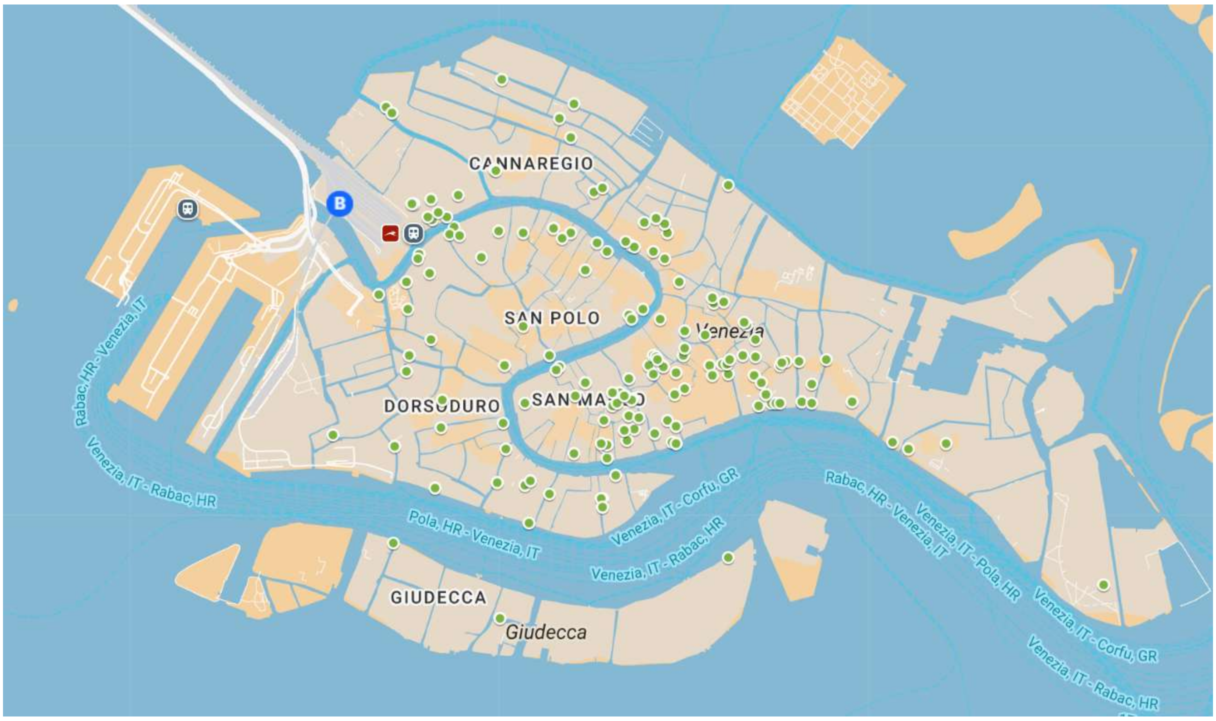

Figure 1. Spatial distribution of hotels in Venice city centre.
Note: Own elaboration using our data and Google My Maps.

3.2. Dataset

Our dataset was collected through web crawling of one of the leading online travel agencies (OTA) platforms: Booking.com. The scrapping began in September 2021 and covers all available hotels (n=151) in the city centre of Venice. [6] We collect data on each hotel's asking price (in current euros) posted on Booking.com by each hotel for a superior room category (economy and standard rooms are therefore excluded), breakfast included, free cancellation, no terrace, and bathroom inside the bedroom during a complete calendar year, with a daily frequency.[7] This specific room type was chosen for the main analysis to maximize the number of observations across hotels and dates. Nonetheless, as a robustness check, we repeat our

[6] The sample is predominantly composed of three-star hotels (132). The remaining establishments include two two-star hotels, sixteen four-star hotels, and one five-star hotel.
[7] Lacetera et al. (2025) show that refundable rooms are more expensive, and that this price premium remains at about 10-15% of the price with little variation as the check-in day nears.

empirical analysis considering only rooms without breakfast included and with non-refundable prices (no cancellation).

We collect asking prices for each selected room in hotel j and check-in date t at various booking horizons k (hereafter leads): 7, 14, 28, 56, 84, 120, and 224 days in advance ($price_{jt_k}$). We also gather information on the number of room varieties listed in the platform by each hotel, for each check-in date t and lead period k (denoted by Z_{jt_k}). Importantly, room varieties refer to the total count of distinct room types offered by the hotel (individual with breakfast, double without breakfast, triple, etc.), capturing quality variety instead of the number of physical rooms.[8]

The resulting datasets comprise seven unbalanced hotel check-in date panels, each corresponding to a different lead period. Since data collection began in September 2021, the calendar periods covered by the individual panel datasets are not identical. Table 1 summarizes the calendar periods, the number of observations for each lead period, and the number of hotels included in the sample. When a hotel has no availability for the selected room, there is no asking price, and that hotel is therefore missing for that check-in and lead period. However, the number of observations and hotels remains relatively stable overall across lead periods (ranging from 147 to 151). The total number of observations is quite balanced across lead periods as well.

Table 1. Lead periods, calendar periods and number of observations.

Lead period	**Calendar period**		**Observations**	**Num. hotels**
	Start date	End date		
7	01/10/2021	30/09/2022	31,512	149
14	01/10/2021	30/09/2022	33,414	150
28	01/10/2021	30/09/2022	36,180	150
56	01/11/2021	31/10/2022	39,263	151
84	01/12/2021	30/11/2022	37,431	150
140	01/02/2022	31/01/2023	34,390	150
224	01/05/2022	30/04/2023	31,890	147

[8] Publicly available information was collected through a web crawler that connected every day at the same time and retrieved information for each booking horizon k (7, 14, 28, 56, 84, 140, and 224 days ahead). The crawler mimicked a search for a one-night stay by two guests, thereby displaying all accommodation options available for such a request. No personal data were collected, and the collection respected reasonable request rates.

3.3. Descriptive statistics

Table 2 reports summary statistics of asking prices and room varieties by the booking horizon (lead time). Average prices range between €305 and €322, with a very high standard deviation, particularly when considering very short and very long lead times. The unconditional price distribution exhibits a U-shaped pattern over lead periods: mean prices decrease up to lead 56, over which they increase again. Concerning available room varieties, they decrease gradually as the check-in date approaches. It is also relevant to note that there is high dispersion across lead times, especially for calendar periods close to the check-in date.

Table 2. Descriptive statistics of prices and room varieties by lead time

	Price				**Room varieties (Z)**			
Lead	Mean	SD	Min	Max	Mean	SD	Min	Max
7	308.30	200.39	51.000	3201	8.881	9.199	1.000	94
14	307.86	194.32	62.000	2690	9.117	9.189	1.000	130
28	305.85	189.47	59.000	2027	9.27	8.91	1.000	89
56	307.49	183.64	63.000	2645	9.711	8.635	1.000	94
84	307.87	183.76	70.000	2172	9.955	8.671	1.000	89
140	308.41	186.15	64.000	2095	10.244	8.677	1.000	89
224	322.11	227.49	74.000	6755	10.485	8.94	1.000	96

Figure 2 reports the average monthly price (Panel A) and room varieties (Panel B) for each booking horizon (k=7, 14, 28, 56, 84, 140, and 224), both expressed in logarithms. While we observe one full year of daily data for each lead time k, the corresponding observations span different calendar periods (see Table 1). As a result, Figure 2 compares monthly patterns across booking horizons rather than prices and room availability for the same calendar year.

Prices follow a clear seasonal pattern, increasing during the summer season and falling since the beginning of autumn. Interestingly, this seasonal variation differs by lead time. During the low season (i.e., at both ends of the year), hotels ask higher prices for longer booking advances, which tend to decrease as the check-in date approaches. This pattern reverses during the high season: prices are typically higher for short booking windows, reflecting stronger last-minute demand.

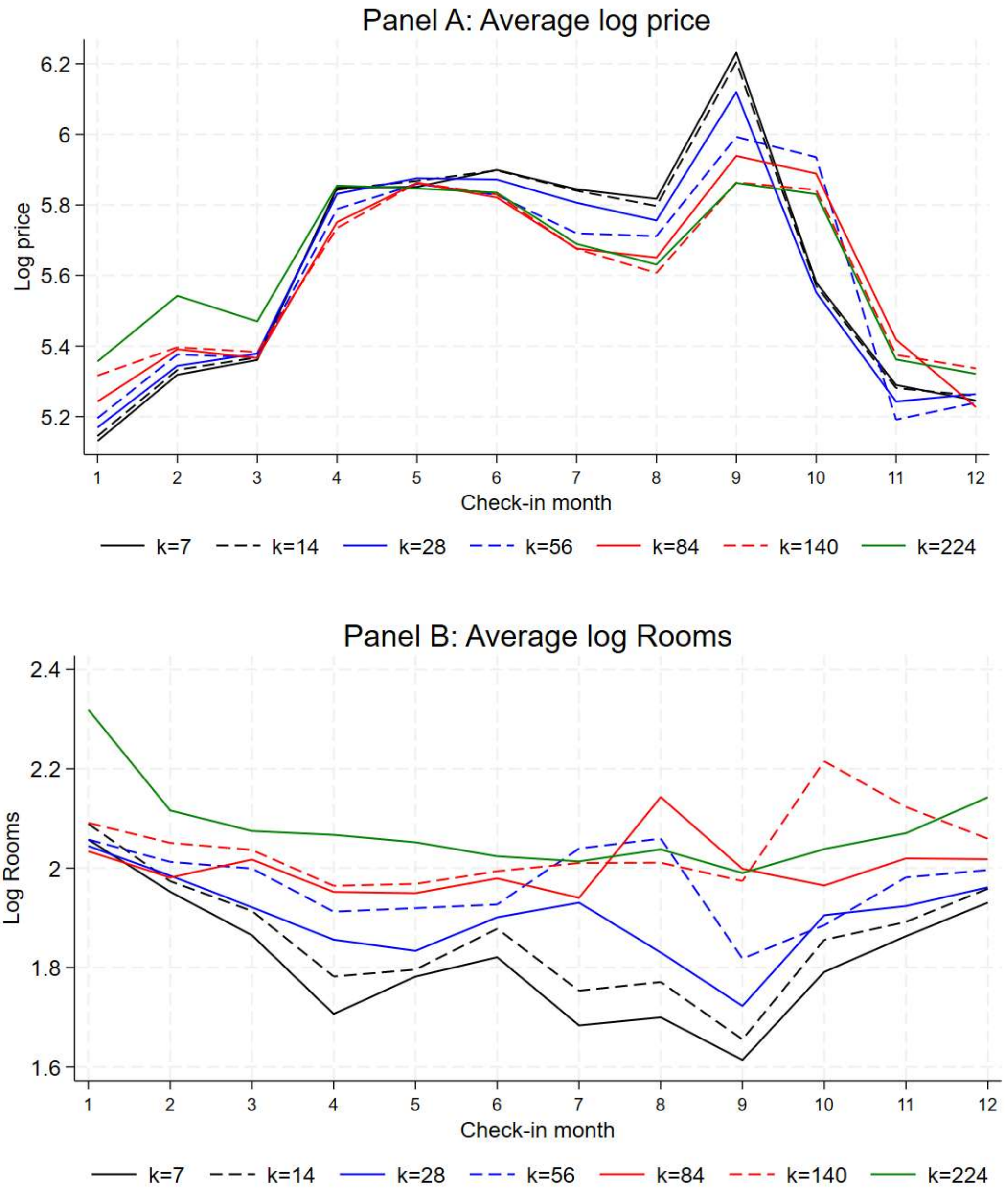

Figure 2. Average monthly prices and room varieties (in logs), by lead time *k*.

Looking at room varieties, availability is higher at more distant lead times, especially in the lower season. This pattern reflects the natural booking process, where more room types are listed earlier and gradually become unavailable as bookings are made. We also see there are relevant seasonal fluctuations in the availability of room varieties. During the peak season (summer and early autumn), medium-range lead times (e.g., 84 days) show higher availability than more distant leads (e.g., 224). This suggests that the number of room types available for the same month does not decrease monotonically over time, but fluctuates depending on the booking horizon. This non-monotonic pattern could be explained by two main factors: booking cancellations and strategic supply management. On the one hand, rooms reserved well in advance may be cancelled, especially under more lenient refund policies, making them available again at medium lead times. On the other hand, hotels may withhold certain room types from early listings and release them progressively as the check-in date approaches, depending on expected demand and market conditions at each period.

3.4. Spatial weighting matrix

Each hotel listed on the platform is georeferenced with latitude and longitude data. This allows us to construct a spatial weighting matrix (*W)* that identifies a set of neighbours for each individual hotel *j* for each booking window *k*. This, in turn, enables us to evaluate the influence of the prices charged and the room variety offered by the set of neighbouring competitors (*m*), which stand as key variables for hotel's pricing decisions according to our theoretical framework.

The extension of the historical centre of Venice is of approximately 7 square kilometres. The average distance between hotels is around 1.3 km, ranging from a minimum distance to the nearest neighbour of 200 m to a maximum distance of 4 km. Consistent with the literature on spatial price competition that shows that price rivalry decays abruptly with distance (e.g., Pinkse et al., 2002), we consider a row-standardized inverse distance spatial weights matrix truncated at a 400 m radius (i.e., hotels are not considered neighbours if they fall more than 400 m apart from each other). For robustness, we also computed alternative spatial weights matrices using 300 m and 500 m distance thresholds (see Section 5.2).

Formally, the off-diagonal elements of the weights matrix (*W*) are defined as follows:

$$w_{jm} = \begin{cases} \frac{1}{d_{jm}} \; if \; d_{jm} \leq 400 \; m \\ 0 \; if \;\; d_{jm} > \; 400 \; m \end{cases}. \tag{4}$$

Considering this matrix, the average number of neighbours is 16.1, which is about 10.4% of the hotel sample. Table A1 in the Appendix presents descriptive statistics on the average number of neighbours (as a share of the total number of hotels), as well as the number of hotels that would be excluded from the analysis depending on the threshold used. These results also support the choice of a specific maximum distance threshold.

4. EMPIRICAL STRATEGY

To model hotels' asking prices for each lead time k (k = 7, 14, 28, 56, 84, 140, 224), we adopt the following empirical specification:

$$log\ price_{jt_k} = \gamma_k log\ Z_{jt_k} + \sum_{m \neq j}^{M} \rho_k\ log\ price_{mt_k} \times w_{jm} + \sum_{m \neq j}^{M} \theta_k log\ Z_{mt_k} \times w_{jm} + \delta_{j_k} + D_{t_k} + T_{t_k} + \varepsilon_{jt_k}, \tag{5}$$

where $price_{jt_k}$ is the asking price set by hotel j for a night stay in date t, set k days in advance (e.g., the price for a night on 15th March set by hotel j 28 days before, on 15th February); Z_{jt_k} is the number of room varieties supplied by the hotel in period k to be sold for date t; $price_{mt_k}$ and Z_{mt_k} are the price and number of room varieties supplied by each neighbouring hotel operating in the same market; w_{jm} is a weight indicator obtained as the inverse of the distance d_{jm} between hotel j and each competitor m following (4); ρ_k, γ_k and θ_k are parameters to be estimated for each booking window k, δ_{j_k}, D_{t_k} and T_{t_k} are booking-window-specific hotel, day-of-the-week and month-year fixed effects, and ε_{jt_k} is a random error term.[9] The parameter ρ_k measures the strength of the influence of neighbouring asking prices, weighted by the inverse of distance, on hotel j's asking prices k days before the check-in.

Equation (5) characterizes the spatial interdependence in hotel pricing. Hotel prices for a given check-in period t at each booking horizon k are expected to be (i) increasing with competitors' prices, whose effect is decreasing with geographical distance ($\frac{p_{mt}}{d_{jm}}$); (ii) increasing with room variety supply (Z_{jt}); and (iii) decreasing with competitors' room variety ($\frac{Z_{mt}}{d_{jm}}$), whose impact is also decreasing with distance. Moreover, Equation (5) allows for price differences arising from hotel-specific amenities (δ_j), and seasonal variation in hotel demand across months and days of the week (D_{t_k} and T_{t_k}).

[9] The error term is assumed to have a constant variance σ^2 across periods. This implies that Equation (5) is a static panel regression that assumes that changes in the explanatory variables only exert contemporaneous impacts on the dependent variable.

Please note that the hotel fixed effects capture all time-invariant factors like chain management, star rating, closeness to points of interest, and hotel-specific marginal costs in services provision. As such, Equation (5) exploits the *within* hotel variation in prices over time for each lead k to identify γ_k, ρ_k and θ_k.

In a matrix form, equation (5) can be written for each booking window k as follows:

$$P_k = \gamma_k Z_k + \rho_k W P_k + \theta_k W Z_k + \delta_k + D_k + T_k + \varepsilon_k \tag{6}$$

where P_k and Z_k are M x 1 vectors of $log\ price_{jt_k}$ and $log\ Z_{jt_k}$ for all j in period t (with $M = N*T$), δ_k, D_k and T_k are M x 1 vectors of unit, day-of-the-week and month-year fixed effects, and W is an (exogenous) spatial row-standardized weights matrix.

The model in Equation (6) is a panel Spatial Durbin Model (hereafter, SDM) specification that considers spatial lags of the dependent variable and one of the predictors (Z_{jt}). Because prices appear at both sides of the equation, OLS would produce biased estimates due to simultaneity bias. The parameters can nonetheless be consistently estimated from the following reduced-form equation that is non-linear in parameters:

$$P_k = (I - \rho_k W)^{-1}(\gamma_k Z_k + \theta_k W Z_k + \delta_k + D_k + T_k + \varepsilon_k). \tag{7}$$

Equation (7) can be estimated by Maximum Likelihood. However, in the presence of high-dimensional fixed effects (here hotel, month-year, and day-of-the-week), analytical solutions for the inverse are rather intractable. Therefore, following the methodology introduced by Grieser et al. (2022a; 2022b), Equation (7) is estimated through numerical optimization, combining Maximum Likelihood with Monte Carlo Monte Chain (MCMC) methods.[10] This is done in Stata 19 using *nwxtregress* (Ditzen, 2022).

[10] Intuitively, this consists of generating a sequence of parameter values for ρ that form a Markov chain, where each new value depends on the previous one. This chain is designed so that, over many iterations, the sampled values approximate the true distribution of the parameters. By combining MCMC with Maximum Likelihood estimation, one can approximate the likelihood function through these simulated draws, and then identify the parameter values that maximize it.

Because of the spatial structure of the model, any change in the number of rooms supplied by a competitor m (Z_{mt}) will generate an impact on the price set by hotel j both directly (if m is a neighbour of j) and indirectly (if m is a neighbour of a neighbour of j). Following Elhorst (2014) and Belotti et al. (2017), the direct and indirect elasticities of prices to competitors' room supply (omitting subscript k for notational convenience) will be given by:

Direct effect:

$$\frac{\partial log\, p_{jt}}{\partial log\, Z_{mt}} = \left\{(I - \rho W)^{-1} \times (\gamma I + \theta W)\right\}^{\underline{d}}; \quad (8)$$

Indirect effects:

$$\frac{\partial log\, p_{jt}}{\partial log\, Z_{mt}} = \left\{(I - \rho W)^{-1} \times (\gamma I + \theta W)\right\}^{\overline{rsum}}; \quad (9)$$

where $\underline{d}$ denotes the mean diagonal element of W and $\overline{rsum}$ the mean row sum. The total effects will be given by the sum of the direct and the indirect effects.

5. RESULTS

5.1. Main findings

Table 3 presents the estimation results from the Spatial Durbin model in Equation (4). Figures 3-6 depict the coefficient estimates and 95% confidence intervals across booking lead times for visualisation purposes. Table 4 reports the corresponding direct, indirect, and total effects of rooms variety and the day-of-the-week fixed effects, computed according to Equations (8) and (9).

Asking prices are positively correlated with the prices set by competitors: conditional on day-of-week and month-year fixed effects that capture common demand shocks, hotels' prices move in parallel with those set by their neighbours. This is consistent with our theoretical framework: when the price set by a given hotel is higher (potentially driven by a shift in marginal costs) consumers are more likely to switch to their second-best options, which—given strong location preferences—are typically hotels located in the same neighbourhood. The residual demand curve for a close substitute, hotel B, rotates and becomes comparatively more inelastic than before. According to Equation (3), hotels are expected to capitalize on this change in their elasticity of substitution by also raising their prices, leading to second- and third-order effects on nearby competitors. This suggests the existence of price-mimicking behaviour directly tied to location.

Interestingly, this correlation follows an inverted-U pattern across lead times (Figure 3): the estimated price dependence strengthens between 28 and 140 days before check-in, but weakens at both very short (k = 7, 14) and very long (k = 224) horizons. Accordingly, spatial price competition appears to be most active at mid-range lead times, when most bookings are made according to related research (Bigne et al., 2021).

Table 3. Coefficient estimates from Spatial Durbin model for each lead period *k*.

Dep. Variable: ln p	(1) k=7	(2) k=14	(3) k=28	(4) k=56	(5) k=84	(6) k=140	(7) k=224
ρ_k: W Ln P	0.534***	0.525***	0.588***	0.609***	0.575***	0.595***	0.465***
	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
γ_k: Ln Z	0.008***	0.002	0.009***	0.022***	0.023***	0.021***	-0.003
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)
θ_k: W Ln Z	-0.073***	-0.094***	-0.077***	-0.043***	-0.048***	0.011	0.005
	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.007)	(0.009)
Tuesday	-0.005	-0.002	-0.003	-0.002	0.001	-0.000	0.002
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Wednesday	-0.007*	-0.003	-0.004	-0.002	-0.001	0.001	0.001
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Thursday	0.003	0.005	0.001	0.002	0.005*	0.004	0.003
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Friday	0.102***	0.098***	0.078***	0.066***	0.070***	0.063***	0.085***
	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)
Saturday	0.154***	0.146***	0.111***	0.092***	0.091***	0.083***	0.101***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Sunday	0.002	0.004	0.003	0.003	0.002	0.001	0.003
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Hotel FE	YES	YES	YES	YES	YES	YES	YES
Month-year FE	YES	YES	YES	YES	YES	YES	YES
Observations	31,512	33,414	36,180	39,263	40,947	41,321	38,786
R-squared	0.327	0.329	0.330	0.290	0.252	0.241	0.170
Number of groups	149	150	150	151	150	150	147

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

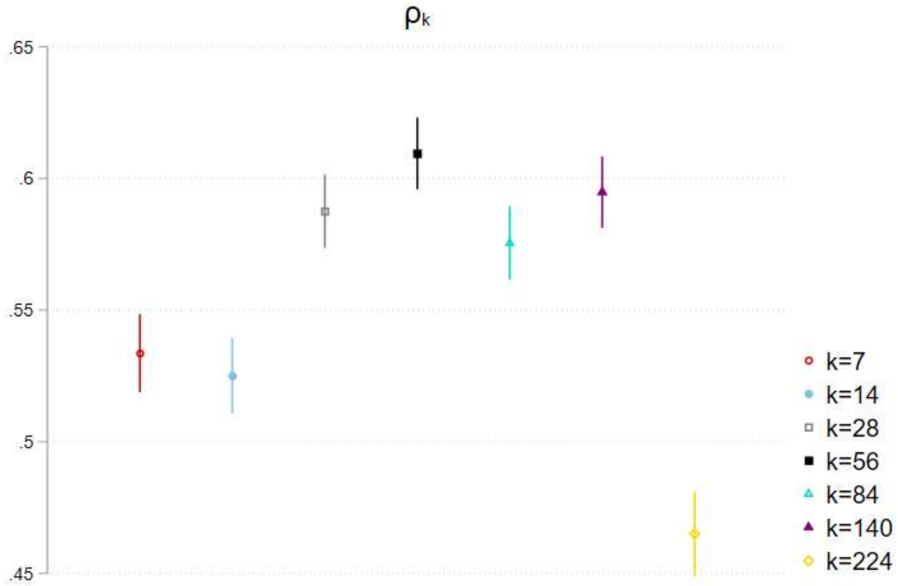

Figure 3. Coefficient estimates of spatial price lag from Spatial Durbin model for each lead period *k*.

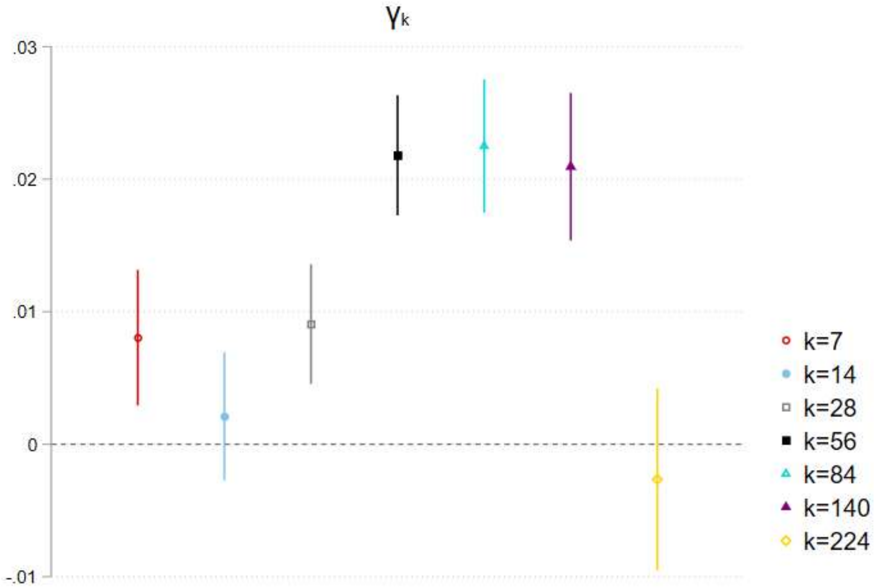

Figure 4. Coefficient estimates of ln Z from Spatial Durbin model for each lead period *k*.

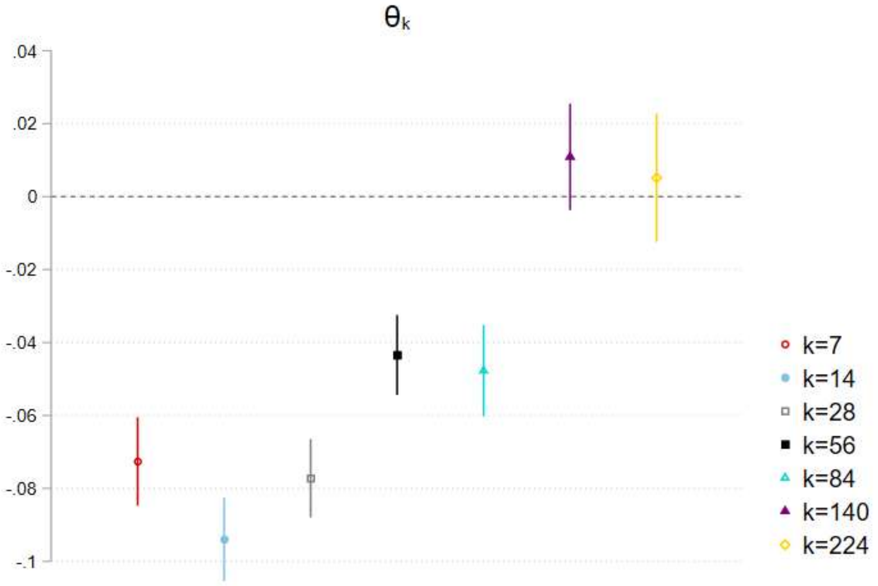

Figure 5. Coefficient estimates of spatial lag of ln Z from Spatial Durbin model for each lead period *k*.

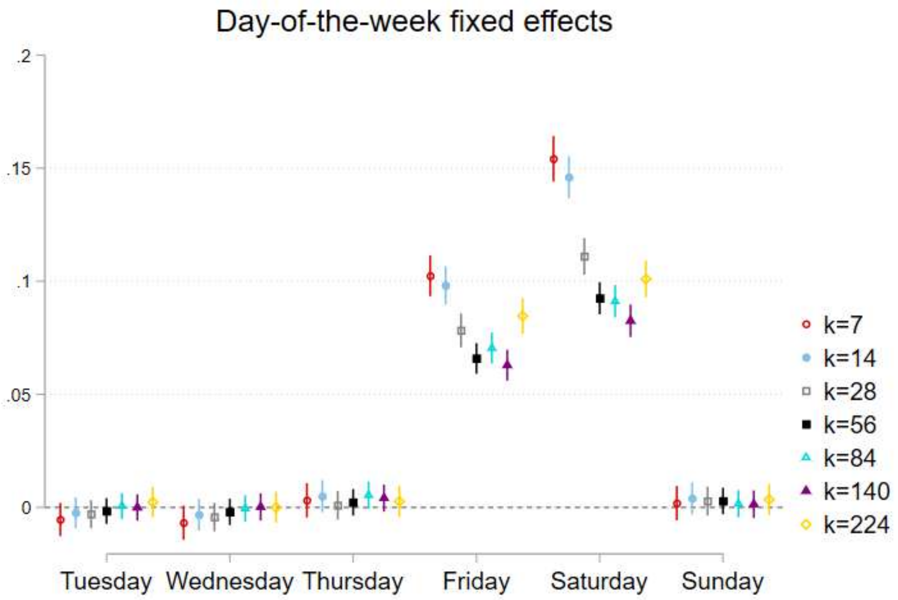

Figure 6. Coefficient estimates of day-of-the-week fixed effects from Spatial Durbin model for each lead period *k*.

Table 4. Direct and indirect effects from Spatial Durbin model in Table 3 for each lead period *k*.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Direct effect	k=7	k=14	k=28	k=56	k=84	k=140	k=224
Ln Z	0.007***	7.1e-04	0.008***	0.021***	0.022***	0.021***	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Tuesday	-0.005	-0.002	-0.003	-0.001	6.1-e04	-3.3e-05	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Wednesday	-0.006*	-0.003	-0.004	-0.002	-4.7e-04	2.0e-04	4.4e-05
	0.003	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Thursday	0.003	0.005	9.3e-04	0.002	0.005	0.004	0.002
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Friday	0.103***	0.098***	0.079***	0.066***	0.070***	0.063***	0.084***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Saturday	0.155***	0.147***	0.112***	0.093***	0.091***	0.083***	0.101***
	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)
Sunday	0.001	0.004	0.002	(0.002)	0.001	0.001	0.003
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Indirect effect	k=7	k=14	k=28	k=56	k=84	k=140	k=224
Ln Z	-0.145***	-0.194***	-0.173***	-0.076***	-0.081***	0.057***	0.007
	(0.013)	(0.012)	(0.013)	(0.014)	(0.015)	(0.018)	(0.016)
Tuesday	-0.006	-0.002	-0.004	-0.002	8.1e-04	-5.1e-05	0.002
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
Wednesday	-0.007*	-0.003	-0.006	-0.003	-6.4e-04	2.8e-04	3.6e-04
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
Thursday	0.003	0.005	0.001	0.003	0.007	0.006	0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
Friday	0.116***	0.107***	0.110***	0.102***	0.095***	0.091***	0.073***
	(0.006)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)	(0.004)
Saturday	0.175***	0.160***	0.157***	0.143***	0.123***	0.120***	0.087***
	(0.008)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.004)
Sunday	0.002	0.004	0.004	0.004	0.002	0.002	0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
Total effect	k=7	k=14	k=28	k=56	k=84	k=140	k=224
Ln Z	-0.138***	-0.193***	-0.165***	-0.055***	-0.059***	0.078***	0.004
	(0.014)	(0.013)	(0.014)	(0.015)	(0.016)	(0.019)	(0.017)
Tuesday	-0.011	-0.004	-0.007	-0.004	0.001	-8.4e-05	0.004
	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)
Wednesday	-0.014*	-0.006	-0.010	-0.005	-0.001	4.8e-04	8.1e-05
	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)
Thursday	0.006	0.010	0.002	0.005	0.012*	0.010	0.005
	(0.008)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.006)
Friday	0.219***	0.206***	0.189***	0.168***	0.165***	0.155***	0.158***
	(0.010)	(0.009)	(0.009)	(0.009)	(0.008)	(0.009)	(0.008)
Saturday	0.330***	0.307***	0.269***	0.236***	0.214***	0.203***	0.188***
	(0.012)	(0.011)	(0.011)	(0.010)	(0.009)	(0.009)	(0.008)
Sunday	0.004	0.008	0.006	0.007	0.003	0.003	0.006
	(0.008)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.006)

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

In line with our framework, hotel prices also respond positively and significantly to own room variety, except at k = 14 and k = 224. As shown in Figure 4, the elasticity of the prices of the chosen room with respect to other room varieties available in the same hotel is modest in magnitude and peaks at medium-range horizons, ranging from 0.007 at k = 7 to 0.022 in k = 84 (Table 4). In contrast, the variety of nearby competitors exerts a negative price effect at shorter horizons. A one-percent increase in competitors' room variety is associated with a 0.14%, 0.19% and 0.17% reduction in own prices at k = 7, k = 14 and k = 28, respectively.

Finally, day-of-the-week fixed effects show that prices are significantly higher on Friday and Saturday nights. No differences are found between Monday nights (reference category) and the rest of weekday or Sunday nights. Interestingly, the weekend price premium displays a U-shaped pattern across lead times (Figure 6): the price increase is most pronounced at very short and very long horizons.

5.2. Robustness checks

For robustness, we re-estimated the spatial price equations for each booking window considering 300 m and 500 m as the distance thresholds for the inverse-distance weighting matrix. The results, presented in Tables A2-A3 in the Appendix, are consistent with those in Table 3, indicating robustness to the distance threshold chosen.

We also repeated the empirical analyses using data for (i) hotel rooms with non-refundable prices, and (ii) hotel rooms without breakfast. The coefficient estimates and the corresponding direct, indirect, and total effects are reported in Tables A4-A7 in the Appendix. We obtain highly consistent results, both in magnitude, sign direction and statistical significance. This indicates that our results are not driven by the specific room typology chosen, and also hold when removing the price premiums associated with the inclusion of breakfast (Anguera-Torrell and Nicolau, 2025) or the possibility of cancellation (Lacetera et al., 2025).

5.3. Differences by season of the year

As a final empirical exercise, we evaluate whether spatial dependence follows specific patterns across different times of the year. Panels A to D in Table 5 presents the regression results from estimating the Spatial Durbin Model according to Equation (5), separately for each quarter of the year.[11] In the table, the results are organized as follows: vertically, we can compare the coefficients for each lead time across different quarters of the year; horizontally, we can evaluate how coefficients differ across lead times for a given quarter.

Table 5 indicates that the inverted-U pattern of spatial dependence documented in Table 3 is not homogeneous across the year, but varies significantly with seasonality. During the low season (first and fourth quarters), hotels display the highest degree of price interdependence across booking horizons, with estimated spatial lag price coefficients systematically larger than those obtained in the aggregate specification. This finding is consistent with our theoretical framework: when demand is weaker and consumers face a larger choice set, the elasticity of substitution increases, intensifying competitive pressures and inducing hotels to mimic local competitors' pricing more closely. In this context, competitors' room variety also exerts stronger negative effects, particularly at short horizons, which further supports the notion of heightened substitutability under thin demand conditions.

By contrast, in the second and especially the third quarter, which coincide with the high season, the estimated spatial dependence weakens considerably. Hotels appear less constrained by local rivals, suggesting that strong demand and location-driven preferences make consumers less price-sensitive. In such circumstances, the elasticity of substitution declines, granting hotels greater scope for independent pricing. The estimates for competitors' variety reinforce this interpretation: in the third quarter, the traditional negative effect is muted or even turns positive at long horizons, implying that early planners may perceive clusters of variety-rich hotels as complementary rather than strictly substitutable.

[11] The corresponding direct, indirect and total effects are reported in Tables A8-A11 in the Appendix.

Table 5. Coefficient estimates from Spatial Durbin model for each lead period *k* and quarter of the year.

Dep. Variable: ln p	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: First quarter	k=7	k=14	k=28	k=56	k=84	k=140	k=224
ρ_k: W Ln P	0.664***	0.666***	0.675***	0.715***	0.696***	0.690***	0.501***
	(0.013)	(0.012)	(0.012)	(0.011)	(0.012)	(0.012)	(0.017)
γ_k: Ln Z	0.024***	0.019***	-0.007	-0.009	-0.010	0.011	-0.058***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.013)
θ_k: W Ln Z	-0.053***	-0.094***	-0.133***	-0.036**	-0.077***	0.001	-0.137***
	(0.014)	(0.013)	(0.016)	(0.016)	(0.020)	(0.018)	(0.033)
Day-of-the-week FE	YES	YES	YES	YES	YES	YES	YES
Hotel FE	YES	YES	YES	YES	YES	YES	YES
Month-year FE	YES	YES	YES	YES	YES	YES	YES
Observations	8,982	9,359	9,894	10,263	10,319	9,806	7,807
R-squared	0.468	0.461	0.445	0.403	0.370	0.314	0.199
Number of groups	145	145	145	147	146	143	121
Dep. Variable: ln p	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel B: Second quarter	k=7	k=14	k=28	k=56	k=84	k=140	k=224
ρ_k: W Ln P	0.494***	0.461***	0.572***	0.541***	0.527***	0.557***	0.236***
	(0.016)	(0.015)	(0.013)	(0.013)	(0.013)	(0.013)	(0.018)
γ_k: Ln Z	-0.029***	-0.031***	-0.011**	0.007	-0.010**	0.008*	0.015***
	(0.006)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)
θ_k: W Ln Z	-0.037***	-0.076***	-0.060***	-0.052***	-0.043***	-0.028*	0.006
	(0.012)	(0.011)	(0.009)	(0.012)	(0.013)	(0.014)	(0.012)
Day-of-the-week FE	YES	YES	YES	YES	YES	YES	YES
Hotel FE	YES	YES	YES	YES	YES	YES	YES
Month-year FE	YES	YES	YES	YES	YES	YES	YES
Observations	6,833	7,433	8,564	9,616	10,091	10,047	9,880
R-squared	0.347	0.358	0.376	0.301	0.298	0.283	0.222
Number of groups	144	146	147	146	147	142	137
Dep. Variable: ln p	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel C: Third quarter	k=7	k=14	k=28	k=56	k=84	k=140	k=224
ρ_k: W Ln P	0.209***	0.199***	0.255***	0.226***	0.250***	0.279***	0.247***
	(0.019)	(0.018)	(0.019)	(0.019)	(0.018)	(0.018)	(0.019)
γ_k: Ln Z	-0.005	0.007	0.009**	0.010***	0.011***	0.000	-0.026***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
θ_k: W Ln Z	-0.039***	-0.050***	-0.032***	-0.059***	-0.017**	-0.015	0.080***
	(0.012)	(0.012)	(0.010)	(0.008)	(0.008)	(0.013)	(0.017)
Day-of-the-week FE	YES	YES	YES	YES	YES	YES	YES
Hotel FE	YES	YES	YES	YES	YES	YES	YES
Month-year FE	YES	YES	YES	YES	YES	YES	YES
Observations	6,694	7,218	8,322	9,526	10,317	10,991	10,562
R-squared	0.203	0.197	0.250	0.282	0.259	0.245	0.240
Number of groups	143	143	142	141	143	144	140

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5. (cont.) Coefficient estimates from Spatial Durbin model for each lead period k and quarter of the year.

Dep. Variable: ln p Panel D: Fourth quarter	(1) k=7	(2) k=14	(3) k=28	(4) k=56	(5) k=84	(6) k=140	(7) k=224
ρ_k: W Ln P	0.594***	0.606***	0.606***	0.642***	0.639***	0.693***	0.636***
	(0.013)	(0.013)	(0.014)	(0.013)	(0.013)	(0.012)	(0.013)
γ_k: Ln Z	-0.016***	-0.009	-0.007	0.025***	0.032***	0.041***	0.035***
	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.007)	(0.008)
θ_k: W Ln Z	-0.087***	-0.136***	-0.131***	-0.103***	-0.165***	-0.007	0.082***
	(0.014)	(0.013)	(0.014)	(0.012)	(0.015)	(0.014)	(0.017)
Day-of-the-week FE	YES	YES	YES	YES	YES	YES	YES
Hotel FE	YES	YES	YES	YES	YES	YES	YES
Month-year FE	YES	YES	YES	YES	YES	YES	YES
Observations	9,001	9,402	9,399	9,857	10,219	10,476	10,535
R-squared	0.372	0.407	0.366	0.316	0.289	0.327	0.291
Number of groups	141	140	141	149	147	141	142

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Overall, these results underscore the importance of accounting for the seasonal composition of demand when analysing spatial competition. While Table 3 showed that spatial dependence peaks at mid-range booking horizons, coinciding with the timing of most reservations, the disaggregated results in Table 5 demonstrate that this pattern is conditional on the prevailing demand environment. In low-demand quarters, competitive pressures are amplified and persist across horizons, whereas in high-demand quarters, hotels benefit from greater market power and weaker spatial linkages. This duality is in line with the model's prediction that elasticities of substitution are not constant, but vary systematically with both booking horizon and seasonality.

6. DISCUSSION AND CONCLUSIONS

This study investigates the multifaceted nature of service markets, where temporal and spatial dimensions interact to shape pricing strategies and competitive dynamics. Building on a framework of monopolistic competition à la Dixit and Stiglitz (1977), and following the extensions introduced by Zhelobodko et al. (2012), we examine how price competition evolves over the time span between purchase and service consumption. Our empirical application focuses on the accommodation industry, which offers a particularly suitable context for analysing market interactions driven by this dual temporal dimension, alongside the well-documented spatial competition among differentiated products. The context of the Venetian hotel industry represents an appropriate testing ground, given the city's high tourist inflows and the strong heterogeneity in both seasonal demand and the geographic concentration of accommodation structures. Using a panel of 151 hotels observed over 365 check-in dates, we employ Spatial Durbin Models (SDM) to disentangle local price interdependencies across booking horizons. This approach not only captures spatial price dynamics, but also accounts for the influence of hotels' own and competitors' room variety, offering a nuanced perspective on how competitive pressure evolves across time and space.

The results reveal three key insights. First, in line with theoretical predictions, prices move in parallel with those of nearby competitors, suggesting the presence of spatial price mimicry rooted in geographic proximity. Second, greater variety commands higher prices, while greater variety from nearby rivals exerts a negative effect, consistent with intensified competition and more elastic residual demand. Third, and most importantly, these relationships vary systematically across booking horizons and seasons. Spatial dependence follows a nonlinear pattern over the booking horizon, peaking at mid-range leads (when most reservations occur), while weakening at very short and very long booking horizons. Across seasons, spatial competition intensifies in low-demand quarters, when consumers exhibit higher price sensitivity and firms respond more closely to local competitive conditions. Conversely, in high-demand periods, firms enjoy greater autonomy in pricing, reflecting lower substitutability and more inelastic demand.

These findings underscore that the strength of spatial competition is not constant, but is jointly determined by two quality–time dimensions that characterise service markets: the timing of booking and the seasonal demand environment. This evidence contributes to the literature on intertemporal pricing and spatial competition by showing how the elasticity of substitution varies not only across firms, but also across time, shaping the dynamics of strategic interactions in perishable service markets.

Given the context of the study, our findings carry relevant implications for hotel managers. Revenue strategies should explicitly incorporate the interaction between seasonality and booking horizons. In the low season, when spatial price interdependence is strongest, hotels may benefit from closely monitoring and reacting to local competitors' pricing and variety strategies. In contrast, in the high season, hotels can exercise greater autonomy, emphasizing differentiation and premium positioning rather than reactive adjustments. Moreover, since spatial competition peaks at mid-range booking horizons, this window should be prioritised in revenue management systems, with a balanced mix of price competitiveness and strategic release of room varieties.

There are also important practical implications for researchers investigating markets characterised by this two-sided temporal structure, such as ticketing, ride-sharing, and other sectors that share similar features with the lodging industry. While accounting for spatial dependence has become standard in this type of analysis, it is equally important to recognise that the existence and magnitude of spatial dependence are themselves related to the underlying time horizon. As a result, estimates may vary and potentially mask the true effect of the temporal dimension.

This work has some limitations that could inspire future research on the topic. First, our analysis focuses on a single urban context, Venice, whose unique spatial configuration and tourism profile may not generalise to more dispersed or business-oriented markets. In this sense, given the geographical setting and level of spatial dispersion, it may also be interesting to consider other distance-decay functions for different urban or spatial assets (e.g., Martínez and Viega, 2013). Second, we do not observe hotel occupancy data or actual room availability at each booking window, thereby missing information on residual room availability. Our variety variable serves more as a proxy for the diversity of offered room types rather than a direct measure of inventory. Another data limitation is that we lack information on online hotel ratings and their dynamics. Because higher prices reduce value for money, which on average worsens review ratings, some recent work argues that accommodation firms may strategically adjust prices to raise their reputation on online platforms (e.g., Carnehl et al., 2024; Johnen and Ng, 2024). Future research should therefore extend our analysis to other cities with different spatial structures, incorporate direct measures of occupancy and cancellation dynamics, consider additional (non-spatial) channels of price mimicking (such as trade associations or star level), and explore the role of online reputation in shaping spatial dependencies across booking horizons.

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APPENDIX

The Timing of Spatial Competition: Price Interdependence Across Booking Horizons

PRICE SETTING UNDER MONOPOLISTIC COMPETITION

(DIXIT AND STIGLITZ, 1977)

Suppose hotels operate under monopolistic competition so that each hotel is monopolistic of its own variety, defined based on its location and specific amenities. Following Dixit and Stiglitz (1977), let us assume that consumers' aggregate sub-utility for a hotel stay in a given calendar day *d* is given by the following CES function:

$$U = \left(x_0, \left(\sum_{j=1}^{J} \alpha_j q_j^{\rho} \right)^{\frac{1}{\rho}} \right) \tag{A1}$$

where x_0 is an outside good, q_j is the number of individuals staying at hotel j, α_j is a preference parameter that captures consumers' preference for hotel j, $\rho = \frac{\sigma-1}{\sigma}$ is a "love-of-variety" parameter, and σ is the elasticity if substitution between hotels (varieties). The larger the ρ, the larger the substitutability of hotels within them. For concavity and to allow for zero values in non-chosen hotels ($q_j = 0$), ρ must lie between 0 and 1 (i.e., $0 < \sigma < \infty$) so that hotels might not be perfect substitutes nor perfect complements. U is also assumed to be homogeneous of degree 1 in x_0 and $V = \left(\sum_{j=1}^{J} \alpha_j q_j^{\rho}\right)^{\frac{1}{\rho}}$ and additively separable.

The budget constraint is given by $M = x_0 + \sum_{j=1}^{J} p_j q_j$, where M denotes consumers' income in terms of the numeraire (x_0) and p_j the price per night of a stay in hotel *j* in day *d*. From the first-order utility maximization conditions, the Marshallian demand function for each hotel *j* is given by:

$$q_j = Q\alpha_j \left(\frac{p_j}{P}\right)^{-\sigma} \tag{A2}$$

where $Q = \sum_{j=1}^{J} q_j$ is the total market demand for day *d* and $P = \left(\sum_{k=1}^{K} \alpha_k p_k^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$ is a price index that measures the prices set by competitors $k \neq j$ in the market. The demand for hotel *j* (number of consumers willing to stay in day *d*) is therefore an increasing function of market demand, hotel idiosyncratic features that determine utility (α_j) and other hotels' prices but a decreasing function of hotel j's own prices. The price elasticity of hotel j's demand is constant and given by $-\sigma$: the higher the elasticity of substitution, the less differentiated hotels are and therefore the more sensitive the quantity demanded is to hotel prices, and vice versa.

Assuming hotels have a fixed marginal cost per overnight stay supplied (c), firms' profit-maximization implies that prices are set as a constant mark-up over marginal costs as follows:

$$p_j{}^* = \frac{c}{\rho} = c\left(\frac{\sigma}{\sigma - 1}\right) \tag{A3}$$

Accordingly, hotels' pricing depends on a constant and symmetrical mark-up they charge over their marginal costs, which depends on the (constant) price elasticity of their individual demand curves.

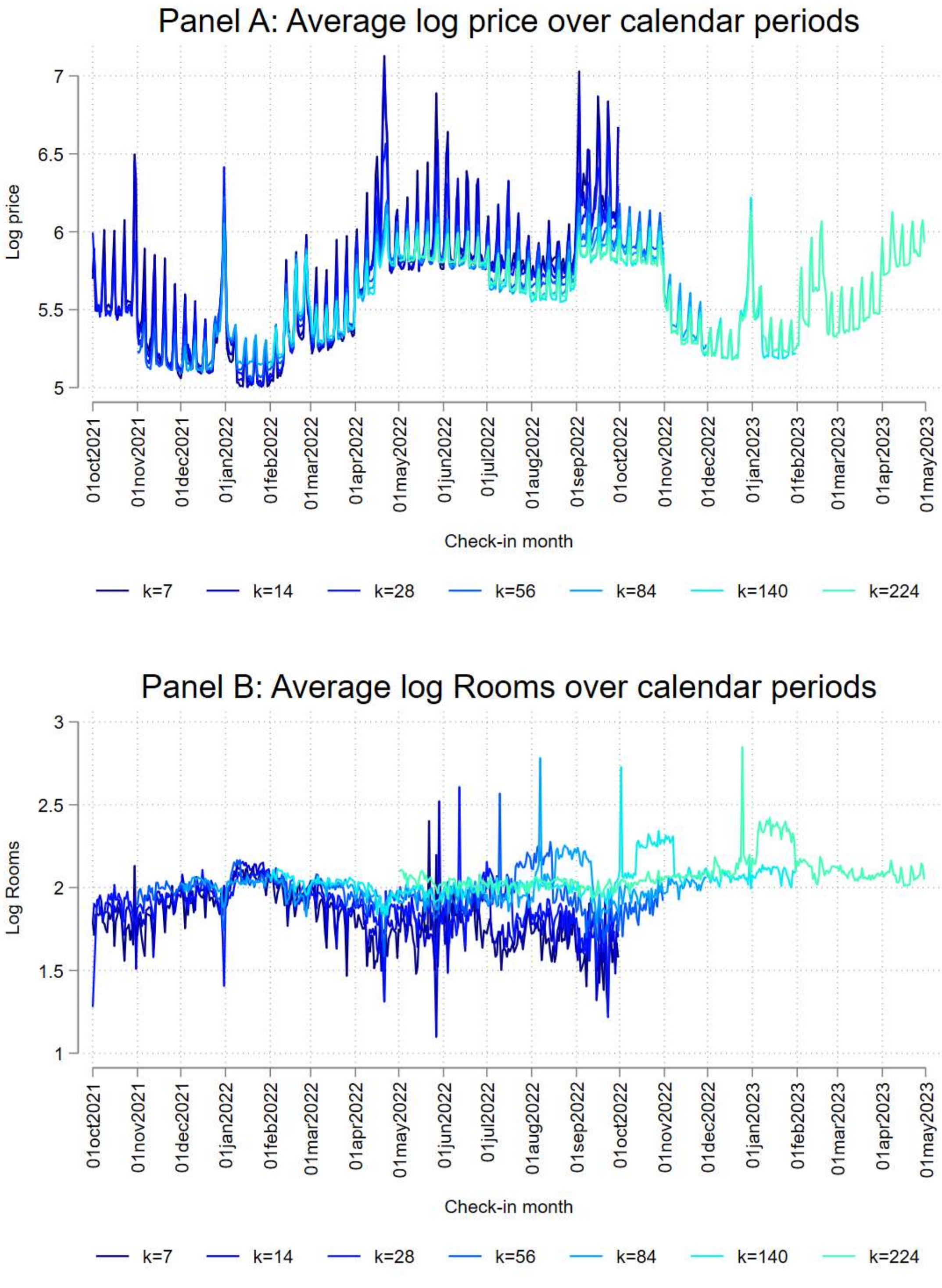

Figure A1. Average prices and room varieties (in logs) for each calendar period, by lead time *k*.

Table A1. Descriptive statistics on neighbourhood density by distance threshold.

Distance threshold	**Neighbours per Hotel**	**% of sample**	**Hotels with 0 Neighbours**	**% of sample**
2 km	130.93	84%	0	0%
1 km	66.59	43%	3	2%
500 m	23.44	15%	4	3%
450 m	19.19	12%	7	5%
400 m	16.10	10%	10	6%
350 m	12.56	8%	11	7%
300 m	9.65	6%	12	8%
250 m	6.21	4%	16	10%
200 m	3.74	2%	24	15%
150 m	1.40	1%	56	36%

Table A2. Rob. Check: coefficient estimates from Spatial Durbin model for each lead period *k*: 300-metre distance weighting matrix.

Dep. Variable: ln p	(1) k=7	(2) k=14	(3) k=28	(4) k=56	(5) k=84	(6) k=140	(7) k=224
ρ_k: W Ln P	0.433***	0.441***	0.482***	0.501***	0.487***	0.530***	0.430***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
γ_k: Ln Z	0.004*	-0.001	0.007***	0.022***	0.021***	0.025***	-0.006
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
θ_k: W Ln Z	-0.060***	-0.068***	-0.046***	-0.036***	-0.048***	-0.045***	-0.008
	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.008)
Tuesday	-0.007*	-0.003	-0.003	-0.002	0.000	-0.000	0.003
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Wednesday	-0.009**	-0.005	-0.005	-0.003	-0.000	0.001	0.000
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Thursday	0.004	0.006	0.003	0.003	0.007**	0.005	0.003
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Friday	0.126***	0.120***	0.103***	0.084***	0.086***	0.073***	0.091***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Saturday	0.192***	0.177***	0.147***	0.118***	0.111***	0.093***	0.107***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Sunday	0.001	0.003	0.002	0.003	0.002	0.002	0.004
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Hotel fixed effects	YES	YES	YES	YES	YES	YES	YES
Month-year fixed effects	YES	YES	YES	YES	YES	YES	YES
Observations	31,512	33,414	36,180	39,263	40,947	41,321	38,786
R-squared	0.296	0.296	0.286	0.252	0.225	0.220	0.169
Number of groups	149	150	150	151	150	150	147

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A3. Rob. Check: coefficient estimates from Spatial Durbin model for each lead period *k*: 500-metre distance weighting matrix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Variable: ln p	k=7	k=14	k=28	k=56	k=84	k=140	k=224
ρ_k: W Ln P	0.562***	0.553***	0.603***	0.619***	0.596***	0.633***	0.494***
	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
γ_k: Ln Z	0.008***	0.003	0.010***	0.024***	0.025***	0.022***	-0.002
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
θ_k: W Ln Z	-0.080***	-0.106***	-0.091***	-0.065***	-0.057***	-0.011	-0.018*
	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)	(0.008)	(0.010)
Tuesday	-0.004	-0.002	-0.003	-0.002	0.000	-0.000	0.002
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Wednesday	-0.006	-0.003	-0.004	-0.002	-0.000	0.000	0.000
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Thursday	0.003	0.005	0.001	0.002	0.005	0.004	0.003
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Friday	0.094***	0.090***	0.075***	0.064***	0.068***	0.057***	0.080***
	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)
Saturday	0.141***	0.135***	0.107***	0.090***	0.087***	0.074***	0.094***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Sunday	0.002	0.004	0.003	0.003	0.002	0.001	0.003
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Hotel fixed effects	YES	YES	YES	YES	YES	YES	YES
Month-year fixed effects	YES	YES	YES	YES	YES	YES	YES
Observations	31,512	33,414	36,180	39,263	40,947	41,321	38,786
R-squared	0.335	0.339	0.334	0.291	0.257	0.253	0.174
Number of groups	149	150	150	151	150	150	147

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A4. Rob. Check: coefficient estimates from Spatial Durbin model for each lead period *k;* non-refundable sample.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Variable: ln p	k=7	k=14	k=28	k=56	k=84	k=140	k=224
ρ_k: W Ln P	0.429***	0.442***	0.497***	0.483***	0.485***	0.552***	0.418***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)	(0.011)
γ_k: Ln Z	0.002	-0.009**	0.032***	0.043***	0.031***	0.016***	0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
θ_k: W Ln Z	-0.105***	-0.112***	-0.106***	-0.084***	-0.065***	0.004	-0.057***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.009)	(0.009)	(0.013)
Tuesday	-0.009*	-0.003	0.000	-0.001	0.000	0.000	0.001
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Wednesday	-0.011**	-0.005	-0.005	-0.001	-0.000	0.002	-0.001
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Thursday	0.001	0.006	0.004	0.001	0.005	0.002	-0.000
	(0.006)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Friday	0.134***	0.122***	0.098***	0.079***	0.079***	0.068***	0.086***
	(0.007)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Saturday	0.198***	0.180***	0.143***	0.122***	0.111***	0.092***	0.109***
	(0.007)	(0.007)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
Sunday	0.001	0.005	0.003	0.002	0.000	0.002	0.006
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)
Hotel FE	YES	YES	YES	YES	YES	YES	YES
Month-year FE	YES	YES	YES	YES	YES	YES	YES
Observations	17,920	19,211	19,645	21,444	23,352	23,972	22,783
R-squared	0.332	0.339	0.314	0.248	0.214	0.227	0.161
Number of groups	104	106	106	107	104	115	111

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A5. Direct and indirect effects for non-refundable sample from Spatial Durbin model in Table A4 for each lead period *k*.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Direct effect	k=7	k=14	k=28	k=56	k=84	k=140	k=224
Ln Z	2.4e-04	-0.010***	0.029***	0.041***	0.029***	0.016***	0.003
	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)
Tuesday	-0.009*	-0.003	4.1e-04	-9.1e-04	1.3-e04	-3.4e-04	0.001
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Wednesday	-0.011**	-0.005	-0.004	-8.8e-04	-3.0e-04	0.001	-0.001
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Thursday	9.1e-04	0.005	0.003	9.9e-04	0.005	0.002	-3.7e-04
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Friday	0.135***	0.123***	0.099***	0.079***	0.079***	0.068***	0.086***
	(0.006)	(0.006)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)
Saturday	0.199***	0.181***	0.144***	0.122***	0.112***	0.092***	0.109***
	(0.007)	(0.006)	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)
Sunday	5.0e-04	0.005	0.002	0.002	4.1e-04	0.002	0.006
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Indirect effect	k=7	k=14	k=28	k=56	k=84	k=140	k=224
Ln Z	-0.180***	-0.205***	-0.178***	-0.121***	-0.096***	0.028	-0.095***
	(0.013)	(0.013)	(0.014)	(0.014)	(0.016)	(0.021)	(0.022)
Tuesday	-0.007*	-0.002	4.0e-04	-8.5e-04	1.1e-04	4.0e-04	0.001
	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
Wednesday	-0.008**	-0.004	-0.004	-8.1e-04	-2.8e-04	0.002	-8.9e-04
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.005)	(0.003)
Thursday	6.7e-04	0.004	0.003	9.1e-04	0.004	0.003	-2.6e-04
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.005)	(0.003)
Friday	0.099***	0.095***	0.096***	0.073***	0.074***	0.083***	0.061***
	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.004)
Saturday	0.147***	0.141***	0.140***	0.113***	0.104***	0.112***	0.077***
	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)	(0.005)
Sunday	3.7e-04	0.003	0.002	0.002	3.8e-04	0.003	0.004
	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.005)	(0.003)
Total effect	k=7	k=14	k=28	k=56	k=84	k=140	k=224
Ln Z	-0.179***	-0.215***	-0.148***	-0.079***	-0.066***	0.045**	-0.091***
	(0.014)	(0.014)	(0.015)	(0.015)	(0.016)	(0.022)	(0.023)
Tuesday	-0.016*	-0.006	8.0e-04	-0.001	2.4e-04	7.4e-04	0.002
	(0.009)	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)	(0.007)
Wednesday	-0.019**	-0.009	-0.009	-0.001	-5.8e-04	0.003	-0.002
	(0.009)	(0.009)	(0.008)	(0.008)	(0.007)	(0.009)	(0.007)
Thursday	0.001	0.010	0.007	0.002	0.010*	0.005	-6.4e-04
	(0.009)	(0.009)	(0.009)	(0.008)	(0.007)	(0.009)	(0.007)
Friday	0.235***	0.219***	0.195***	0.153***	0.153***	0.153***	0.148***
	(0.012)	(0.011)	(0.011)	(0.009)	(0.008)	(0.010)	(0.009)
Saturday	0.346***	0.322***	0.284***	0.235***	0.216***	0.205***	0.187***
	(0.014)	(0.012)	(0.012)	(0.010)	(0.009)	(0.011)	(0.009)
Sunday	8.8e-04	0.008	0.005	0.004	8.0e-04	0.005	0.010
	(0.009)	(0.009)	(0.009)	(0.008)	(0.007)	(0.009)	(0.007)

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A6. Rob. Check: coefficient estimates from Spatial Durbin model for each lead period *k;* room without breakfast.

Dep. Variable: ln p	(1) k=7	(2) k=14	(3) k=28	(4) k=56	(5) k=84	(6) k=140	(7) k=224
ρ_k: W Ln P	0.465***	0.463***	0.482***	0.504***	0.451***	0.429***	0.288***
	(0.010)	(0.010)	(0.009)	(0.009)	(0.010)	(0.009)	(0.011)
γ_k: Ln Z	0.018***	0.015***	0.030***	0.037***	0.038***	0.034***	0.006
	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.006)
θ_k: W Ln Z	-0.068***	-0.065***	-0.069***	-0.069***	-0.048***	0.020**	0.053***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.009)	(0.012)
Tuesday	-0.010*	-0.004	-0.005	-0.002	-0.000	-0.001	0.002
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.006)
Wednesday	-0.011**	-0.004	-0.005	-0.001	-0.000	0.001	-0.002
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.006)
Thursday	0.004	0.007	0.001	0.003	0.007	0.006	0.001
	(0.006)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.006)
Friday	0.128***	0.127***	0.110***	0.093***	0.099***	0.097***	0.123***
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)
Saturday	0.201***	0.192***	0.164***	0.132***	0.137***	0.134***	0.161***
	(0.007)	(0.007)	(0.006)	(0.005)	(0.005)	(0.005)	(0.007)
Sunday	0.001	0.005	0.001	0.002	0.000	0.001	0.003
	(0.006)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.006)
Hotel FE	YES	YES	YES	YES	YES	YES	YES
Month-year FE	YES	YES	YES	YES	YES	YES	YES
Observations	17,029	18,107	19,261	20,407	20,992	21,160	19,739
R-squared	0.324	0.311	0.307	0.272	0.230	0.201	0.135
Number of groups	104	86	87	86	82	80	80

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A7. Direct and indirect effects from Spatial Durbin model in Table A6 for each lead period *k*.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Direct effect	k=7	k=14	k=28	k=56	k=84	k=140	k=224
Ln Z	0.016***	0.013***	0.028***	0.036***	0.037***	0.034***	-0.006
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)
Tuesday	-0.009*	-0.003	-0.004	-0.002	4.1-e04	-0.001	0.002
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Wednesday	-0.010**	-0.003	-0.005	-9.5e-04	-1.8e-04	9.8e-04	-0.001
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Thursday	0.004	0.007	8.0e-04	0.002	0.007	0.006	0.001
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Friday	0.129***	0.128***	0.111***	0.094***	0.100***	0.097***	0.123***
	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Saturday	0.202***	0.193***	0.165***	0.133***	0.138***	0.135***	0.161***
	(0.007)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)
Sunday	0.001	0.004	8.3e-04	0.001	2.6e-05	0.001	0.002
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Indirect effect	k=7	k=14	k=28	k=56	k=84	k=140	k=224
Ln Z	-0.109***	-0.107***	-0.105***	-0.100***	-0.056***	0.060***	0.076***
	(0.013)	(0.012)	(0.012)	(0.013)	(0.014)	(0.015)	(0.016)
Tuesday	-0.008*	-0.003	-0.004	-0.002	3.3e-04	-7.6e-04	9.6e-04
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)
Wednesday	-0.009**	-0.003	-0.005	-9.5e-04	-1.5e-04	7.2e-04	-6.1e-04
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)
Thursday	0.003	0.006	7.3e-04	0.002	0.005	0.004	5.6e-04
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)
Friday	0.110***	0.108***	0.101***	0.093***	0.080***	0.072***	0.049***
	(0.007)	(0.006)	(0.006)	(0.006)	(0.005)	(0.004)	(0.003)
Saturday	0.172***	0.163***	0.150***	0.132***	0.111***	0.099***	0.064***
	(0.009)	(0.008)	(0.007)	(0.007)	(0.006)	(0.005)	(0.004)
Sunday	0.001	0.004	7.5e-04	0.001	2.2e-05	8.0e-04	0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)
Total effect	k=7	k=14	k=28	k=56	k=84	k=140	k=224
Ln Z	-0.092***	-0.093***	-0.076***	-0.065***	-0.018	0.095***	0.082***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)	(0.016)	(0.018)
Tuesday	-0.018*	-0.007	-0.009	-0.004	-7.4e-04	-0.001	0.003
	(0.010)	(0.009)	(0.009)	(0.008)	(0.007)	(0.007)	(0.007)
Wednesday	-0.020**	-0.007	-0.010	-0.002	-3.3e-04	0.001	-0.002
	(0.010)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)
Thursday	0.008	0.012	0.001	0.005	0.013*	0.010	0.002
	(0.010)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)
Friday	0.239***	0.237***	0.213***	0.188***	0.181***	0.170***	0.173***
	(0.013)	(0.012)	(0.011)	(0.010)	(0.009)	(0.009)	(0.009)
Saturday	0.375***	0.357***	0.315***	0.266***	0.249***	0.234***	0.226***
	(0.015)	(0.014)	(0.012)	(0.011)	(0.010)	(0.010)	(0.010)
Sunday	0.002	0.008	0.001	0.003	4.8e-05	0.001	0.004
	(0.010)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A8. Direct and indirect effects from Spatial Durbin model in Panel A in Table 5 (first quarter of the year) for each lead period *k*.

First quarter	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Direct effect	k=7	k=14	k=28	k=56	k=84	k=140	k=224
Ln Z	0.023***	0.017***	-0.009	-0.010	-0.012	0.010	-0.059***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)	(0.006)	(0.013)
Tuesday	-0.013**	-0.009	-0.009	-0.006	-0.003	-0.007	-0.002
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.010)
Wednesday	-0.017***	-0.013**	-0.013**	-0.009*	-0.008	-0.010	-0.011
	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.010)
Thursday	-0.009	-0.008	-0.010*	-0.006	-0.003	-0.006	-0.006
	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.010)
Friday	0.068***	0.065***	0.052***	0.047***	0.050***	0.046***	0.097***
	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)	(0.011)
Saturday	0.125***	0.112***	0.090***	0.078***	0.071***	0.060***	0.102***
	(0.008)	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)	(0.011)
Sunday	0.006	0.006	0.007	0.005	0.002	0.009	0.017
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.010)
Indirect effect	k=7	k=14	k=28	k=56	k=84	k=140	k=224
Ln Z	-0.109***	-0.241***	-0.421***	-0.148**	-0.276***	0.025	-0.330***
	(0.042)	(0.040)	(0.051)	(0.058)	(0.067)	(0.058)	(0.067)
Tuesday	-0.026**	-0.018	-0.018	0.014	-0.008	-0.016	-0.002
	(0.004)	(0.011)	(0.011)	(0.014)	(0.013)	(0.014	(0.010)
Wednesday	-0.033***	-0.026**	-0.026**	-0.023	-0.018	-0.023	-0.011
	(0.012)	(0.011)	(0.012)	(0.014)	(0.013)	(0.014)	(0.010)
Thursday	-0.018	-0.015	-0.020*	-0.016	-0.007	-0.013	-0.006
	(0.012)	(0.011)	(0.012)	(0.014)	(0.013)	(0.014)	(0.010)
Friday	0.132***	0.127***	0.107***	0.117***	0.112***	0.100***	0.096***
	(0.015)	(0.015)	(0.015)	(0.018)	(0.016)	(0.017)	(0.013)
Saturday	0.243***	0.220***	0.185***	0.192***	0.162***	0.133***	0.101***
	(0.021)	(0.019)	(0.018)	(0.020)	(0.018)	(0.018)	(0.013)
Sunday	0.012	0.011	0.015	0.014	0.006	0.020	0.017*
	(0.012)	(0.012)	(0.012)	(0.014)	(0.013)	(0.015)	(0.010)
Total effect	k=7	k=14	k=28	k=56	k=84	k=140	k=224
Ln Z	-0.086**	-0.223***	-0.430***	-0.158***	-0.289***	0.036	-0.390***
	(0.043)	(0.042)	(0.052)	(0.060)	(0.070)	(0.060)	(0.071)
Tuesday	-0.039**	-0.028	-0.027	-0.020	-0.011	-0.023	-0.004
	(0.017)	(0.017)	(0.017)	(0.020)	(0.018)	(0.020)	(0.020)
Wednesday	-0.050***	-0.040**	-0.040**	-0.033	-0.026	-0.033	-0.023
	(0.018)	(0.017)	(0.017)	(0.020)	(0.019)	(0.021)	(0.020)
Thursday	-0.027	-0.023	-0.030*	-0.023	-0.010	-0.019	-0.012
	(0.018)	(0.017)	(0.017)	(0.020)	(0.019)	(0.021)	(0.020)
Friday	0.001***	0.192***	0.159***	0.165***	0.162***	0.146***	0.194***
	(0.022)	(0.021)	(0.021)	(0.024)	(0.022)	(0.024)	(0.024)
Saturday	0.368***	0.333***	0.276***	0.271***	0.233***	0.194***	0.203***
	(0.028)	(0.026)	(0.024)	(0.026)	(0.024)	(0.025)	(0.024)
Sunday	0.018	0.018	0.023	0.019	0.009	0.029	0.035
	(0.018)	(0.018)	(0.018)	(0.020)	(0.019)	(0.022)	(0.021)

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A9. Direct and indirect effects from Spatial Durbin model in Panel A in Table 5 (second quarter of the year) for each lead period *k*.

Second quarter	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Direct effect	k=7	k=14	k=28	k=56	k=84	k=140	k=224
Ln Z	-0.029***	-0.032***	-0.011***	0.006	-0.010**	0.008	0.014***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)
Tuesday	-5.7e-04	-0.002	4.2e-04	0.001	-7.7-e04	3.0e-04	-0.001
	(0.007)	(0.006)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Wednesday	-0.005*	-0.001	1.1e-04	0.004	0.001	0.003	-0.002
	(0.008)	(0.007)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Thursday	0.019**	0.020***	0.009	0.009*	0.009*	0.006	0.005
	(0.008)	(0.007)	(0.006)	(0.005)	(0.004)	(0.004)	(0.004)
Friday	0.154***	0.144***	0.094***	0.075***	0.075***	0.066***	0.108***
	(0.011)	(0.009)	(0.007)	(0.006)	(0.005)	(0.005)	(0.005)
Saturday	0.221***	0.205***	0.130***	0.106***	0.096***	0.082***	0.125***
	(0.012)	(0.010)	(0.008)	(0.006)	(0.005)	(0.005)	(0.005)
Sunday	0.011	0.012	0.008	0.004	0.001	-0.001	0.005
	(0.008)	(0.007)	(0.006)	(0.005)	(0.004)	(0.004)	(0.004)
Indirect effect	k=7	k=14	k=28	k=56	k=84	k=140	k=224
Ln Z	-0.101***	-0.165***	-0.152***	-0.104***	-0.101***	-0.051	0.012
	(0.023)	(0.020)	(0.021)	(0.025)	(0.027)	(0.032)	(0.015)
Tuesday	-5.6e-04	-0.001	5.4e-04	0.001	-8.5e-04	3.6e-05	-3.6e-04
	(0.007)	(0.005)	(0.007)	(0.005)	(0.005)	(0.005)	(0.001)
Wednesday	-0.005	0.001	1.5e-04	0.004	0.002	0.004	-6.7e-04
	(0.007)	(0.006)	(0.007)	(0.005)	(0.005)	(0.005)	(0.001)
Thursday	0.018**	0.017***	0.012	0.010*	0.010*	0.008	0.001
	(0.008)	(0.006)	(0.008)	(0.006)	(0.005)	(0.005)	(0.001)
Friday	0.148***	0.121***	0.124***	0.088***	0.083***	0.082***	0.033***
	(0.014)	(0.011)	(0.012)	(0.008)	(0.007)	(0.008)	(0.003)
Saturday	0.212***	0.174***	0.172***	0.123***	0.106***	0.102***	0.038***
	(0.018)	(0.014)	(0.014)	(0.010)	(0.008)	(0.008)	(0.004)
Sunday	0.011	0.010*	0.011	0.004	0.002	-0.002	0.001
	(0.007)	(0.006)	(0.007)	(0.006)	(0.005)	(0.005)	(0.012)
Total effect	k=7	k=14	k=28	k=56	k=84	k=140	k=224
Ln Z	-0.131***	-0.197***	-0.164***	-0.098***	-0.112***	-0.043	0.026*
	(0.024)	(0.021)	(0.022)	(0.026)	(0.029)	(0.034)	(0.016)
Tuesday	-0.001	-0.003	9.7e-04	0.002	-0.001	6.6e-04	-0.001
	(0.015)	(0.012)	(0.013)	(0.010)	(0.009)	(0.009)	(0.005)
Wednesday	-0.010*	0.002	2.6e-04	0.008	0.004	0.008	-0.002
	(0.015)	(0.013)	(0.013)	(0.011)	(0.009)	(0.009)	(0.005)
Thursday	0.038**	0.038***	0.022	0.019*	0.019*	0.014	0.007
	(0.016)	(0.014)	(0.014)	(0.011)	(0.009)	(0.009)	(0.005)
Friday	0.303***	0.265***	0.219***	0.163***	0.158***	0.148***	0.142***
	(0.024)	(0.019)	(0.018)	(0.014)	(0.012)	(0.012)	(0.007)
Saturday	0.434***	0.379***	0.302***	0.229***	0.203***	0.185***	0.164***
	(0.028)	(0.022)	(0.020)	(0.015)	(0.013)	(0.013)	(0.008)
Sunday	0.023	0.023*	0.020	0.008	0.003	-0.003	0.006
	(0.016)	(0.013)	(0.013)	(0.011)	(0.009)	(0.010)	(0.005)

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A10. Direct and indirect effects from Spatial Durbin model in Panel A in Table 5 (third quarter of the year) for each lead period *k*.

Third quarter	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Direct effect	k=7	k=14	k=28	k=56	k=84	k=140	k=224
Ln Z	-0.005	0.006	0.009**	0.009***	0.010***	4.3e-04	-0.025***
	(0.005)	(0.005)	(0.004)	(0.003)	(0.003)	(0.004)	(0.005)
Tuesday	0.003	0.006	0.007	-0.002	0.002	-0.002	3.8e-04
	(0.007)	(0.007)	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)
Wednesday	0.002	0.001	0.006	0.005	0.006	0.002	0.001
	(0.007)	(0.007)	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)
Thursday	-7.9e-04	0.006	0.008	4.6e-04	0.001	-0.003	-0.004
	(0.008)	(0.007)	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)
Friday	0.140***	0.145***	0.132***	0.123***	0.117***	0.098***	0.096***
	(0.009)	(0.008)	(0.007)	(0.005)	(0.005)	(0.004)	(0.004)
Saturday	0.192***	0.189***	0.179***	0.173***	0.157***	0.126***	0.118***
	(0.009)	(0.009)	(0.008)	(0.006)	(0.006)	(0.005)	(0.005)
Sunday	-0.024***	-0.017**	-0.014	-0.001	-5.0e-04	-0.002	-0.003
	(0.007)	(0.007)	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)
Indirect effect	k=7	k=14	k=28	k=56	k=84	k=140	k=224
Ln Z	-0.050***	-0.060***	-0.039***	-0.072***	-0.018*	0.021	0.097***
	(0.015)	(0.015)	(0.013)	(0.009)	(0.010)	(0.018)	(0.022)
Tuesday	9.1e-04	0.001	0.002	7.1e-04	6.9e-04	-9.8e-04	-1.2e-04
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Wednesday	5.6e-04	3.7e-04	0.002	0.001	0.002	8.0e-04	4.6e-04
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Thursday	-2.0e-04	0.001	0.003	1.3e-04	5.9e-04	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Friday	0.037***	0.036***	0.045***	0.036***	0.039***	0.038***	0.031***
	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)
Saturday	0.050***	0.047***	0.061***	0.050***	0.052***	0.048***	0.039***
	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)	(0.004)	(0.004)
Sunday	-0.006***	-0.004**	-0.004**	-4.7e-04	-1.6e-04	-9.8e-04	-0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Total effect	k=7	k=14	k=28	k=56	k=84	k=140	k=224
Ln Z	-0.055***	-0.054***	-0.030**	-0.063***	-0.008	-0.020	0.072***
	(0.017)	(0.016)	(0.014)	(0.010)	(0.010)	(0.019)	(0.023)
Tuesday	0.004	0.008	0.009	-0.003	0.002	-0.003	-5.1e-04
	(0.009)	(0.009)	(0.007)	(0.005)	(0.005)	(0.005)	(0.004)
Wednesday	0.002*	0.001	0.009	0.006	0.008	0.002	0.001
	(0.009)	(0.009)	(0.007)	(0.005)	(0.005)	(0.005)	(0.004)
Thursday	-0.001	0.007	0.011	5.9e-04	0.002	-0.004	-0.006
	(0.010)	(0.009)	(0.007)	(0.006)	(0.005)	(0.005)	(0.004)
Friday	0.177***	0.182***	0.177***	0.159***	0.156***	0.137***	0.128***
	(0.012)	(0.011)	(0.010)	(0.008)	(0.008)	(0.007)	(0.007)
Saturday	0.243***	0.236***	0.240***	0.224***	0.209***	0.175***	0.157***
	(0.013)	(0.013)	(0.012)	(0.010)	(0.009)	(0.008)	(0.007)
Sunday	-0.031***	-0.021**	-0.019	-0.002	-6.7e-04	-0.003	-0.004
	(0.010)	(0.009)	(0.007)	(0.006)	(0.005)	(0.005)	(0.005)

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A11. Direct and indirect effects from Spatial Durbin model in Panel A in Table 5 (fourth quarter of the year) for each lead period *k*.

Fourth quarter	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Direct effect	k=7	k=14	k=28	k=56	k=84	k=140	k=224
Ln Z	-0.017***	-0.011**	-0.009	0.023***	0.029***	0.041***	0.037
	(0.006)	(0.005)	(0.005)	(0.004)	(0.005)	(0.006)	(0.008)
Tuesday	-9.9e-04	0.001	0.001	0.002	0.008	0.009	0.007
	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Wednesday	0.001	0.002	6.3e-04	-0.001	0.006	0.010	0.008
	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Thursday	0.010	0.011*	0.006	0.007	0.016**	0.016***	0.014
	(0.007)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)
Friday	0.090***	0.075***	0.070***	0.058***	0.063***	0.062***	0.063***
	(0.008)	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
Saturday	0.117***	0.102***	0.086***	0.064***	0.064***	0.080***	0.083***
	(0.009)	(0.008)	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)
Sunday	9.0e-04	6.8e-04	-0.001	-7.9e-04	-0.001	-0.002	-0.004
	(0.007)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)
Indirect effect	k=7	k=14	k=28	k=56	k=84	k=140	k=224
Ln Z	-0.236***	-0.355***	-0.340***	-0.243***	-0.400***	0.068	0.286***
	(0.035)	(0.034)	(0.038)	(0.036)	(0.045)	(0.044)	(0.047)
Tuesday	-0.001	0.002	0.001	0.004	0.015	0.021	0.013
	(0.009)	(0.009)	(0.008)	(0.010)	(0.010)	(0.013)	(0.010)
Wednesday	0.002*	0.004	9.5e-04	-0.002	0.010	0.022	0.014
	(0.009)	(0.009)	(0.008)	(0.010)	(0.010)	(0.013)	(0.010)
Thursday	0.015	0.016*	0.010	0.013	0.028**	0.037***	0.025**
	(0.010)	(0.009)	(0.009)	(0.010)	(0.011)	(0.014)	(0.010)
Friday	0.129***	0.114***	0.107***	0.102***	0.110***	0.138***	0.110***
	(0.013)	(0.012)	(0.012)	(0.012)	(0.014)	(0.017)	(0.013)
Saturday	0.168***	0.155***	0.130***	0.114***	0.112***	0.178***	0.144***
	(0.016)	(0.015)	(0.013)	(0.013)	(0.014)	(0.019)	(0.014)
Sunday	0.001	0.001	-0.001	-0.001	-0.002	-0.004	-0.008
	(0.010)	(0.009)	(0.009)	(0.010)	(0.010)	(0.014)	(0.010)
Total effect	k=7	k=14	k=28	k=56	k=84	k=140	k=224
Ln Z	-0.253***	-0.366***	-0.349***	-0.219***	-0.270***	0.110**	0.323***
	(0.037)	(0.036)	(0.039)	(0.037)	(0.047)	(0.046)	(0.049)
Tuesday	-0.002	0.003	0.002	0.006	0.023	0.031	0.020
	(0.016)	(0.015)	(0.014)	(0.015)	(0.016)	(0.019)	(0.016)
Wednesday	0.004*	0.006	0.001	-0.003	0.016	0.032	0.022
	(0.016)	(0.015)	(0.014)	(0.015)	(0.016)	(0.020)	(0.016)
Thursday	0.026	0.027*	0.017	0.020	0.043**	0.053***	0.039**
	(0.017)	(0.015)	(0.015)	(0.015)	(0.017)	(0.020)	(0.016)
Friday	0.219***	0.190***	0.177***	0.160***	0.173***	0.200***	0.174***
	(0.021)	(0.019)	(0.018)	(0.018)	(0.021)	(0.024)	(0.020)
Saturday	0.286***	0.258***	0.217***	0.178***	0.176***	0.259***	0.227***
	(0.025)	(0.022)	(0.019)	(0.019)	(0.020)	(0.025)	(0.020)
Sunday	0.002	0.001	-0.002	-0.002	-0.003	-0.006	-0.012
	(0.017)	(0.016)	(0.015)	(0.015)	(0.017)	(0.020)	(0.017)

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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