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The effect of disruptive change on the spatial variation of commercial rental prices: The case of the COVID-19 pandemic

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A R T I C L E I N F O

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A B S T R A C T

This study examines spatial variations in the rental price of commercial premises and the factors that explain these variations in the event of a disruptive change such as the COVID-19 pandemic. A novelty of this work is the methodology used to determine the form and radius of influence on these prices (monotonically decreasing buffer with threshold) of heritage monuments as tourist attractions. The methodology is applied to a case study of the city of Granada, Spain, although it could be extrapolated to other cities displaying similar characteristics. The results indicate that commercial rental prices varied in a non-uniform manner throughout the city during the COVID-19 pandemic and that the main streets and prime locations were the most affected. The proposed methodology can be used to guide political and business decision-making in other disruptive situations.

1. Introduction

Several studies have highlighted the negative effects of the COVID-19 pandemic on the real estate sector (Balemi et al., 2021; Beze and Thiel, 2024; Tanrıvermiş, 2020; Zakaria and Ries, 2023), especially on housing prices (Bricongne et al., 2023; Yilmazkuday, 2023; Zhou et al., 2022). However, studies on how commercial real estate prices were affected are less common. In general, these studies indicate that the effects were very significant, although they varied across regions and property types. For example, the retail and hospitality sub-sectors experienced very pronounced declines, while the industrial and residential sub-sectors were more resilient. In particular, and in line with this article, very sharp decreases ranging from 15% to over 30% were observed in the rental prices of retail properties in the Asia-Pacific region and European markets (Allan et al., 2021; Hoesli and Malle, 2022), while decreases of 14–19% were observed in the US (Van Dijk et al., 2020). Few studies have examined changes in the spatial distribution of these prices (Bhat et al., 2023; Chen and Luo, 2022; Yang et al., 2023). Even fewer have used a spatial approach to analyze the effects of the COVID-19 pandemic on the business activity of commercial premises, one of the main economic drivers of cities (Rosenthal et al., 2022; Wen et al., 2022; Yiu et al., 2024). In this regard, it is important to note that commercial rentals are a form of income for owners of the premises and an expense on tenants' income statement. Given that commercial rental prices are an important indicator of economic activity and contribute to a city's GDP, it is of interest to study the factors that affect these prices. To determine the implicit price of these factors, which are generally of a structural and locational nature, the hedonic model has classically been used (Rosen, 1974). In cities with a strong tourism sector, the price of commercial premises is related to their proximity to areas with tourist attractions, such as heritage monuments, since the demand for the products and services they offer (restaurants, bars, souvenirs, etc.) is expected to be greater (Cheung and Yiu, 2023). However, the outbreak of the COVID-19 pandemic may have affected not only the variation in prices, but also the importance of factors that explain the rental prices of these premises. In addition, the pandemic may have caused changes in the spatial distribution of rental prices and had a greater negative impact in some areas than in others (Liu et al., 2022; Rosenthal et al., 2022; Ryan et al. 2022, 2022, 2022; Yiu et al., 2024). For example, rental prices may have been more affected in prime locations than in other areas, as was the case in some Spanish cities (Idealista/news, 2022). Along the same lines that point to the fact that prime locations experienced a greater decline in attractiveness, Rosenthal et al. (2022) estimated that commercial rents in urban areas of the US declined by more than 1.5% per kilometer from the city center before COVID, but after the onset of COVID this gradient fell by approximately 15% in transit cities heavily dependent on subway and light rail due to mobility restrictions and the fear of contagion on mass transit. In tourist cities where tourism

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is concentrated in these prime areas, commercial rental prices may have been more affected by the pandemic (Cheung and Yiu, 2023; Frago, 2021), since there was a drastic drop in visitors due to the mobility restrictions implemented during the COVID-19 pandemic.

The pandemic's impact on commercial real estate prices was influenced by factors such as containment measures, the spread of the virus and vaccination rates, the region, or the typology of geographical areas and property types (Deghi et al., 2022). However, the rental prices of commercial premises may have been affected not only by health issues during the crisis, but also by the use of teleworking, the absence of shoppers, the economic recession and the increase in e-commerce (Beckers et al., 2021); all of which led to a significant drop in business activity and the consequent decrease in investment in commercial premises (Balemi et al., 2021; Guthrie et al., 2021; Hoesli and Malle, 2022). The pandemic also affected the dynamics of the commercial premises themselves, which saw higher vacancy rates and the closure of small establishments, while large brands took advantage of the situation to reduce the number of franchised premises. In Spain, for example, vacancy rates reached as high as 30% compared to the average of the previous three years, with the consequent decrease in rents provided by this type of real estate. According to the Bank of Spain (de España, B., 2021), the maximum relative rental prices of commercial premises was reached in 2019, while price declines up to the second quarter of 2021.[1] According to different press media (Idealista/news, 2022), the average rental prices of commercial properties decreased by 7%–30%, with prime locations being the most affected.

Given the importance of the commercial sector and the variations in rents from leased properties during the COVID-19 pandemic, it is of interest to study the factors that explain such variations. To this end, this study compares the effect of structural and locational factors that may explain the rental prices of commercial properties and the rents they provided their owners before (2019) and during (2021) the COVID-19 pandemic, using the city of Granada, Spain (a services city with a strong commercial and tourism sector), as an example or practical case.

This work is novel in that it analyzes spatial variations in the rental price of commercial premises (*RPCP* hereafter) but also because of its methodological contributions, since few or no studies have examined and quantified the effect of tourism heritage (considering monuments as tourist attractions) on these prices and its area of influence (buffer). Furthermore, this methodology could be generalizable and applied to other cities of similar characteristics, places of attraction other than heritage monuments, and in situations other than the pandemic that may cause an abrupt change in the spatial structure of prices, such as an economic crisis, a real estate crash, a social or military conflict, or less serious situations, such as significant changes in government policies, among others.

As concerns the main findings of this study, it is important to highlight the impact of the pandemic on both the structural and locational characteristics that explain the *RPCP*. In this regard, a strong decrease was observed in the effect of certain structural variables, such as the visibility in store windows of products offered by the commercial premises or the modernization and refurbishment of the premises, both of which may have been influenced by mobility constraints. As for the effects of locational factors, it is worth noting the significant decrease in the *RPCP* of premises located on main streets and prime areas. In addition, it should be noted that although the proximity of commercial premises to heritage monuments is positive, its importance decreased during the pandemic, probably due to the marked drop in tourist demand.

[1] After the onset of the pandemic, prices bottomed out in the second quarter of 2021. Therefore, this is the quarter with the largest differences with respect to the pre-COVID prices of the second quarter of 2019 to which they are compared in this paper (in the absence of official statistics, see Fernández--Cerezo et al., 2021; Lamas and Romaniega, 2022; Savills Aguirre Newman, 2021).

In terms of policy implications, the results of this study can be of aid in decision-making by public and private managers. In the public sphere, the findings could be useful in a variety of areas, including urban planning, taxation on commercial premises, funding to rehabilitate and maintain city centers, housing policies, accessibility, gentrification, touristification, and other problems affecting historical city centers. From the viewpoint of private managers, the availability of estimated prices of commercial premises can aid them in making business decisions related to the location of commercial establishments, as well as investments in the improvement, purchase, sale, and lease of this type of urban real estate.

The study is structured as follows. The second section provides a review of the literature. The third section presents the research methodology, research questions and hypotheses, and explains the types of buffers that determine the threshold of a heritage zone. The fourth section shows the study area while the fifth section shows the data and results of the econometric models. The main conclusions and implications of the study results are presented in the last section.

2. Literature review

The leasing of commercial properties carries a strong weight in the real estate and financial markets. In this regard, the literature has highlighted the importance of speculation in the commercial property market for the growth of this type of assets in the portfolios of large investors (Fabozzi et al., 2013). Also from this financial point of view, Geltner (1990) indicated that entrepreneurs' decision to lease rather than acquire commercial properties is related to company's lower risk of return and cash flow as it allows them to implement business ideas with less risk.

The real estate assets market and the stock market function in much the same way. For example, the rental price of a commercial space, which is the price of the right to use the space for a given period of time, is similar to the profits gained from financial assets. Thus, it is possible to estimate the value of a space as the capitalization rate of the rental price of that space. In other words, this value is a proxy variable for the financial profitability of the premises, although it can also be estimated using hedonic models. Classically, the hedonic model has been used in the real estate field to estimate house prices (Chica-Olmo et al., 2019; Khoshnoud et al., 2023) and even to explain house prices in terms of the price of commercial premises and the accessibility of these premises to houses for which prices need to be estimated (Shen et al., 2020; Song and Sohn, 2007).

As indicated above, the hedonic model is used to determine the effect or implicit price of various factors that explain real estate prices. A feature of interest of these models is that they are widely used both by professionals in the field and the public administration for the mass appraisal of these assets in an objective and efficient manner (Binoy et al., 2022; Dearmon and Smith, 2024). However, the hedonic model has not been widely used for the analysis of commercial real estate (Humaran Nahed et al., 2008; Özyurt, 2014; Zhang et al., 2015), and even less so for the analysis of commercial rental properties (Liang and Wilhelmsson, 2011; Usman et al., 2021).

2.1. Spatial dependence in the modeling of commercial real estate values

Various econometric methods can be used in hedonic modeling. The most widely used method is ordinary least squares (OLS) regression. However, the OLS method may provide biased and inefficient parameter estimates in the presence of spatial dependence (or spatial autocorrelation) because the model is not well specified (Dubin, 1998). To avoid these problems, several models have been proposed to analyze and take into account spatial dependence and spatial heterogeneity, among them spatial lag and spatial error models (Anselin, 2013; Deppner and Cajias, 2024), geographically weighted regression (Fotheringham et al., 2015; Garang et al., 2021), neural networks (Ding et al., 2024; Tabales et al., 2017), or machine learning algorithms (Lu et al., 2024). In particular, the use of spatial dependence for modeling real estate values has been widely addressed in the literature (Anselin and Lozano-Gracia, 2009; Dubin et al., 1999; Ismail, 2006; Moralı and Yılmaz, 2022; Yiu and Tam, 2004), especially with respect to the housing market, but less so in the commercial real estate market. Spatial dependence is thought to be caused by the effect of locational characteristics of the environment and by the spatial contagion effect among sellers. It is assumed that nearby properties are affected similarly by locational factors and face-to-face contagion, leading to similar property values. Conversely, as the distance between properties increases, these variables are less similar and contagion is lower, causing their values to be less similar. According to the classic work of Derycke (1979), locational characteristics that influence real estate are in a more or less proximate environment, such as local accessibility and transportation; accessibility to the central business district (CBD); the physical and urban environment; neighborhood services (schools, hospitals, commercial establishments); the social, economic, and demographic context; public safety; proximity to places of interest (parks, recreational areas, monumental areas); residential density and urban-planning laws.

Although somewhat scarcer, the literature also supports the use of spatial dependence analysis to obtain good explanatory and predictive models for the study of commercial real estate rents and prices (Usman et al., 2021). In the specific case of rents, several investigations have maintained the base hedonic model to analyze the impact of structural (constructive) and locational characteristics on the price of commercial establishments and introduce some novelties or additional characteristics as well as methodological variants. This is the case of the seminal work of Sirmans and Guidry (1993), who used weighted least squares regression analysis and included attractiveness to customers and general economic conditions as additional factors. Hui et al. (2007) conducted similar research using a hedonic regression model in which the additional factor was the market position of the establishment (district center, local center, estate center, or shop). Liang and Wilhelmsson (2011) used hedonic and spatial econometric models and included various accessibilities and the district in which the property was located as locational characteristics. Ke and Wang (2016) implemented the base hedonic model, adding market conditions and potential attraction. In a spatial hedonic framework, Orr and Stewart (2022) applied a spatial fixed-effects panel model to investigate high street retail rents and included only neighborhood locational variables, such as use, investor diversity, and spatial accessibility. Research on commercial real estate prices has a similar focus to the literature on rents. Humaran Nahed et al. (2008), for example, used the base hedonic model and included constructive and locational characteristics of commercial real estate, highlighting the importance of level of accessibility and visualization from the public road. Özyurt (2014) used a spatial econometric model that included the appraised capital value prior to the sale and the commercial property subsector (retail, office, industrial, and residential) as additional factors. Additionally, Zhang et al. (2015) incorporated constructive variables in their spatial econometric model (a spatial error model modified by fuzzy mathematics to estimate the spatial weights matrix) to perform a mass valuation of real estate.

2.2. Factors considered in the modeling of rental prices of commercial premises

In line with the literature discussed above, structural and locational factors that may explain the rental price of commercial premises have been considered in this paper. Structural factors include the surface area and state of conservation of the premises, whether the premises have been renovated, the number of store windows, and whether there is a stockroom or other types of spaces, among other factors (Formánek and Sokol, 2022; Humaran Nahed et al., 2008; Liang and Wilhelmsson, 2011; Özyurt, 2014; Pivo and Fisher, 2011; Zhang et al., 2015). These factors are usually easier to measure objectively than locational factors. However, locational factors have a strong effect on rental prices because the decision to set up a business in a commercial location that enables direct contact with customers involves an important location strategy to maximize the number of potential customers and improve the profitability of the location as an investment value (Fabozzi et al., 2013). Thus, as indicated above, it is essential to include the geographic dimension in the analysis of the decision-making process for retail location (Aversa et al., 2021; Hernandez, 2007). In addition, although the growth of retail e-commerce may mean that store location is becoming a less important factor than in the past, it should be noted that different consumer types (e.g., by age) exhibit different e-commerce adoption rates (Hood et al., 2020), so store location remains a key determinant of business viability (Hoesli and Malle, 2022).

In fact, the classical theories of Von Thünen (1966) and Alonso (1964), which have served as a basis for the subsequent development of agglomeration economies, already highlighted the need to consider the spatial location of commercial businesses, since location has a direct impact on sales (Formánek and Sokol, 2022; Lu et al., 2024; Yiu et al., 2024) and hence on the price and rent of the premises (Liu et al., 2018). In addition, the consumer theory (Lancaster, 1966) posits that buyers of real estate not only pay for the property but also other locational attributes, such as services, accessibility, or walkability. In accordance with these theories, distance has traditionally been the most widely used variable to measure accessibility to the most demanded services or the CBD and it has been shown that the price of real estate decreases as the distance increases (Cvijanović et al., 2022; Garang et al., 2021; Kopczewska and Lewandowska, 2018; Liang and Wilhelmsson, 2011).

Additionally, the price of commercial premises is generally expected to be positively related to the number of pedestrians on the street where the property is located, since this increases rental prices in the most privileged locations (Kang, 2016; Orr and Stewart, 2022; Tinessa et al., 2021). The proximity of premises to streets with the greatest influx of potential customers will also have an impact on the company's sales. In this regard, greater walkability is associated with higher sales and retail rental prices, as higher operating income is expected. Consequently, tenants are willing to pay a higher price for commercial properties in more walkable locations (Shin and Woo, 2024; Yim Yiu, 2011), as they are considered a low-risk investment (Pivo and Fisher, 2011). Moreover, the pedestrianization of city centers attracts both the city's inhabitants and tourists, as well as having obvious environmental benefits and contributing to sustainability, the circular economy, mobility, and the proximity economy (Collazo, 2020).

Another factor expected to be positively related to rental prices is accessibility to places of attraction, which in our case are heritage sites. It is well known that highly attractive cities due to their cultural, historical, and architectural heritage have a higher tourism demand (Gao et al., 2023; Mariani and Guizzardi, 2020). The influx of tourists in areas with more heritage monuments has a clear effect on commercial activity, sales, and the price of premises (Berg, 2017; Cheung and Yiu, 2023; Özdemir and Selçuk, 2017). As some works have highlighted, the COVID-19 pandemic had a strong impact on tourism activity, particularly in the heritage tourism sector and the commercial real estate market in eminently tourist destinations (Tanrıvermiş, 2020), as this study will also show.

2.3. Spatial dependence in marketing research: analysis of retail location

Given the importance of the spatial dimension and locational factors in the analysis of retail location, this subsection reviews the literature on spatial dependence in marketing research. Indeed, ignoring spatial effects can lead to biased, inconsistent, and/or inefficient estimates, as noted by Plummer (2010), who also cautioned that the measures used in entrepreneurship and management research are often subject to spatial dependence. Therefore, incorporating a spatial dependence analysis is crucial in various areas of marketing, such as the study of the location of commercial establishments, spatial competition, spatial segmentation of markets, or consumer behavior. Given that this paper focuses on factors that affect the valuation of commercial establishments, particularly those of a locational nature, attention is placed on works that consider the most appropriate locations of commercial establishments based on spatially observed variables, such as population density, sociodemographic characteristics, or proximity to competitors (Gonzlez-Benito and Gonzlez-Benito, 2005). As is well known, store location is a crucial aspect in the strategy of retail companies, and spatial modeling provides valuable tools to optimize these decisions. There are several works in this line, among them Thrall (2002), who used data on neighborhood characteristics to improve store location decisions, and Kuo et al. (2002), who analyzed demographic variables, pedestrian traffic, competition, and accessibility to guide the decision-making process. Similarly, Sung (2022) examined how the physical environment and socioeconomic and demographic characteristics of neighboring areas and proximity to other stores and services affect retail sales. Chan et al. (2007) focused on the proximity of competitors and proposed an econometric model of location and price competition among retail outlets. The authors constructed a location model based on the premise that local potential demand is influenced by the demographic characteristics of the neighborhood. Along the same line of incorporating spatial competition in location decision-making, Netz and Taylor (2002) analyzed the tendency to locate retail outlets at a certain distance from competitors and considered entry costs, demand patterns, and competition indicators. Additionally, Koster and Rouwendal (2013) explained the location of retail outlets within the city, considering agglomeration benefits and commuting costs.

These studies underline the importance of the spatial dimension and application of spatial models in marketing research since they estimate market responses better, select explanatory and predictive models more accurately, and provide a deeper understanding of spatial patterns in markets, all of which improves information in the decision-making process.

3. Research methodology

Commercial economic activities, particularly those related to tourism, benefit from their proximity to places of tourist attraction, such as heritage monuments. In some cities these monuments are located near each other, creating heritage zones. In turn, the price of commercial premises will be affected by their distance to these heritage monuments. In this regard, the real estate literature has examined the radius of influence of heritage monuments on real estate income or prices, including house prices (Franco and Macdonald, 2018; Gong et al., 2020), hotel room rates (Chica-Olmo, 2020), or the price of private Airbnb accommodations (Ayouba et al., 2020). However, few or no studies have quantified the radius of influence of heritage monuments on the rental price of commercial premises.

Typically, the effect of heritage monuments (or other places of attraction) on property prices has been specified in hedonic regression models by measuring the Euclidean distance between the monument and the properties. For the sake of simplicity, most studies have shown a monotonically decreasing relationship between the distance to the point of interest and the property, without considering a radius of influence as this influence extends across the entire city (Ahlfeldt and Maennig, 2010). However, this effect may decrease at a certain distance (threshold) with respect to the heritage monument (Kee, 2019; Franco and Macdonald, 2018), giving rise to a buffer. The threshold of the buffer indicates the radius of influence of the place of attraction. This is usually predetermined in a subjective manner (Zhang and Dong, 2018) as very few works have proposed an objective method to determine such a threshold (Chica-Olmo et al., 2019).

In addition, it should be noted that the geography and regional science literature considers that the spatial influence between objects in space can decay exponentially, so this distance decay can often offer a more a realistic mechanism for capturing influence or interaction across space with respect to the heritage sites or other tourist attractions (Tan et al., 2023). This exponential relationship can be modeled econometrically using a semilogarithmic model, such as the one specified here.

Classically, it has been usual to use geographical information systems (GIS) to obtain buffers zones (Longley et al., 2001), which provide two types of buffers known as “single buffers” or “multiple ring buffers” (donuts) depending on whether one or more concentric rings are considered at the point of interest. To obtain both types of buffers, it is necessary to previously indicate the radius of the buffer zone (single ring) or radius of each ring (multiple ring), which are usually arbitrary (Perchoux et al., 2016). In both cases, the effect of the place of attraction on the variable of interest is considered to be discrete, that is, the effect will be the same on all properties within the radius of influence (threshold) of the place of attraction, which is the case of the single ring or within each annulus of the multiple ring. In addition to these two classic cases, a less restrictive option than the previous ones, would be to consider that the effect of the place of attraction is monotonically decreasing (with threshold). In these three cases, it is considered that properties outside the radius of influence will not be affected by the place of attraction.

A novelty of this work is that three perspectives are compared to analyze the spatial interaction between heritage monuments (which are our points of attraction) and the *RPCP* (see Fig. 1): 1) the effect is monotonically decreasing throughout the city (classic case in the literature; Fig. 1a); 2) a single buffer ring, that is, the effect is constant inside the buffer and disappears outside the buffer (Fig. 1b); and 3) a buffer with a monotonically decreasing effect inside the buffer which remains constant outside the buffer (Fig. 1c), which is the most novel case.

3.1. Research questions and hypotheses

The context in which the research questions and hypotheses are formulated is marked by the adverse impact of the pandemic on the commercial real estate market, particularly on the *RPCP* in the retail sector. As mentioned above, the negative effects stem from factors such as the reduction in shoppers in brick-and mortar stores, the containment measures that limited mobility, the increase in teleworking and online shopping, and the economic recession due to the stoppage or slowdown of many activities. To deepen our understanding of changes in the *RPCP* during the pandemic, the analysis employs an econometric modeling approach in which the spatial dimension is a key element. This allows for an empirical assessment of how the pandemic affected the spatial distribution of the *RPCP*. Given the scarcity of research in this area, as indicated in the literature review, this represents a novel contribution. The analysis places special emphasis on spatial modeling alternatives to assess how the proximity of commercial premises to attractions, such as heritage monuments, influences the *RPCP*. Further insights into *RPCP* variation are gained by comparing econometric models, enabling us to determine whether the locational and structural factors that explained the *RPCP* before the pandemic continued to influence this variable during the pandemic. Additionally, we quantify the differences in the level of influence or size of the effects of these explanatory factors and consider which pandemic-related changes could be driving these differences.

Additionally, given the importance of spatial dependence in the study of commercial real estate valuation, as highlighted in the literature review, we not only examine variations in the geographic distribution of the *RPCP*, but also discuss the reasons that might explain these changes. The research questions and hypotheses discussed in this section address all aspects related to the change in *RPCP* behavior before and during the COVID-19 pandemic, including the magnitude of the variations and changes in both the spatial distribution and influence of the explanatory factors.

In line with the above, the first research question we pose is.

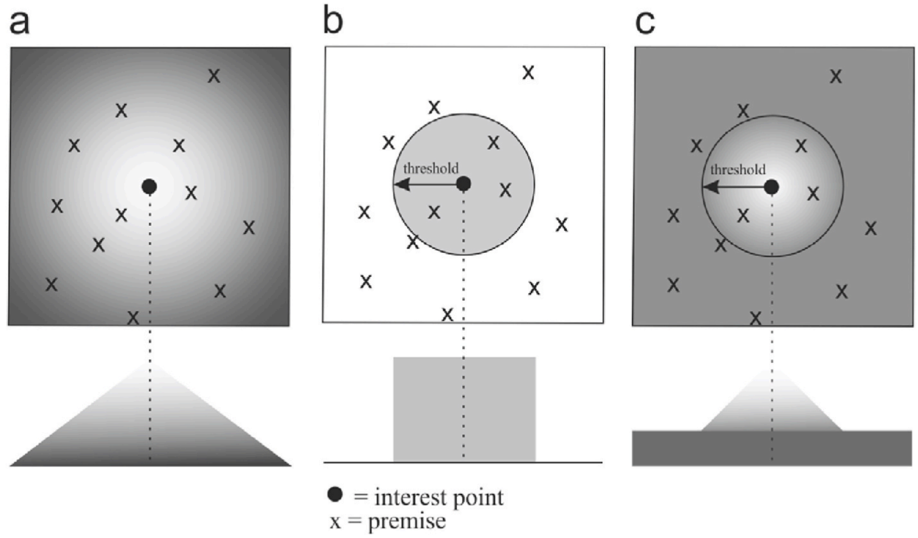

Fig. 1. Effect of place of attraction (heritage landmark) on commercial premises (x): a = monotonically decreasing; b = single buffer ring, and c = monotonically decreasing buffer with threshold.

- Q1. Did the pandemic affect the *RPCP* equally throughout the urban space?

The pandemic may have altered the attractiveness to customers from different zones of the urban area of a city. Thus, variations in *RPCP* would not necessarily be uniform across the city, but some areas may have experienced a greater negative impact than others. This spatial heterogeneity can be manifested in different ways. For example, between prime areas and those of a lower category; between areas close to the CBD and outside the city; between tourist and non-tourist areas; between pedestrian areas and those without traffic restrictions, etc. In this context, the pandemic may also have modified the *RPCP* gradient across the city.

Moreover, the decision on where to locate a commercial establishment is crucial to attract the greatest number of customers and increase the chances that the business will thrive. This decision entails not only paying to occupy the property but also paying for the attributes associated with the location, such as accessibility, pedestrian density, level of commerce, surrounding characteristics, etc. Given the importance of locational factors in explaining commercial real estate values, it is relevant to inquire into whether the pandemic has changed the way these factors influence the *RPCP*, that is.

- Q2. Was the effect of locational characteristics on the *RPCP* the same before and during the pandemic?

As mentioned above, the structural characteristics of establishments are also key to explaining commercial real estate values. Therefore, it is important to determine whether the pandemic has altered how these features influence real estate values. Specifically, we examine if certain structural characteristics may have had a weaker effect on the *RPCP*, including: i) store fronts, due to the sharp decline in pedestrian traffic caused by mobility restrictions; ii) the need to modernize premises, as the drop in commercial activity in brick-and-mortar shops lowered sales expectations; iii) the availability of customer restrooms, given reduced demand and concerns about hygiene; or iv) the layout of premises on a single floor rather than multiple floors, as the latter allows for greater physical distancing between clients). In contrast, the effect of other structural characteristics on the *RCPC* may have increased, such as the surface area of the premises, since larger spaces create the feeling of openness and allow for social distancing.

This leads us to the following question.

Q3. Was the effect of structural characteristics on the *RPCP* the same before and during the pandemic?

The search for answers to these questions has led to the hypotheses presented below. Several of the studies cited above found that in the wake of the pandemic and the resulting drop in shoppers in brick-and mortar stores, the value of commercial real estate in prime locations was affected more negatively, as more expensive stores need a higher revenue stream to avoid losses. This may also have been influenced by the fact that shoppers opted for nearby establishments, thus avoiding the crowds in prime areas that may be pedestrianized as well as having to travel, often by public transport. In tourist cities, prime areas may coincide with areas with a high influx of visitors, so the drop in the number of visitors may also have influenced the decline in commercial real estate values. All these factors led us to consider the following hypothesis.

- H1. Being located on a main street or in a prime area has a positive effect on the *RPCP*, but this effect decreased during the pandemic.

Given that commercial real estate values are positively correlated with pedestrian traffic, the mobility restrictions and fear of personal interaction caused by the pandemic, which reduced pedestrian traffic, may have diminished the importance of this factor, leading to the following hypothesis.

- H2. A higher pedestrian density in the area where a commercial property is located increases the *RPCP*, but this effect decreased during the pandemic.

In line with the above, given that proximity to heritage sites (as places of attraction) has a positive influence (up to a certain distance) on commercial real estate values in cities with a strong tourism sector, the sharp drop in tourists caused by the pandemic could have significantly reduced this influence, thus leading us to the following hypothesis.

- H3. The proximity of a commercial premise to a heritage landmark had a positive influence on rental prices before the pandemic, but this effect decreased during the pandemic and became insignificant.

4. Study area and data

To illustrate in a practical manner the methodology developed in this work for analyzing the research questions and testing the formulated hypotheses, we study the case of Granada. However, this approach could also be implemented in other cities. The city of Granada is located in the region of Andalusia (southern Spain) and has a population of nearly a quarter million inhabitants (more than half a million if the metropolitan area is considered). The commercial and services sector employs approximately 50% of the total number of social security affiliates, indicating the importance of this sector in the city's economic activity. This sector is largely driven by the fact that the city is the main commercial hub of the province and the large number of tourists that visit it. In the year before the pandemic (2019), the city received a record two million tourists. In 2021, however, the number of visitors dropped by half. These data rank the city as the fifth most visited city in Spain (INE-Instituto Nacional de Estadística, 2022); one of the world's leading countries in number of tourists (World Tourism Organization, 2021). In addition, the city boasts several monuments designated World Heritage Sites by the UNESCO, among them the Alhambra, the Generalife, and the Albayzín district.

To examine variations in the *RPCP* between the pre-COVID and COVID period, two perspectives will be considered. Firstly, a classical perspective, which analyzes how the effects of some explanatory factors of prices changed and, secondly, a spatial perspective to determine changes in the spatial distribution of prices. To this end, two samples were used: a pre-COVID sample obtained during the second quarter of 2019 that includes 172 commercial premises and a during-COVID sample obtained in the second quarter of 2021 that includes 254 commercial premises (both samples include vacant commercial premises). The same quarters were chosen in both years to avoid a possible seasonality effect on rental prices. The same variables were observed in both periods on the Idealista.com real estate portal; the most widely used source of real estate information in Spain according to the Alexa Internet ranking of commercial website traffic data analytics. Both samples included the total number of rental premises in the city and complete information on them as advertised on Idealista.com.

In line with other studies (Deschermeier et al., 2014), a hedonic model is proposed in which the explained variable is the monthly *RPCP*. Consistent with the literature review, the explanatory variables were divided into two groups: structural variables and locational variables. The description, units of measurement, and sources of the variables are shown in Table 1.

The coefficients of the structural variables are expected to have a positive and significant sign in the model, except for the coefficient of the variable *Renovation*, which is expected to be negative and significant. Considering that commercial premises tend to be located near main streets (Wang et al., 2014), two locational variables were included in the model: 1) *Prime_street*, which is a binary variable indicating whether the premises are located on a street that the City Council considers to be a prime commercial location for tax purposes; and 2) *Main_street*, which is a binary variable indicating that the premises are located on a principal thoroughfare of the city, regardless of its tax treatment. Additionally, given that walkability is expected to have a positive effect on the *RPCP* as mentioned above, the variable *Pedestrian_dens* was also included in the model. This variable captures the index of pedestrian street density and is expected to have a positive influence on the *RPCP*. In addition to the accessibility variable classically considered in other studies, such as distance to the CBD, the accessibility of commercial premises to main heritage monuments was considered given their importance in the city's tourism sector.

To analyze the effect of accessibility on the *RPCP*, three explanatory variables were considered, in line with the three perspectives stated above (see Fig. 1): 1) the effect is monotonically decreasing throughout the urban space of the city (variable *Dist_herit*; see Fig. 1a); 2) a single ring buffer with a constant effect inside the buffer that disappears outside the buffer (variable *Bf_ring_herit*; see Fig. 1b); and 3) a buffer with a monotonically decreasing effect inside the buffer and a constant effect outside the buffer (variable *Bf_dist_herit*; see Fig. 1c). Moreover, following Chica-Olmo et al. (2019), we aim to determine the radius of influence or threshold using a procedure that maximizes the explanatory capacity of the model in terms of the R-squared, as indicated below.

Table 2 shows the descriptive statistics for the variables considered in the two samples, as well as the tests for means and proportions of the variables between both years (2019 and 2021). The mean *RPCP* was found to decrease 177 euros between both years. As for the structural control variables, the tests indicate significant differences between the two years in two of the four variables considered (*Floor* and *Renovation*), although these differences have no effect on the value of the location of the *RPCP*. However, only one of the seven locational variables (*Main_street*) shows significant differences at 95% between the two years.

Fig. 2A and B shows the *RPCPs* for the 2019 and 2021 samples, respectively. These figures show that the spatial distribution of the location of the commercial premises is similar, with a certain degree of clustering, especially in the city center. In addition, to analyze whether the two samples are spatially distributed in a similar way, the Clark–Evans test was used. This test analyzes the type of spatial pattern, that is, whether the commercial premises are spatially distributed in a random, clustered, or regular manner. The test results indicate at a 99% confidence level that the two samples are spatially distributed in a clustered manner and that the nearest neighbor ratio (NNR) of both samples is similar (NNR = 0.783 [2019]; NNR = 0.755 [2021]). Hence,

Table 1
Description and source of variables.

Variables	Description	Source
Price (RPCP)	Rental price of commercial premises (€)	(1)
Structural		
Area	Surface area of the premises (m^2)	(1)
Storewindow	Number of store windows	(1)
Floor	Binary variable: 1 if the premises have one floor, 0 otherwise	(1)
Restroom	Binary variable: 1 if the premises have two or more restrooms, 0 otherwise	(1)
Renovation	Binary variable: 1 if the premises need refurbishment, 0 otherwise	(1)
Locational		
Prime_street	Binary variable: 1 if the premises are on a prime street, 0 otherwise	(2)
Main_street	Binary variable: 1 if the premises are on a main street, 0 otherwise	(2)
Pedestrian_dens	Pedestrian street density index	(3)
Dist_CBD	Distance to central business district (km)	(4)
Dist_herit	Distance from the premises to the nearest heritage monument (km) (km)	(4)
Bf_ring_herit	Binary variable: 1 if the premises are within a radius of 0.7 km to the nearest heritage monument, 0 otherwise	(4)
Bf_dist_herit	Distance from the premises to the nearest heritage monument within a radius of 0.7 km and equal to 0.7 km for greater distances.	(4)

Note: (1) = Idealista.com; (2) = Granada City Council; (3) = Own elaboration based on data from the Granada City Council; (4) = Own elaboration based on data from the Statistics and Cartography Institute of Andalusia (IECA.com).

Table 2
Descriptive statistics.

Variables	Mean		SD		Min.		Max.		*diff-test*	*p*-value
Year	2019	2021	2019	2021	2019	2021	2019	2021		
Dependent variable										
Price (RPCP)	1016	839	1053	507.10	130	166.5	6000	2275	2.539	0.012[a]
Structural										
Area	111.4	106.6	117.5	76.349	10	13	830	605	0.804	0.422
Storewindow	1.343	1.272	1.244	1.075	0	0	6	5	0.529	0.597
Floor	0.186	0.071	0.390	0.257	0	0	1	1	7.005	0.008[b]
Restroom	0.227	0.291	0.420	0.455	0	0	1	1	2.372	0.123
Renovation	0.250	0.134	0.434	0.341	0	0	1	1	5.918	0.015[a]
Locational										
Prime_street	0.355	0.331	0.480	0.471	0	0	1	1	1.038	0.308
Main_street	0.174	0.283	0.381	0.452	0	0	1	1	5.362	0.021[a]
Pedestrian_dens	5.913	5.995	9.958	10.302	0	0	35.479	44	0.567	0.571
Dist_CBD	1.680	1.376	1.117	0.975	0.081	0.022	4.753	4.089	1.632	0.103
Dist_herit	0.857	0.702	0.657	0.546	0.070	0.042	2.943	2.882	0.870	0.385
Bf_ring_herit	0.564	0.677	0.497	0.468	0	0	1	1	1.115	0.291
Bf_dist_herit	0.516	0.494	0.206	0.204	0.070	0.042	0.700	0.700	0.042	0.966

Note: Sample sizes: N(2019) = 172; N(2021) = 254. Sig-level: " " $p \geq 0.1$; $*p < 0.1$. diff-test is the test for difference in means or proportions (binary variables) between 2019 and 2021.The tests were performed considering premises located at a maximum distance of 2.6 km from the city center (this radius covers 85% of the premises of both samples).

[a] $p < 0.05$.

[b] $p < 0.01$.

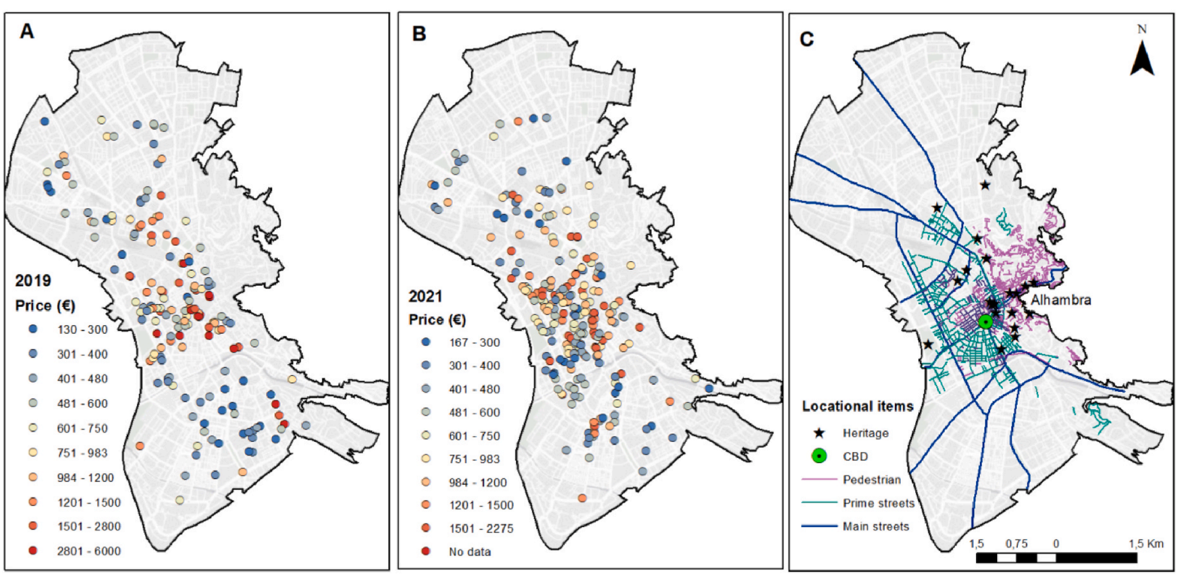

Fig. 2. Rental prices of commercial premises (€), heritage, main streets, prime streets, pedestrian streets, and the CBD.

both samples are spatially distributed in a similar way. The tests for means and proportions indicate that there are no significant differences between the two samples in most of the locational variables. Additionally, the Clark–Evans test shows no differences in the spatial distribution pattern between the two years.

As can be observed in Fig. 2A and B, the rental prices of premises close to each other are similar, thus indicating the possible presence of spatial autocorrelation. Moreover, the highest values are found mainly in the central area of the city around the CBD, particularly in the prime zone (see Fig. 2C), while the lowest values are found in areas farther away from the center. To test for the presence of global spatial autocorrelation, the Global Moran's *I* value was obtained for the variable of interest (*RPCP*). The value of *I* was significant in both years, thus indicating that locations close in space have similar *RPCPs* (*I* value $= 0.151$, $p < 0.000$ [2019] and *I* value $= 0.121$, $p < 0.000$ [2021]). This result was expected because, as discussed in detail in the literature review, the presence of spatial autocorrelation in retail prices is common (Zhang et al., 2015). However, the *I* values indicate that the spatial autocorrelation in the *RPCP* variable is not high in either year, as reflected in Fig. 2A and B by the presence of a certain confetti effect in the color of this variable.

Additionally, Fig. 2C shows the coverages associated with locational characteristics, such as heritage, prime streets, main streets, pedestrian streets, and the CBD. The figure shows that these characteristics are mainly concentrated in the central area of the city.

The central neighborhood where the CBD is located (see Fig. 2C) has traditionally concentrated a large number of mostly commercial and financial businesses. It is also a tourist area with a large supply of tourist accommodations (hotels and apartments) and bars and restaurants for both visitors to the city and the local population. This neighborhood is formed by a maze of narrow streets, many of which are pedestrian-only and where much of the city's retail commerce is concentrated. This network of pedestrian streets spans the central area to the eastern limits next to the Alhambra–Generalife monumental site. Many heritage monuments are in this area, which falls within the heritage zone declared a World Heritage Site (see Fig. 2C).

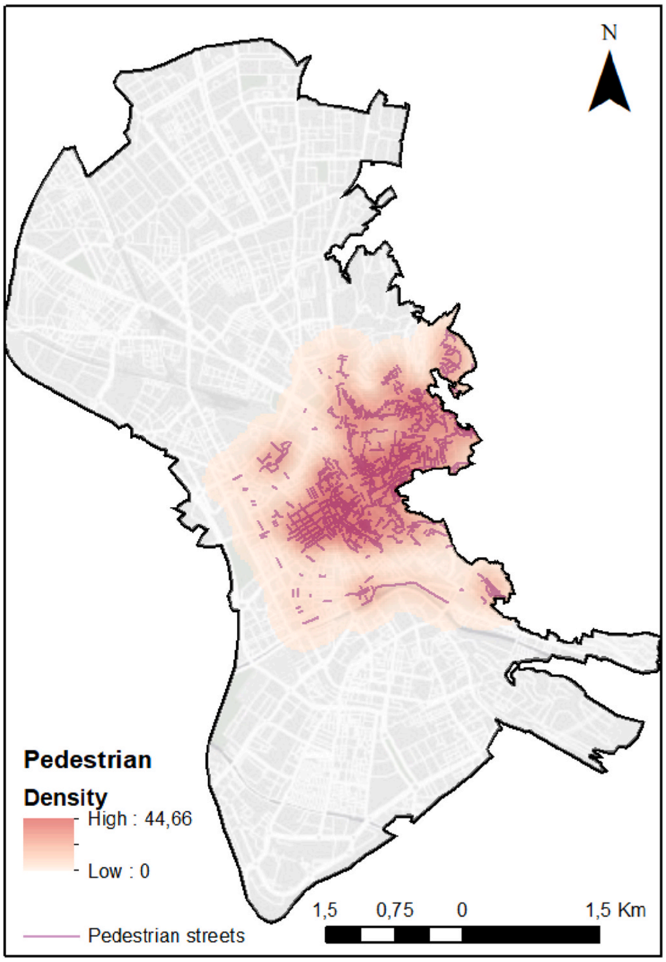

Fig. 3. Pedestrian streets and density.

Fig. 3 shows the location and density of the pedestrian streets. The density index of the pedestrian streets was obtained using the kernel density method and considering a search radius of 250 m per km^2. As can be seen in the figure, the pedestrian streets are mostly concentrated in the city center and the Albayzín neighborhood near the Alhambra (see Fig. 2C).

5. Methods, models, and results

5.1. Methods

As is usual in other studies that employ hedonic models (Zhou et al., 2022), a semilogarithmic regression model (i.e., the linearization of a nonlinear exponential model) was specified in this work:

$$\log(y) = \boldsymbol{X\beta} + \boldsymbol{u} \tag{1}$$

where $\mathbf{y}$ is the *RPCP*, $\mathbf{X}$ is an *nxk* matrix where *k* is the number of explanatory variables, $\boldsymbol{\beta}$ is a *kx1* vector of parameters, and $\mathbf{u}$ is an *nx1* vector of disturbances. The semilogarithmic specification makes the model disturbances tend to normal. As indicated above, the OLS estimator is an inefficient estimator when the disturbances show spatial autocorrelation. To detect the presence of autocorrelation in the disturbances, different tests such as the Moran's *I* error test or the Lagrange multiplier (LM) error statistic (LM-error) can be used. Although both tests are similar, the LM-error test is more accurate than the Moran's *I* test for distinguishing spatial autocorrelation in the disturbances (Anselin and Rey, 1991).

Moreover, given that a semilogarithmic model has been specified, the interpretation of the coefficients of the estimated models depends on whether the explanatory variable is continuous or binary. When the explanatory variable is continuous, the coefficient multiplied by 100 represents the impact on rental prices in percentages. When the explanatory variable is binary, the impact is $100(\exp\beta - 1)$, where $\boldsymbol{\beta}$ is the coefficient of the binary variable. Mitigating multicollinearity in the estimated models is another methodological problem. To overcome this problem, the orthogonal regression or residualization method was used (García et al., 2020) to filter the effect of the distance from the commercial premises to the city center on the variable representing the density of pedestrian streets.

5.2. Buffer

As indicated above, an additional contribution of this work of interest from a methodological viewpoint is that two alternative variables are compared to specify the type of heritage buffer (single ring and monotonically decreasing ring with threshold; see Fig. 1b and c). To this end, a procedure was used to improve the explanatory capacity of the model. The procedure is iterative and consists of maximizing the R-squared of the first regression model for both years (see models M1_19 and M1_21 in Table 3) but replacing the variable *Dist_herit* in these models with a distance that varies from 0.5 km to 2 km by 0.1 km in 0.1 km. The distance that maximizes this R-squared was found to be 0.7 km in both years (see Fig. 4), which represents the radius of the buffer.

Once the radius of the heritage buffer (0.7 km) was determined, two alternative variables were obtained to capture the spatial effect of heritage in the model:

$$\begin{aligned} Bf_{ring_{herit}} &= \begin{cases} 1, \text{if distance to heritage} \leq 0.7 \text{ km} \\ 0, \text{if distance to heritage} > 0.7 \text{ km} \end{cases} \\ Bf_{dist_{herit}} &= \begin{cases} \textit{distance to heritage, if this distance} \leq 0.7 \textit{ km} \\ \quad 0.7, \textit{if distance to heritage} > 0.7 \textit{ km} \end{cases} \end{aligned} \tag{2}$$

Thus, *Bf_ring_herit* is a binary variable that takes the value of 1 if the commercial premises are at a distance from the nearest heritage monument that is less than or equal to 0.7 km, and 0 otherwise. This is the case of the single ring buffer (see Fig. 1b). On the other hand, *Bf_dist_herit* is a variable that is equal to the distance from the commercial premises to the nearest heritage monument when this distance is less than or equal to 0.7 km and takes the value of 0.7 if the distance to the monument is greater than 0.7 km, such that the heritage effect remains constant from that distance. This is the case of the monotonically decreasing buffer with threshold (see Fig. 1c).

Fig. 5 shows the location of the heritage monuments as well as the two types of buffers considered: Fig. 5A shows the single buffer ring with a radius of 0.7 km (*Bf_ring_herit*) and Fig. 5B shows the monotonically decreasing buffer with a threshold of 0.7 km (*Bf_dist_herit*). As can be observed in Fig. 5A, the effect of the monument on *RPCP* is the same for any location within the 0.7 km radius, while the effect is greater the closer the location is to the monument as shown in Fig. 5B.

5.3. Models and results

To test the hypotheses put forward in this work, four econometric models were specified for each of the two years. To this end, a baseline model for each of the years (M0_19 and M0_21) was used. The model only includes the structural variables and the three models of interest that include the structural and locational variables are then specified (see Table 3). As can be seen in the table, none of the models presents serious multicollinearity problems, since none of the variance inflation factors (*VIF*) exceeds the value of 5. However, according to the results of the Breusch–Pagan test, the hypothesis of homoscedasticity in these disturbances is rejected. To overcome this problem, a robust estimator

Table 3
Models.

Dep.variable = log(*Price*)	2019											
	M0_19			M1_19			M2_19			M3_19		
	Estim.	Std. Error	*t*-val.	Estim.	Std. Error	*t*-val.	Estim.	Std. Error	*t*-val.	Estim.	Std. Error	*t*-val.
Const.	6.071[c] (0.000)	0.094	64.387	6.171[c] (0.000)	0.141	43.728	5.896[c] (0.000)	0.165	35.655	6.108[c] (0.000)	0.125	49.056
Structural												
Area	0.003[c] (0.000)	0.001	3.867	0.003[c] (0.000)	0.001	6.768	0.003[c] (0.000)	0.000	6.913	0.003[c] (0.000)	0.000	6.842
Storewindow	0.089[b] (0.021)	0.036	2.482	0.098[c] (0.003)	0.032	3.032	0.104[c] (0.002)	0.032	3.222	0.099[c] (0.002)	0.032	3.118
Floor	0.503[c] (0.000)	0.143	3.509	0.288[c] (0.008)	0.107	2.690	0.277[b] (0.010)	0.107	2.593	0.279[c] (0.009)	0.106	2.640
Restroom	0.243[a] (0.070)	0.144	1.691	0.250[b] (0.030)	0.114	2.187	0.248[b] (0.031)	0.114	2.179	0.230[b] (0.044)	0.113	2.031
Renovation	−0.372[c] (0.001)	0.102	−3.651	−0.227[b] (0.018)	0.095	−2.392	−0.228[b] (0.017)	0.095	−2.415	−0.247[c] (0.010)	0.094	−2.622
Locational												
Prime_street	–	–	–	0.354[c] (0.001)	0.107	3.307	0.299[c] (0.008)	0.112	2.675	0.369[c] (0.001)	0.105	3.507
Main_street	–	–	–	0.378[c] (0.001)	0.110	3.441	0.378[c] (0.001)	0.109	3.462	0.367[c] (0.001)	0.108	3.394
Pedestrian_dens	–	–	–	0.019[c] (0.001)	0.006	3.344	0.019[c] (0.001)	0.006	3.264	0.014[b] (0.016)	0.006	2.432
Dist_CBD	–	–	–	−0.164[c] (0.003)	0.054	−3.017	−0.069 (0.209)	0.055	−1.262	−0.122[c] (0.007)	0.044	−2.746
Dist_herit	–	–	–	0.094 (0.204)	0.073	1.274	–	–	–	–		
Bf_ring_herit	–	–	–	–	–	–	0.222[a] (0.074)	0.123	1.801	–		
Bf_dist_herit	–	–	–	–	–	–	–	–	–	−0.632[b] (0.012)	0.249	−2.540
Tests												
max-VIF	1.445			2.409			2.485			1.649		
JB	*X-squared* = 1.889, *p*-value = 0.389			*X-squared* = 4.369, *p*-value = 0.112			*X-squared* = 4.088, *p*-value = 0.129			*X-squared* = 3.267, *p*-value = 0.195		
BP	*BP* = 21.04[c], *p*-value = 0.001			*BP* = 33.6[c], *p*-value = 0.000			*BP* = 30.9[c], *p*-value = 0.001			*BP* = 31.62[c], *p*-value = 0.000		
LM-error	*LMerr* = 21.038[c], *p*-value = 0.000			*LMerr* = 0.682, *p*-value = 0.409			*LMerr* = 0.332, *p*-value = 0.564			*LMerr* = 0.094, *p*-value = 0.759		
Chow-test	–			–			–			–		
Goodness-of-fit												
R^2	0.415			0.597			0.601			0.609		
$\overline{R}^2$	0.397			0.572			0.576			0.585		
%Δ − $\overline{R}^2$	–			44.080			45.088			47.103		
AIC	324.567			270.42			268.72			265.39		

Dep.variable = log(*Price*)	2021												2019–21
	M0_21			M1_21			M2_21			M3_21			%Δ-β
	Estim.	Std. Error	*t*-val.	Estim.	Std. Error	*t*-val.	Estim.	Std. Error	*t*-val.	Estim.	Std. Error	*t*-val.	
Const.	5.983[c] (0.000)	0.059	100.708	6.012[c] (0.000)	0.085	70.404	6.029[c] (0.000)	0.109	55.308	6.061[c] (0.000)	0.104	58.011	
Structural													
Area	0.004[c] (0.000)	0.000	9.161	0.004[c] (0.000)	0.000	10.411	0.004[c] (0.000)	0.000	10.375	0.004[c] (0.000)	0.000	10.301	33.33
Storewindow	0.069[c] (0.009)	0.027	2.612	0.055[b] (0.028)	0.025	2.210	0.055[b] (0.028)	0.025	2.205	0.055[b] (0.028)	0.025	2.215	−44.44
Floor	0.247[b] (0.029)	0.113	2.196	0.180[aa] (0.094)	0.107	1.683	0.178[a] (0.099)	0.108	1.653	0.172 (0.111)	0.107	1.601	–
Restroom	0.197[c] (0.007)	0.073	2.708	0.204[c] (0.003)	0.068	3.027	0.201[c] (0.003)	0.067	2.991	0.199[c] (0.003)	0.067	2.953	−13.48
Renovation	−0.171[b] (0.042)	0.084	−2.049	−0.136[a] (0.080)	0.078	−1.760	−0.138[a] (0.078)	0.078	−1.773	−0.139[a] (0.075)	0.078	−1.791	−43.72
Locational													
Prime_street	–	–	–	0.155[b] (0.016)	0.064	2.430	0.155[b] (0.017)	0.065	2.394	0.152[b] (0.018)	0.064	2.376	−58.81
Main_street	–	–	–	0.141[b] (0.017)	0.059	2.394	0.141[b] (0.018)	0.059	2.380	0.143[b] (0.016)	0.059	2.429	−61.04
Pedestrian_dens	–	–	–	0.011[c] (0.001)	0.003	3.345	0.011[c] (0.001)	0.003	3.335	0.010[c] (0.003)	0.003	3.006	−28.57
Dist_CBD	–	–	–	−0.116[c] (0.005)	0.041	−2.827	−0.104[c] (0.005)	0.036	−2.861	−0.093[c] (0.006)	0.034	−2.770	−23.77
Dist_herit	–	–	–	0.036 (0.608)	0.070	0.514	–	–	–	–	–	–	
Bf_ring_herit	–	–	–	–	–	–	−0.009 (0.907)	0.074	−0.117	–	–	–	
Bf_dist_herit	–	–	–	–	–	–	–	–	–	−0.097 (0.526)	0.152	−0.635	–
Tests													
max-VIF	1.422			2.348			1.853			1.586			
JB	*X-squared* = 4.362, *p*-value = 0.113			*X-squared* = 0.547, *p*-value = 0.761			*X-squared* = 0.518, *p*-value = 0.771			*X-squared* = 0.594, *p*-value = 0.7432			
BP	*BP* = 11.112[b], *p*-value = 0.049			*BP* = 22.33[b], *p*-value = 0.014			*BP* = 22.01[b], *p*-value = 0.015			*BP* = 21.86[b], *p*-value = 0.016			
LM-error	*LMerr* = 42.692[c], *p*-value = 0.000			*LMerr* = 3.002[a], *p*-value = 0.083			*LMerr* = 3.055[a], *p*-value = 0.081			*LMerr* = 3.282[a], *p*-value = 0.070			
Chow-test	*F-value* = 1.068, *p*-value = 0.377			*F-value* = 2.329[b], *p*-value = 0.011			*F-value* = 2.385[c], *p*-value = 0.009			*F-value* = 2.480[c], *p*-value = 0.007			
Goodness-of-fit													
R^2	0.454			0.543			0.543			0.543			
$\overline{R}^2$	0.443			0.524			0.524			0.525			
%Δ − $\overline{R}^2$	–			18.284			18.284			18.510			
AIC	322.306			287.08			287.35			286.94			

Note. N(2019) = 172. N(2021) = 254. Sig-level: *p*-value in brackets. " " $p \geq 0.1$. %Δ-β: percentage of variation of the significant parameters in models M3-19 (pre-COVID-19) and M3_21 (post-COVID-19). *VIF:* variance inflation factor. *JB*: Jarque–Bera test. *BP*: Breusch–Pagan test. *LM-error*: Lagrange Multiplier error test. R^2: multiple R-squared. $\overline{R}^2$: R^2*-adjusted*. %Δ-$\overline{R}^2$: percentage increase of the R^2*-adjusted* ($\overline{R}^2$) from the model that only includes the structural variables ($\overline{R}^2_{ph} = 0.397$ in 2019; $\overline{R}^2_{ph} = 0.443$ in 2021) to the model that includes all the variables ($\overline{R}^2$). *AIC*: Akaike information criterion.

[a] $p < 0.1$.
[b] $p < 0.05$.
[c] $p < 0.01$.

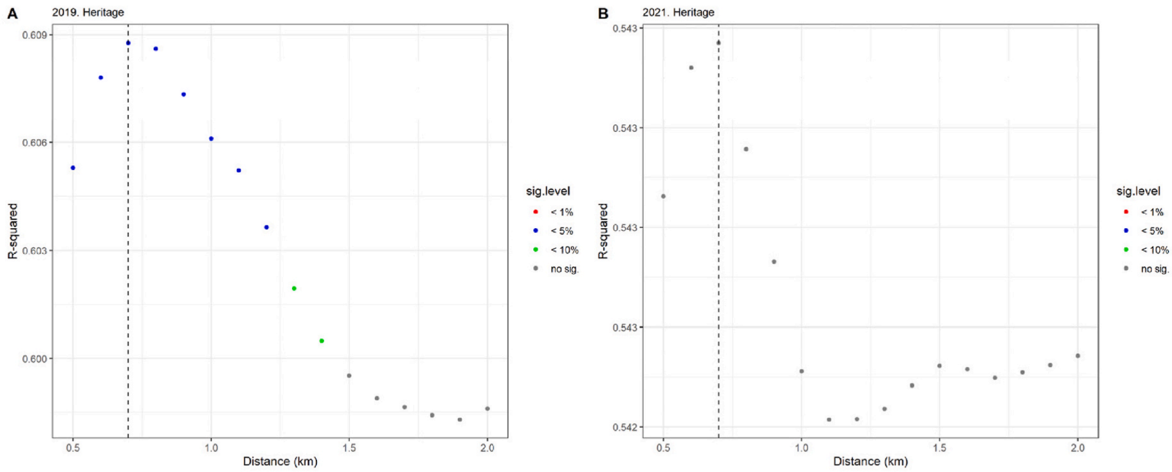

Fig. 4. R-squared of models M1_19 and M1_21 (Table 2) replacing the variable *Dist_herit* in the models with a distance that varies from 0.5 km to 2 km by 0.1 km in 0.1 km. The maximum R-squared value is obtained for 0.7 km in both years.

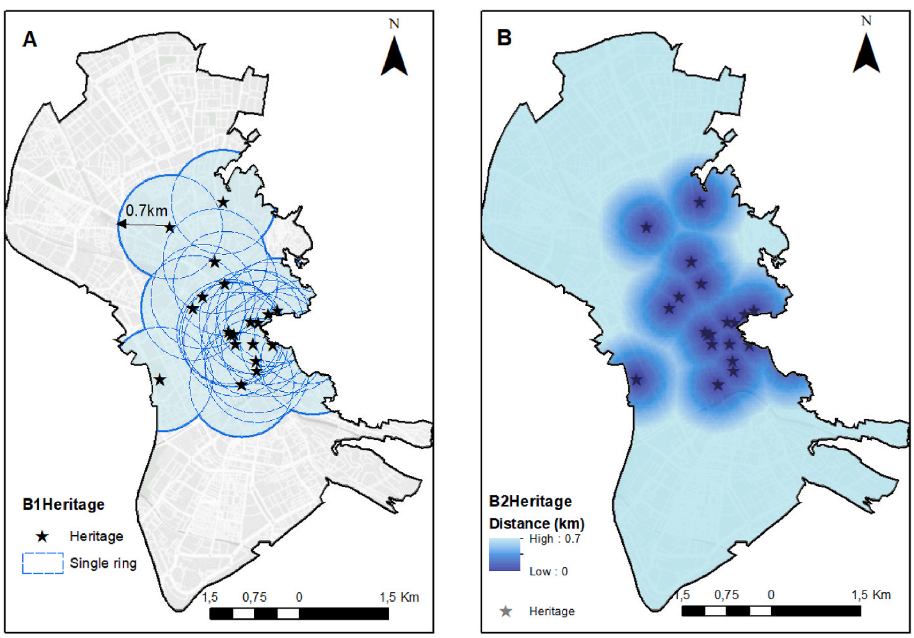

Fig. 5. Heritage buffer. A. Single buffer ring with a radius of 0.7 km (*Bf_ring_herit*). B. Monotonically decreasing buffer with respect to the distance to the nearest heritage monument with a threshold of 0.7 km (*Bf_dist_herit*).

considering an HCI-type standard error was used. As regards the problem of spatial autocorrelation in the disturbances, the results of the LM-error test (see Table 3) indicate that only the baseline models present a high degree of spatial autocorrelation in both 2019 and 2021. However, the results of the LM-error test for the models that include the locational variables show that four out of six of these models do not present spatial autocorrelation at 99% (M1_19, M2_19 and M3_19, M2_21) and only two present low spatial autocorrelation at 90% (M1_21 and M3_21). Therefore, when the locational variables are included in the model, the presence of spatial autocorrelation in the disturbances due to a specification error is reduced (Anselin, 2013). Hence, although the explained variable *RPCP* initially showed spatial autocorrelation as previously observed by means of Moran's *I*, if the model is sufficiently well specified, its disturbances will not present spatial autocorrelation, thus allowing the models to be estimated by OLS.

On the other hand, by including the locational variables in the baseline models (M0_19 and M0_21) to obtain models M1_19 and M1_21 not only has the specification error been reduced but the explanatory capacity has also improved considerably. As can be seen in Table 3, there is a decrease in the Akaike information criterion (AIC) statistic and a considerable increase in the R2-adjusted (more than 44% in 2019 and more than 18% in 2021). However, it is noteworthy that the best model for each year is M3_19 and M3_21, respectively. These models were obtained by including the effect of heritage through a monotonically decreasing buffer with threshold, as they show the largest increases in R2-adjusted (47.1% in 2019 and 18.5% in 2021) and the lowest AIC values.

Table 3 also shows the results of the Chow structural change test (Chow test) for each of the four models for 2019 compared with their corresponding four models for the year 2021. This test is used to determine if any significant changes occurred in the model structure between 2019 and 2021. As can be observed in the table, the null hypothesis of structural permanence between the two years cannot be rejected when only the structural variables (M0_19 and M0_21) are considered. Moreover, when the locational variables are included, the structural permanence hypothesis is rejected at a 95% confidence level

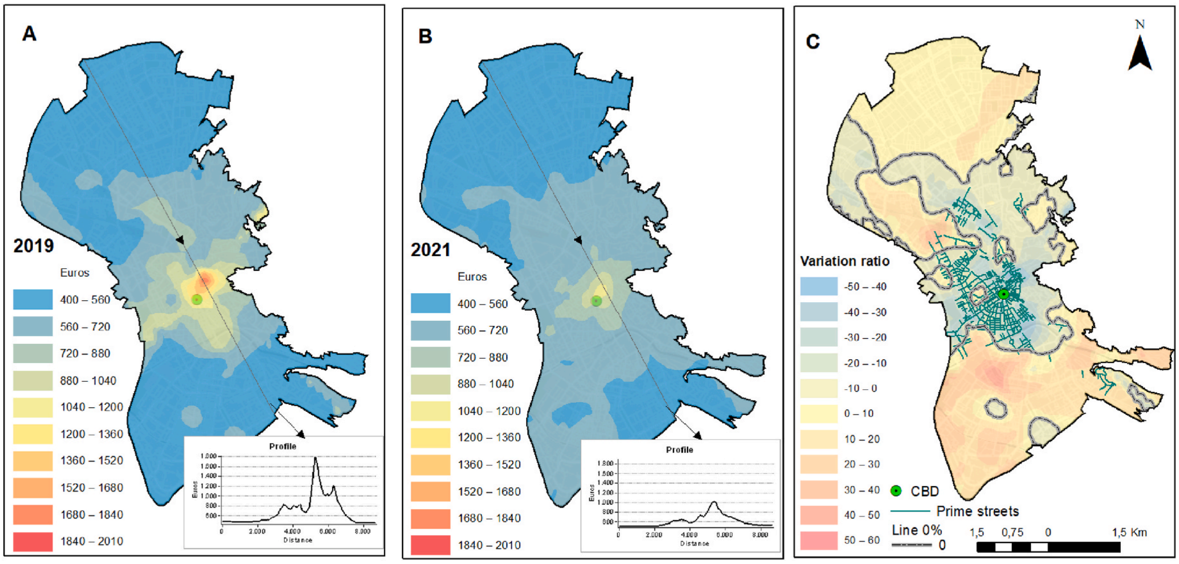

Fig. 6. A and B show the estimated rental prices of commercial premises with standard characteristics (RPCP-sd) for 2019 and 2021. C shows the percentage change in RPCP-sd between 2019 and 2021.

for the first type of model (M1_19 and M1_21), which increases to 99% for the second (M2_19 and M2_21) and third models (M3_19 and M3_21). This indicates that locational factors were the main reason for the significant change in the pre-COVID and during-COVID rental prices. However, the results of this test do not indicate where in the city these changes occurred. Therefore, an analysis of the spatial distribution of the changes in the estimated *RPCP* between the two years is performed below to detect the locations where they occurred (see Fig. 6).

As regards the significance of the coefficients of the control variables representing the structural characteristics of the premises, the results in Table 3 for the third model for both years (M3_19 and M3_21) indicate that the coefficients have the expected signs and are significant at least at a 90% confidence level, except for the variable *Floor,* which was significant in 2019 (see M3_19), but ceases to be significant in 2021 (see M3_21). This change may have been due to a lower preference for single-story premises during the pandemic since customers feel more physically separated and perceive fewer people around them in multi-story premises. It would also explain the increase in the coefficient of the variable *Area* in the two years considered, which also increased its effect on the *RPCP*, since a store with a larger surface area permits more separation between customers and reduces the perception of crowding. Likewise, the decrease in the coefficient of the variable *Restroom* may be due to concerns about sharing small personal spaces. It is also noteworthy that the effect of the variables *Storewindow* and *Renovation* on the *RPCP* decreased by approximately 44% each; the largest variations in the coefficients of all the structural characteristics. In the case of *Storewindow*, the decrease in the effect on the *RPCP* may have been due to a decrease in foot traffic due to mobility limitations and the fact that citizens were apprehensive about going out for walks during the pandemic. In the case of *Renovation*, the decrease could be explained by the fact that the owners or tenants of the premises did not invest in improvements due to the difficulties in making these investments profitable because of the lower sales expectations resulting from the drop in commercial activity caused by the pandemic. Despite the changes in the effects of these factors during the pandemic, from the viewpoint of investors it is still a key strategy to invest in the expansion, improvement, and modernization of physical spaces (Wen et al., 2022), as will be discussed further in the following section.

As regards the locational variables, Table 3 shows that practically all the coefficients of the locational variables of the third model are significant and have the expected signs for both years (M3_19 and M3_21). As regards *Prime_street* and *Main_street*, a sharp drop in the effect of these variables on the *RPCP* can be observed; an effect that decreased to less than half between 2019 and 2021 (*Prime_street* = −58.81% and *Main_street* = −61.04%). This finding supports Hypothesis 1, which posits that the pandemic led to a decrease in the effect of location on *RPCP* for premises on main streets and in prime areas. A decrease in the effect of *Dist_CBD* on *RPCP* (−23.77%) can also be observed, although it is of a lesser magnitude than that of the other two locational variables discussed above. Therefore, during the pandemic, the magnitude of the effects of these locational factors in explaining commercial real estate values declined sharply. As mentioned above, this was due to the decrease in the number of customers in commercial establishments after the COVID-19 outbreak, which affected businesses located in these prime areas (in the central part of the city) to a greater extent. To address this negative trend, below we will discuss the importance of decision-making in both the public and private sectors.

Additionally, the positive and significant effect of pedestrian street density (*Pedestrian_dens*) on the *RPCP* also decreased by 28.57% between 2019 and 2021. This supports Hypothesis 2, which stated that the effect of pedestrian density on *RPCP* decreased because mobility restrictions and the fear of contagion strongly reduced the flow of pedestrians in areas with the highest pedestrian density prior to the pandemic. Since the pedestrianization of urban centers benefits both residents and tourists and positively impacts the *RPCP*, the following section will comment on initiatives that have been proposed to restore the importance of pedestrian-friendly environments.

As for the effect of distance to heritage on the *RPCP*, Table 3 shows that two of the specifications considered in this work (single ring buffer [*Bf_ring_herit*] and monotonically decreasing buffer with threshold [*Bf_dist_herit*]; see Fig. 1) were significant in 2019. Of these two specifications, the second one (*Bf_dist_herit*) was the most appropriate, which is the one included in the third model (M3_19). Therefore, the results show that the influence of distance from tourist monuments on the rental prices of commercial premises was significant before the pandemic and that commercial premises closer to tourist monuments tended to be more expensive. Taking into account the semi-logarithmic specification of estimated model M2_19, the interpretation of the coefficient of the variable *Bf_ring_herit* indicates that the price of retail premises within the 0.7 km buffer from the nearest heritage site is 24.86% (100·exp(0.222–1) = 24.86) higher than that of premises outside the buffer. In model M3_19, the interpretation of the coefficient of the variable *Bf_dist_herit* indicates that for every 100 m from the heritage site, the price of the premises decreases by 6.32% up to a distance of 700 m, beyond which the effect remains constant.

In 2021, however, none of the three specifications used to estimate the effect of the proximity of premises to a heritage site on the *RPCP* was significant, thus verifying Hypothesis 3. Therefore, this effect decreased during the pandemic until it was no longer significant: the rental prices of commercial premises were no longer significantly influenced by their distance from tourist attractions. This loss of significance of the influence of heritage on the *RPCP* in 2021 may have been due to the sharp drop in tourism activity caused by the pandemic, since less than half the number of tourists visited the city in 2021 compared to 2019 (specifically, 49.46% of the figure for 2019; IECA- Instituto de Estadística y Cartografía de Andalucía, 2022). In fact, the city has not yet reached the pre-COVID figures for tourist arrivals (Troyano, 2024). As in other tourist cities (Frago, 2021), the impact of the pandemic on the retail structure was more severe in areas that were most dependent on tourist demand, which are those closest to tourist monuments. Given the importance of the tourism sector and its strong influence on the *RPCP*, sector-related measures to reactivate commercial activity are discussed below.

A fundamental objective of this work has been to spatially estimate variations in the *RPCP* between the pre-COVID year (2019) and the year during the COVID pandemic (2021) to determine the areas where the pandemic had the strongest effect on the *RPCP*. Fig. 6A and B shows the kriging estimate of the *RPCP* for a commercial premise with standard characteristics (RPCP-sd) for 2019 and 2021, respectively. For the sake of comparability, the same scale of values was used in both figures. Premises with standard characteristics were defined as those having an area equal to 111.5 m^2, a store window, one floor, less than two restrooms, and no need for refurbishment. To obtain the RPCP-sd of a commercial premise, the coefficients of models M3_19 and M3_21 were considered as they have the best explanatory capacity and, in addition, they include the specification of the heritage effect by means of the monotonically decreasing buffer with threshold (*Bf_dist_herit*). Fig. 6A and B shows that prices increased from the outskirts to the central area of the city (CBD) and areas close to the prime streets and heritage monuments. However, while the scale of values goes from blue to red (€400–€2010) in Fig. 6A, it goes from blue to yellow (€400–€1200) in Fig. 6B. This indicates that the areas with the highest values in 2021 (€1040–€1200, yellow) are located in the CBD and correspond to an extensive area of average values distributed around the maximum values obtained in 2019, thus pointing to a drop in prices in the CBD. Moreover, as can be observed in these maps, the price gradient changed and was much higher in 2019 than in 2021. This is seen more clearly in the profile that cuts the city longitudinally from north to south and may have been due to the decrease in the effect of prime streets and the lack of significance of heritage on the *RPCP* in the central third area of the city.

The percentage of variation between the 2019 and 2021 RPCP-sd was obtained from their estimates (Fig. 6C), thus allowing us to identify the areas of the city with greater variations in the pre-COVID and during-COVID price estimates. Therefore, given that the two samples have a similar distribution and that the RPCP-sd was obtained for the same type of premises, it can be assumed that the variations shown in Fig. 6C are related to changes caused by the pandemic. The figure also shows the 0% line, which delimits the area of the city where rental prices did not vary from 2019 to 2021. As can be seen, the prime streets are located in the area with negative variation (zone marked in cold colors). In this prime area, rental prices decreased, on average, by 25% and as much as 50%. This decrease is in line with some of the results published in the press, as previously indicated in the literature review. Given that most heritage monuments and the highest pedestrian density are found in prime areas, the sharp decline in the influx of tourists and the general population due to mobility restrictions and aversion to crowds caused by COVID-19 had a particularly strong impact in these areas.

6. Discussion and conclusions

In this work we have shown that variations in the *RPCP* differed across the city during the pandemic and identified areas where variations in the estimates of the pre-COVID and during-COVID rental prices behaved differently. The study has examined the effect of both structural and locational characteristics on the *RPCP* and captured and quantified changes in the level of influence of these explanatory variables of *RPCP*. As mentioned in the previous section, the implications for investors and government arising from these observed changes in the commercial real estate market will be discussed in what follows.

As explained above in relation to the structural variables, the comparison of models for the two years shows that the positive effect on the *RPCP* of having a larger store (*Area*) increased during the pandemic. In contrast, the positive effect of having a single-floor store (*Floor*) and a *Restroom* decreased. These changes may be due to the need to maintain greater interpersonal distance during the pandemic. In this same line, the effect of *Storewindow* and *Renovation* decreased considerably, which can be explained by two factors: a) mobility restrictions and the fact that people were averse to strolling on the streets and looking at store windows and b) the lack of investment in renovations to improve commercial premises due to the drop in sales expectations caused by the pandemic. These changes during the pandemic are important and should be taken into account due to their implications for investors' decision regarding physical spaces. Indeed, these investments can increase the value of the premises by revitalizing them, increasing their attractiveness and functionality, adapting to the changing needs of consumers, and improving customers' experience, who are offered an added value compared to online shopping. To encourage this modernization of the commercial real estate stock, authorities can adopt urban planning policies that simplify and accelerate the approval procedures for these investment projects (Ngoc et al., 2023). This would allow for a more flexible and adaptive use of spaces in response to changes in demand (Wen et al., 2022). They can also ease the financial burden on owners through tax breaks and moratoriums, public sector-backed credit lines, and low-interest loans.

As for the locational variables, the spatial estimates (see Fig. 6) indicate that premises located on a main street or in a prime area (especially those around the CBD), experienced a greater decline in rental prices during the pandemic than those located in other areas. This is in line with Hypothesis 1, according to which the positive effect of *Prime_street* and *Main_street* on the *RPCP* decreased during the pandemic for premises located in these prime areas, which were particularly affected by the decline in sales. In this regard, various measures have been proposed to revitalize commercial activity in these prime areas. For example, it has been suggested that these areas be reinvented with the authorities promoting the mixed use of spaces (commercial, residential, cultural, and recreational), as the diversity of uses has a positive impact on real estate values (Orr and Stewart, 2022; Zhang et al., 2023). In this regard, Lashgari and Shahab (2022) argue that "experience economy" strategies, with spaces that integrate shopping with leisure and entertainment, should be promoted to increase the number of visitors and boost retail. The globalizing tendency to create cloned commercial spaces and identical high streets in many cities does not attract customers, so revitalization requires creating place branding strategies (to enhance the unique identity of urban centers) and reinventing the retail landscape with spaces for social interactions and experiential activities (Wen et al., 2022).

Additionally, Figs. 3 and 6C also show that rental prices decreased during the pandemic in areas with a higher pedestrian density prior to the pandemic. This is in line with Hypothesis 2, according to which the positive influence of pedestrian density on the *RPCP* decreased. As indicated above, this could be due to the marked fall in foot traffic in areas with a previously high pedestrian density, resulting from restrictions on free movement and the fear of contagion. Various measures have been proposed to restore the importance of these pedestrian-friendly environments to stimulate commercial activity and commercial real estate values. According to Orr and Stewart (2022), the pedestrianization of urban centers can increase commercial real estate values if it is accompanied by urban planning and mobility measures to improve accessibility to the main shopping streets and connectivity between them and with adjacent streets. In a similar vein, Merten and Kuhnimhof (2023) consider that measures such as increasing pedestrian zones and facilitating accessibility to them through public transport stops and nearby public parking garages (within a comfortable walking distance) increase the attractiveness of retail locations.

On the other hand, modelling has shown that the effect of the proximity of commercial premises to heritage monuments is significant and positive, with the monotonically decreasing buffer with threshold best capturing this effect prior to the pandemic. However, in line with Hypothesis 3, it has been shown that this effect vanished during the pandemic, probably due to the marked drop in tourist demand. Given the importance of the tourism sector and its significant impact on the *RPCP*, measures must be taken to reactivate the retail sector in the areas most affected by the decline in tourist demand, while avoiding the overexploitation of tourism, as this can lead to problems of touristification, gentrification, and tourism phobia among the local population. These measures (Barata-Salgueiro and Guimarães, 2020; Zaar, 2022) must aim to promote sustainable tourism that is fair to the local population and encourage the diversification of commercial activity in historic centers through a combination of retail businesses that meet both tourist and local demand to avoid over-dependence on tourism and create resilience. Moreover, it is necessary to control real estate speculation of residential/holiday units, implement affordable housing policies, and provide incentives for the conversion of vacation rentals into residential properties in order to increase the resident population and support local businesses. Proximity commerce in city centers has a strong transforming power and the ability to retain the local population in these areas, thus preventing the effects of gentrification and touristification. To achieve this, in addition to these measures, other initiatives, already mentioned, should be taken to improve accessibility to these centers, such as increasing pedestrianization, improving public transport, expanding parking facilities, etc. Such initiatives would require flexible urban and commercial planning that preserves the monumental heritage of historic centers while allowing for the harmonious development of overlapping urban functions (commercial, residential, tourist, cultural, and recreational), thus ensuring the participation and balanced interests of the various stakeholders. As this work has shown, proximity to heritage monuments was a significant variable in explaining the *RPCP* prior to the pandemic and is expected to be significant again as pre-pandemic levels of tourism recover. For this reason, heritage conservation and recovery should be fundamental objectives of public management due to the cultural, social, and economic impact of such measures, particularly in terms of retail trade in commercial premises, the main focus of this study. From a socio-economic point of view, these useful policy implications are of great interest.

As can be seen, this work underscores the policy implications for urban planning and economic, social, and fiscal decision-making related to commercial activity in city centers. Such decisions may involve measures to rehabilitate and maintain city centers, preserve heritage, develop affordable housing policies, improve accessibility and mobility, or even address the growing problems of gentrification and touristification affecting the historic centers of many cities.

Additionally, an interesting result of this study is that the proposed methodology has been used to determine the form and radius of influence of heritage monuments on the *RPCP*. As mentioned above, this method could also be generalized to other places of tourist attraction and other cities.

The methodology used has also made it possible to geographically determine which areas are more sensitive to abrupt changes, such as those caused by the pandemic. It is important to note that these methods can be expanded on and implemented in other circumstances that cause disruptive changes such as an economic crisis, a real estate crash, a social or military conflict, or significant changes in government policies, among others, which may have unequal effects on different areas of a city.

As for the main limitations of this work, it should be mentioned that other locational variables related to the local environment, such as the type of commercial activity of neighborhood locales, income level, or population density, have not been included in the models. It would also have been desirable to obtain information about rental prices for the same commercial premises before and during the COVID-19 pandemic. Another limitation is that the two samples analyzed here include commercial premises that could be used and rented for any type of business (since they were vacant), even under leases of different duration and renewal conditions, which could also affect the rental price. A possible line of research on the determinants of commercial real estate rents could include samples of occupied commercial premises, as well as information on the different types of businesses located in the premises; lease length; renewal conditions; or whether the businesses are small, large brands, brands operating through franchises, etc., since these are situations that can affect the profitability of the locale and hence its rental price.

As an open line of research, we could consider using buffers other than those examined in this study, such as a single buffer ring in which the effect is constant inside the buffer and monotonically decreasing outside the buffer. Another interesting alternative would be to work with a more dynamic radius of buffer that is larger for some heritage sites than others depending on their characteristics, such as potential draw, number of visitors, or size. Size is a reasonable proxy variable, since the physical dimensions of tourist sites influence the number of visits they receive (Bartie and Mackaness, 2016). Moreover, a tourist site's potential demand is closely related to the monument's visitor carrying capacity, which is in turn related to the physical dimensions of the site given the need for a responsible and sustainable management of leisure and tourism activities at the tourist site (Hernández, 2001).

CRediT authorship contribution statement

Rafael Cano-Guervos: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Jorge Chica-Olmo:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Jorge Chica-Garcia:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

Data availability

Data will be made available on request.

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