

Consumption after dark exploring spatio-temporal patterns of spending in the night-time economy

Julia de las Obras-LoCERTALES SampéRiz ^a, Juan Carlos García-Palomares ^{b,*},
Diego Ramiro-Fariñas ^a, María Soledad Hernández Martín-Caró ^c, Javier Gutiérrez ^b

^a Institute of Economics, Geography and Demography, Center for Human and Social Sciences, Spanish National Research Council (CSIC), Spain

^b Department of Geography, Complutense University of Madrid, Spain

^c Madrid City Council, Spain

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ABSTRACT

The concept of the night-time economy has gained attention in recent years as cities around the world recognize the potential of night-time activities. Most research on the night-time economy adopts a social perspective, without examining this topic from an economic approach, probably because official statistics do not provide suitable information for this purpose. The availability of data on bank card transactions opens new avenues in the study of the night-time economy by providing information on night-time spending in city establishments. This article explores the spatial and temporal patterns of night-time spending by combining different data sources -bank transaction data, mobile phone data, social networks, cadastral records, etc.-, taking the city of Madrid as the study area. The results reveal that night-time spending in establishments in the city of Madrid is equivalent to approximately 30 % of total spending. They also show that the spatial concentration of night-time spending increases as the night progresses, and that the structure of spending is much more diversified in the evening than at dinner time and late at night. Explanatory models (Ordinary Least Squares and Random Forest regression) show that variables related to bars and restaurants, retail area, popularity of establishments, and tourist accommodations have strong explanatory power over the spatial distribution of night-time spending. The article shows that the analysis of bank card transaction data provides information of great interest to urban managers and planners.

1. Introduction

Cities around the world are increasingly recognizing the importance of understanding the benefits of the night-time economy. Traditionally, urban studies have focused primarily on daytime activities, neglecting the important economic activities and social vibrancy that occur after dark. Night-time vitality has gained attention in recent years as an important indicator reflecting urban economy and quality of life (Wu et al., 2023).

The concept of the night-time economy has emerged as a dynamic field of research, that offers a new perspective on the economic and social dimensions of night-time activities in urban environments. The night-time economy comprises economic activities that take place between sunset and sunrise (Lin et al., 2022) and includes night-time consumption through activities such as shopping, eating out, drinking, culture, festivals, events, sports, and tourism (Lovatt et al., 1994;

McArthur et al., 2019; Shaw, 2010). These activities exhibit a particular rhythm based on their availability and opening hours (Schwanen et al., 2012). Consumption linked to the night-time economy has a growing impact on employment and local economies, but these activities also produce undesirable effects in urban centers, such as noise, violence, or gentrification (Brands et al., 2014; Measham & Brain, 2005; Nofre, 2020).

Although there is a great deal of research on the social aspects of night-time consumption activities, there is very little work focused on the consumption perspective, probably because official statistical sources do not provide information on the night-time economy, as they do not break down economic data by time of day. Faced with this gap in statistical information, some researchers have opted to analyze the night-time economy using proxies obtained from Big Data sources. Thus, for example, Wang et al. (2018) rely on satellite-derived night-time light data as an informative proxy measure for studying urban consumption,

* Corresponding author.

E-mail address: jcgarcia@ucm.es (J.C. García-Palomares).

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while Li et al. (2022) use mobile phone data, and Yan et al. (2024) rely on POI (Points of Interest) and satellite data. Topics closely related to the night-time economy, such as urban vibrancy and urban nightlife, have been researched using social network data (see, for example, Dorostkar & Najarsadeghi, 2022; Niu et al., 2022, Santiago-Iglesias, Romanillos, Carpio-Pinedo, et al., 2024). To our knowledge, expenditure data were only used by Kim and Kim (2022), who examined the effects of COVID-19 on the night-time economy, but not the geography of urban night-time consumption.

This article starts from the following research question: to what extent can bank card transaction data, combined with other data sources, provide relevant information for the spatiotemporal characterization of urban night-time consumption? This research question is relevant because, to our knowledge, no paper has used bank card transaction data to study the geography of urban night-time consumption. Our research contributes to the literature by analyzing the night-time economy from a consumption perspective, based on bank card transaction data in the city of Madrid (Spain) throughout the year 2022. The contribution of the article is threefold: 1) Our study fills some gaps in the literature by contributing to a deeper characterization of the spatial patterns of urban night-time consumption -what, where, and when it is consumed- that increases knowledge about the geography of night-time spending within the city. In addition, the breakdown of night-time spending into specific time slots allows for a better understanding of the spatiotemporal patterns of the night-time consumption. 2) Bivariate correlation analyses between the spatial distribution of night-time spending and several variables commonly used in the night-time economy literature reveal the extent to which these variables can be used as proxies for the spatial variation in urban night-time spending. 3) In addition, the use of deep learning tools (Random Forest) provides relevant information on the importance of the variables that most influence the spatial distribution of night-time spending according to time slots and partial dependence plots characterize the relationship between predictors, and night-time spending.

The article is structured as follows. After this brief introduction, Section 2 reviews the related literature, and Section 3 describes the study area and establishes a time frame for the analysis of the night-time economy in Madrid. Section 4 presents the data and methodology, Section 5 shows the main results, and Section 6 discusses the results and presents the main conclusions.

2. Literature review

In the mid-seventies, city councils in different cities began to promote the night-time economy as one of the main ways to revitalize urban centers (Heath, 1997; Lovatt & O'Connor, 1995). The emergence of new forms of leisure, work (Rowe et al., 2008), and political concerns favored the promotion of nightlife, often considered an example of democratization, social cohesion, and tolerance (Bianchini, 1995; Nofre, 2020; Yeo & Heng, 2014). Since then, its socio-economic importance has only grown, becoming a fundamental part of city life (Hollands & Chatterton, 2003), a symbol of development and competitiveness (Hobbs et al., 2005), as well as a magnet for foreign investment, human capital, and tourism (Lin et al., 2022; Yeo & Heng, 2014).

The night-time economy has acquired great weight in the economies of Western countries. Thus, for example, in the United Kingdom it is the fifth largest industry and accounts for almost 8 % of employment and 6 % of total annual income (Lin et al., 2022). However, most research on the night-time economy has not examined nightlife from a consumption perspective, but rather from a social dimension. It has focused on issues such as social behavior in public places and socialization (Brands et al., 2014; Rowe et al., 2008), experiences (Hannigan, 1998), and synergies between the social, cultural, and economic aspects that take place during the night-time period (Lovatt & O'Connor, 1995).

The very nature of the night-time economy and the use of urban centers generates a series of contradictions and tensions between

different social groups: residents, tourists, workers, authorities, and consumers. These conflicts are varied in nature, ranging from problems directly associated with nightlife activities, such as noise, alcohol, or public disorder (Aramayona et al., 2019; Aramayona & García-Sánchez, 2019; Bianchini, 1995; Brands et al., 2014), to others more related to the use and dynamics of the city, such as the gentrification and touristification of central areas or the loss of the traditional retail in urban centers (Aramayona & García-Sánchez, 2019; Nofre, 2020).

One of the topics that has particularly interested night-time economy researchers to date is known as liminality and deviance, which has focused attention on the relationship between the night-time economy and alcohol, violence, and crime. This topic gained momentum in the late twentieth century, when increases in the number of licenses granted and the extension of opening hours were associated with an increase in alcohol consumption (Measham & Brain, 2005) and in the number of crimes and public disorder (Dodd et al., 2004; Hobbs et al., 2005). In this area, Graham and Homel (2008) related each type of license (pub, coffee shop, restaurant, nightclub) to the number of crimes associated with it, concluding that while proximity to restaurants was inversely proportional to the number of crimes, the opposite was true for pubs and nightclubs. Given these issues, it is not surprising that another widely studied topic has been the planning and regulation of the night-time economy (Yeo & Heng, 2014). Tiesdell and Slater (2006) briefly review the pros and cons of the different measures introduced, debating whether to extend the opening hours of venues or mix land uses. In this area, different researchers advocate a new approach to the night-time economy, supporting the introduction of activities for families (Roberts, 2009) or the generation of different leisure zones to revitalize neighborhoods (Campo & Ryan, 2008).

In recent years, research has increasingly focused on problems related to touristification. Nofre (2020) analyzed how the (night-time) touristification of southern European cities has led to tourist gentrification, which has resulted in the displacement of residents and retail businesses. Nofre et al. (2017) also investigated the particular case of Erasmus students as a trigger for the abandonment of the area by the local population in Lisbon's Bairro Alto. The city of Madrid has also been investigated, Aramayona and García-Sánchez (2019) interviewed different social groups to find out their opinion, often negative, about night tourism in Madrid and the consequent concentration of different activities in neighborhoods. Research with a similar approach was conducted in Budapest (Pinke-Sziva et al., 2019).

Recently, pioneering research has emerged that exploits the potential of new data sources (Big Data) to explore the characteristics of the night-time economy. The massive volume of geolocated data, the high spatial and temporal resolution of the data, and their continuous updating (Kitchin, 2013) allow the examination of certain topics that are still underexplored. New data sources, such as data generated by cell phones, night light satellite images, and POI data, complement and supplement more traditional approaches based on interviews and focus groups (Rowe et al., 2008) and observation in streets and bars (Eldridge, 2010), allowing a new approach to the study of night-time life in cities. Thus, some scholars (Kim, 2020; Kim & Kim, 2022; Li et al., 2022, 2024, Wu et al., 2021; Lee & Lee, 2024, Santiago-Iglesias, Romanillos, Sun, et al., 2024) used cell phone data to analyze night-time population density on the streets. Niu et al. (2022) generated an index from the density of social network users and POIs to study night-time life, while Santiago-Iglesias, Romanillos, Carpio-Pinedo, et al. (2024) have mapped the recovery of nighttime activity after pandemic restrictions using Google Popular Times data. Other researchers have used light intensity indices to analyze the night-time economy (Liu et al., 2020; Zhong et al., 2018).

Previous research on the night-time economy based on new data sources has contributed to a better understanding of nightlife in cities. However, questions remain to be explored, such as the geography of urban night-time spending, and underexploited data sources, such as bank card transaction data. Some researchers have analyzed bank card data at the intra-urban scale for different purposes. Thus, for example,

Aparicio et al. (2022) analyzed the spatial patterns of tourism expenditure at the intra-urban scale, while Carpio-Pinedo et al. (2022) focused their study on multi-sector spatiotemporal distributions. Yoshimura et al. (2016) used bank transaction data to study the mobility patterns of shopping trips, and Di Clemente et al. (2018) focused their research on the construction of a typology of ‘lifestyles’ and consumer profiles. Yoshimura et al. (2021) related the spatial distribution of spending in the city to the built environment by calculating correlations with density and street network connectivity. More recently, Yoshimura et al. (2022) analyzed the influence of pedestrianization of urban space on the income of surrounding retail stores. These and other articles have demonstrated the great potential of bank card transaction data to study the city. However, the night-time economy has not been studied using bank card transaction data, with the exception of Kim and Kim (2022) on the effects of COVID-19 on the night-economy. Our research contributes to fill this research gap through a spatiotemporal analysis of night-time spending based on bank card transaction data and other data sources (new and old).

Another contribution of this article is the use of deep learning tools that have so far been little used in the field of night-time economics. Only a few research studies have been found that use machine learning techniques to analyze the social impacts of night-time transportation in London (Zhang et al., 2022) or to improve the situation of vibrant areas (Shi et al., 2023). Here, we use one of the most popular algorithms, Random Forest regression (Ahsan et al., 2022). Its widespread use in different fields of study has shown that it has important advantages, for example due to its strong predictive capacity and its ability to explore the relationships between different explanatory variables (Breiman, 2001; Cheng et al., 2019), which will be very useful in this study to identify the factors that explain the spatial distribution of night-time consumption in Madrid.

3. Case study

3.1. The city of Madrid

Madrid, with >3.3 million inhabitants (7.3 million in its metropolitan area) is the largest city in Spain and one of the largest in Europe (Instituto Nacional de Estadística, n.d.). Madrid is an appropriate study area for research on the night-time economy, as it is a city with a vibrant nightlife, especially in the summer months (Aramayona & García-Sánchez, 2019). Madrid is internationally famous for its nightlife, boosted in recent years by international tourism. In fact, Madrid’s City Center nightlife scene has been profoundly affected by the expansion of tourist-oriented night-time leisure activities over the last three decades (Aramayona & García-Sánchez, 2019). Nightlife has become one of the main tourist attractions for the >9 million tourists that visited the city in 2022 (Ayuntamiento de Madrid, 2022).

The greatest concentration of commercial activity and bars and restaurants is found in the historic center of the city (around Puerta del Sol square, Gran Vía street, etc.) and, to a lesser extent, in surrounding areas such as Serrano street and the Salamanca district area (known as the “golden mile”) (see Fig. 1), resulting in a marked center-periphery contrast in spending patterns (Carpio-Pinedo et al., 2022). Nightlife has fostered an economic renaissance in the city center, but it is also a source of conflict with local communities, which endure noise and other nuisances late at night (Aramayona & García-Sánchez, 2019).

3.2. Time frame and time slots for the night-time economy in Madrid

Establishing a universal time frame for the night-time economy is a difficult issue, as different countries have different cultures and time rhythms. Thus, for example, in Australia this period is from 6 pm to 6 am (Beer, 2011), whereas in the Netherlands, it is more limited and runs between 8 pm and 6 am (Brands et al., 2014). In southern Europe, and particularly in Spain, schedules are different (Measham & Brain, 2005)

and nightlife is more vibrant. In this study, the night-time period for the city of Madrid has been considered to be between 7 p.m. (the time at which most people in Madrid have ended their working day) and 7 am (when many people in Madrid get up to start their working day).

Given that the activities and profiles of the clientele change throughout the night (Schwanen et al., 2012), in this study the night-time period has been subdivided into three time slots with contrasting characteristics: 1) “evening”, from 7 pm to 9 pm, in which shopping activities are dominant; 2) “dinner time”, from 9 pm to midnight, which in Spain covers the most frequent time for dining out, and 3) “late night”, between midnight and 7 am, the busiest period for late-night bars and nightclubs. Moreover, a differentiation has been made between Weekdays (from midnight on Monday to 7 pm on Friday) and Weekend (from 7 pm on Friday to the night of Sunday to Monday).

4. Data and methods

4.1. Expenditure dataset

The expenditure database contains the bank transactions of one of the leading banks in Spain during the year 2022. This bank’s data source collects both payments made with its cards and payments received at its Point of Sales Terminals (POS).¹ The dataset provides the amount, time, day, and the commercial sector of the transactions, spatially aggregated in 500 × 500 m grid cells. This tessellation is more suitable than administrative units in order to mitigate the MAUP problem, since the grid consists of spatial units with the same shape and size (Aparicio et al., 2022; Carpio-Pinedo et al., 2022). This type of data has been used in previous academic works for different objectives (see, for example, Alfaro et al., 2016; Aparicio et al., 2022; Hashemian et al., 2017; Lenormand et al., 2015; Sobolevsky et al., 2014, Sobolevsky et al., 2015, Sobolevsky et al., 2016; Yoshimura et al., 2016, 2018, 2021, 2022).

The original dataset classifies the commercial sector of transactions into 17 categories. In this article, the data was reclassified into 4 general categories based on the amount of night-time expenditure in each of them and their importance in the night-time literature. These categories are Bars and Restaurants, Fashion, Food, and Others.

Given that the dataset represents only a portion of total bank card payments in Madrid and that a portion of total spending is in cash, we have used a two-step procedure (based on elevation factors) to infer the spatial distribution of total spending in the city (Carpio-Pinedo et al., 2022). In a first step, we expanded the data taking into account the bank’s market share in order to obtain the value of total spending with bank cards in each cell of Madrid. In a second step, the total bank card spending obtained in the previous step was scaled up by considering the percentage of total spending in Madrid with card by categories according to the results of a Madrid City Council survey to make it representative of the total spending in Madrid (cash and card). This second elevation factor varies as a function of the percentage of card use in each of the spending categories to reduce bias due to different card use by spending categories. However, our dataset is assumed to have some certain bias. Thus, for example, as suggested by Yoshimura et al. (2018), this type of dataset contains a possible bias in terms of the representativeness of bank customers relative to the economically active population in the given area.

4.2. Exploratory variables

To explain the spatial distribution of night-time spending, different variables and data sources have been considered (Table 1). All variables

¹ Source: Developed from statistical data, irreversibly dissociated or anonymized, after being subjected to an aggregation process, of a portion of transactions with cards issued by BBVA in POS terminals of any entity and/or carried out in physical BBVA POS terminals, provided by Geoblinc.

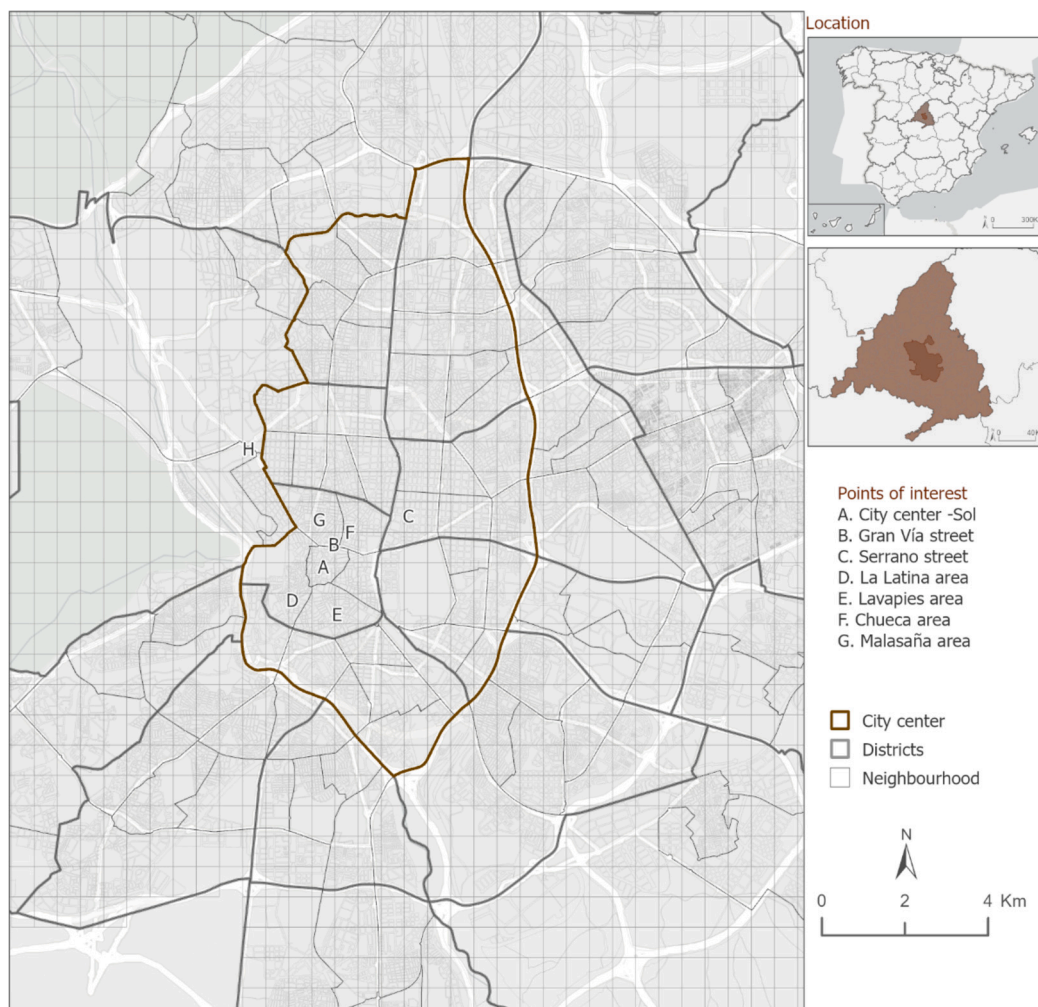


Fig. 1. Study area, main points of interest in Madrid and grid cells.

have been spatially aggregated to the same grid as the spending data. The cadastral registry provides the surface area of each building by type of land. For this work, the land use categories most closely related to night-time activity and consumption have been selected. In particular, commercial surface area has been used, which is directly related to consumption activity, in addition to office and industrial surface area, which in the city of Madrid are in some cases linked to the presence of nightlife areas. Finally, residential surface area is considered to have a positive correlation with consumption, since the mix of activities in residential spaces (as is often the case in Madrid) can turn residential spaces into dynamic and consumer spaces (Lin et al., 2022).

In addition to land uses, some variables directly related to nightlife have been included, such as the number of bars and restaurants and the number of terraces, which play a leading role in the sociocultural life of Spain (Frago, 2020). These variables have been obtained from the Census of Establishments and Activities of the Madrid City Council in 2022.

Consumption is not only explained through the physical offer of the establishments, since the popularity (socio-symbolic dimension) of the same can also play a relevant role (Aparicio et al., 2022). To consider the popularity of the establishments, the activity (check-ins) on the Foursquare social network has been considered. The Foursquare data facilitated the identification of key points in the city and their social relevance (Martí et al., 2019). Foursquare is particularly useful in the area of nightlife consumption, as people tend to go to the most popular establishments in the city (bars, restaurants, fashion stores, theatres, etc.) (Carpio-Pinedo & Gutiérrez, 2020). The Foursquare data was

downloaded in 2017, but accurately reflects the current vibrant spaces in the city.

The increased in night-time vitality has been considered through indicators of population presence obtained from cell phone records. Following a methodology similar to that of Li et al. (2022), we have used two variables that measure the number of people present in each of the grid cells in relation to the residents in that cell, at night-time. Positive balances indicate a higher population presence than expected given the number of residents and, therefore, a high vitality of that cell. Balances of population present compared to the resident population were obtained for weekdays and weekends.

Two other variables related to urban vitality are average household income and the number of Airbnb listings. The latter variable is intended to incorporate the close relationship between the night-time economy and tourism (Eldridge & Smith, 2019), while the former is expected to find a positive relationship with consumption, such that areas with higher incomes are also areas with higher spending.

Finally, distance to the city center has been considered as a predictor, since it is well known that night-time spending is especially concentrated in urban centers. Distance to the city center has previously been used as an exploratory variable (Wu et al., 2023), and its significance for urban vitality has been established (Mouratidis & Poortinga, 2020).

4.3. Methodology

The following methodology was used to analyze the spatial distribution of night-time spending in Madrid and the explanatory variables

Table 1
Candidate independent variables for OLS and RF regression.

Source	Variables	Description	Expected sign (*)
Land registry (2022). Spanish Ministry of Finance.	Commerce (m ²) (C)	Commercial floor area in m ²	(+)
	Offices (m ²) (O)	Office floor area in m ²	(+)
	Industry (m ²) (I)	Industrial floor area in m ²	(+)
	Residential (m ²) (R)	Residential floor area in m ²	(+)
Census of Establishments and Activities. Madrid City Council (2022)	Bars-restaurants (BR)	Number of establishments operating as cafeterias, bars, restaurants, pubs, and nightclubs.	(+)
	Bar terrace (BT)	Number of terraces belonging to bars and restaurants	(+)
Foursquare (2017)	Check-ins (Ch)	Number of check-ins at establishments	(+)
Mobile phone data (2022)	BalanceWD (BWD)	Difference between the population present at night-time on weekdays and the resident population	(+)
	BalanceWE (BWE)	Difference between the population present at night-time on weekends and the resident population	(+)
Atlas of urban income (INE, 2021)	Income (Inc)	Average household income	(+)
InsideAirbnb (2023)	Airbnb (Ab)	Number of accommodation offers on Airbnb	(+)
Own elaboration	Distance (D)	Distance to the city center (Puerta del Sol Square)	(-)

* Positive sign indicates that an increase in the independent variable produces an increase in the dependent variable and the opposite is the case for negative signs.

of these spatial patterns:

- a) Distributions of night-time spending data aggregated by tile were used to produce maps and descriptive statistics to explore the spatial patterns of consumption in the city. The expenditure maps provided a visual view of the spending in the total night-time period and in the three time slots. Descriptive statistics were useful to compare the degree of spatial concentration of payments in these time slots.
- b) A bivariate correlation matrix was calculated between the independent variables, total spending in the night-time period and spending in the three time slots analyzed. All the variables used were aggregated by 500x500m tiles to perform the regressions. The correlation between the explanatory variables also makes it possible to identify possible multicollinearity problems in the OLS models proposed below. Correlations between independent and dependent variables can be useful to identify which independent variables can be a good approximation to the spatial distribution of spending.
- c) Multiple regression analysis was used to generate explanatory models of the spatial distribution of night-time spending. OLS (Ordinary Least Squares) regressions and RF (Random Forest) regressions were used. In the first case, exploratory OLS regressions were constructed using all possible combinations for the candidate dependent variables. The models that provided the best fit (taking into account adjusted R-squared and AIC) with the smallest number of dependent variables were selected. All independent variables included have significant coefficients, and there is no redundancy of variables (all models have VIF values below 7.5). In the selected models, the global Moran's index was used to identify possible spatial autocorrelation in the model residuals.

d) RF is a non-parametric machine learning method for classification and regression analysis (Breiman, 2001), and does not require an assumption about the statistical distribution of the data. RF regression provides complementary information to OLS, allowing the importance of predictor variables to be assessed. In this case, RF regression has been used, employing the bootstrapping technique, with the data randomly split 80/20 between the training and test sets. The quality of model fit was measured using R-squared and OOB R-squared (Breiman, 2001). To measure the importance of the variables, the Mean Squared Error (%IncMSE) was used (Georganos et al., 2021). The higher the %IncMSE, the more important the variable is in predicting the dependent variable.

Partial Dependence Plots (PDP) were plotted for all variables considered in the models. PDPs allow characterizing the dependent relationships with night-time expenditure, showing the type of relationship present (linear, monotonic, curvilinear, or more complex) (Friedman, 2001).

GIS tools (ArcGIS Pro 3.1) were used for mapping, performing spatial analysis and OLS models, while RF models and PDP were obtained using R software (randomForest package).

5. Results

5.1. The importance of night-time spending

In terms of consumption, the night-time economy (from 7 p.m. to 7 a.m.) in Madrid accounted for 4244 million euros in 2022, equivalent to 30.1 % of total spending in the city's establishments (Table 2). If we look at the different time slots within the night-time period, we observe the decreasing contribution of spending in the different time slots, from 14.7 % in the evening to 10.6 % at dinner time, and 4.8 % at late night. The night-time economy is particularly important on weekends, when its contribution represents 32.3 % of total spending. On weekends, spending in the later time slots has a greater weight, representing 7.6 % in the late night and 12.2 % at dinner time, while spending in the evening drops to 12.5 %.

If we differentiate spending by categories of the commercial sector (Table 3), we observe that the categories that contribute most to night-time spending are Bars and Restaurants (40.5 %), Food (14.5 %), and Fashion (10.8 %). These three categories together account for approximately 80 % of total spending at dinner time and late night, while the equivalent figure is only 51 % in the evening, when spending is much more diversified due to the fact that all stores are open. In the evening, the categories that account for the largest share of spending are Fashion and Food, while at dinner time and in the late night the Bars and Restaurants category is clearly dominant.

Table 2
Percentage distribution of spending* by time slot (millions of euros).

Time slots	Total spend		Spend on working days		Spend on weekends	
	Abs.	%	Abs.	%	Abs.	%
Day (7 am-7 pm)	9852.9	69.9	5683.9	71.6	4169.0	67.7
Evening (7 pm-9 pm)	2070.5	14.7	1299.7	16.4	770.8	12.5
Dinner time (9 pm-12 pm)	1496.5	10.6	742.8	9.4	753.6	12.2
Late night (midnight-7 am)	676.8	4.8	208.8	2.6	468.0	7.6
Total spend (midnight-12 pm)	14,097.1	100.0	7935.6	100.0	6161.5	100.0
Total night (7 pm-7 am)	4244.2	30.1	2251.7	28.4	1992.5	32.3

* Data based on total spending, including cards and cash.

Table 3
Contribution of the main spending categories to night-time spending by time slot.

Millions of euros*	Bars and restaurants	Fashion	Food	Others	Total
Evening	269.6	391.6	384.8	1004.9	2050.9
Dinner time	976.8	66.4	112.8	294.8	1450.9
Late night	473.2	1.6	119.2	148.0	742.4
Total - night	1719.7	460.0	616.8	1448.1	4244.2
%	Bars and restaurants	Fashion	Food	Others	Total
Evening	13.1	19.1	18.8	49.0	100.0
Dinner time	67.3	4.6	7.8	20.3	100.0
Late night	63.7	0.2	16.1	20.0	100.0
Total - night	40.5	10.8	14.5	34.1	100.0

* Data based on total spending, including cards and cash

5.2. Night-time economy zones

The distribution of night-time spending in Madrid shows a typical center-outside pattern (Fig. 2). The areas with the highest spending are concentrated in the city center, where there is a high density of bars/restaurants, stores, and entertainment venues. In contrast, night-time spending is much lower in the outskirts, apart from some areas where shopping and leisure centers are located.

The maps of the distribution of spending by time slot (Fig. 3) show how, as the night goes on, not only is there a general decrease in spending, but it becomes more spatially concentrated. Thus, in the evening, consumption is spread practically throughout the city, although with greater intensity in the center and in some peripheral retail areas. At dinner time, this general pattern continues, although consumption drops considerably in many of the peripheral areas. Finally, at night, spending is highly polarized in some central areas and is almost nil in the outskirts.

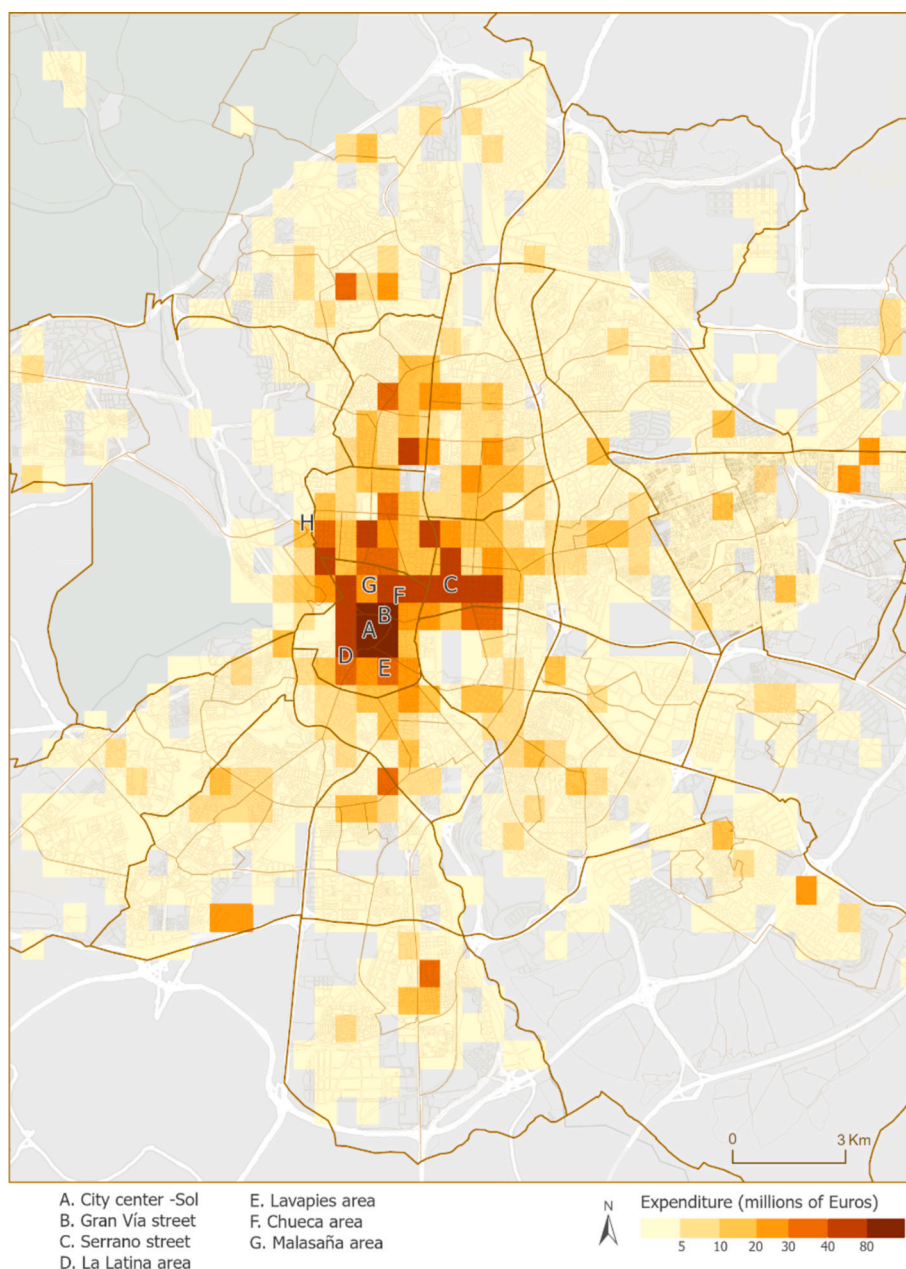


Fig. 2. Spatial distribution of night-time spending in Madrid (in millions of euros).

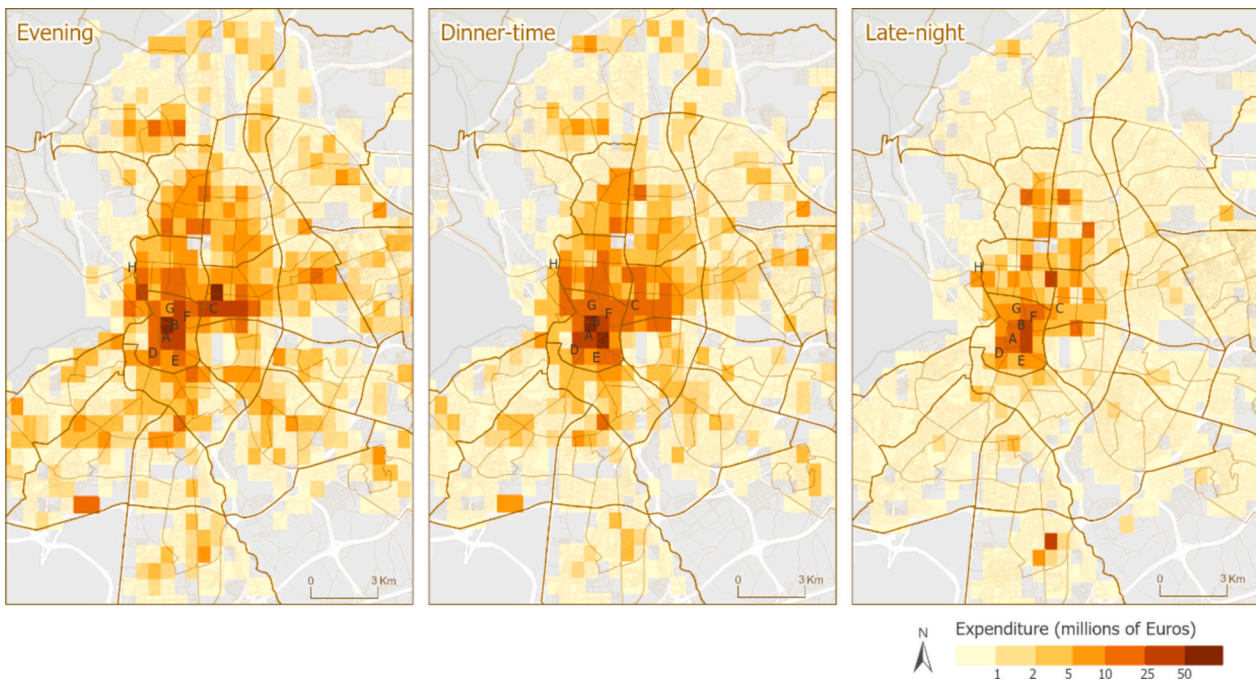


Fig. 3. Spatial distribution of night-time spending in Madrid by time slot (in millions of euros).

Appendix 1 includes the Anselin Local Moran index of the spatial distribution of night-time spending in Madrid. The results highlight the high concentration of night-time spending in the city center and the presence of a few high-low outliers in the periphery.

Table 4 shows the descriptive statistics of spending according to time slots and tiles. The coefficient of variation confirms that the spatial concentration of payments is higher at dinner time (234) than in the evening (259) and much higher in the late night (334).

5.3. Explanatory factors of expenditure distribution

5.3.1. Bivariate correlation analysis

The bivariate correlation matrix shows a very strong relationship between total night-time spending and variables related to the number of bars and restaurants (0.81) or the presence of terraces (0.75) (Table 5). The correlation between night-time spending and the popularity of establishments (check-ins on the social network Foursquare (0.77)), and the number of square meters of commercial space (0.61) is also high. Only the distance to the city center shows an inverse relationship with total night-time spending.

Differentiating by time slot, we observe that in the evening, the correlations with the variables linked to restaurants and bars decrease, while the correlation with commercial space increases. At dinner time and late night, the correlation of spending with the number of bars is very high, especially at dinner time (0.94). In this time slot, the correlations of spending with variables such as the number of terraces and check-ins also stand out.

Table 4
Descriptive statistics of expenditure (in millions of euros*).

	Evening	Dinner time	Late night	Total night
Total tiles	808	808	808	808
Minimum	0	0	0	0
Maximum	95.2	63.6	39.6	168.8
Total spend	2070.5	1496.5	676.8	4244.2
Mean	2.6	1.9	0.8	5.3
Standard deviation	6.0	4.8	2.8	12.4
Coefficient of variation	234.2	259.2	334.3	236.1

* Data based on total spending, including cards and cash.

As for the correlations between the explanatory variables, some are very high, such as the number of bars/restaurants and the number of terraces (0.87). There is also a high correlation between terraces and residential land, between check-ins and bars and restaurants, and between population balances and check-ins.

5.3.2. OLS and RF regressions

The regression models for total night-time spending have high explanatory power ($R^2 > 0.75$ in the OLS and RF regressions) (Table 6). By time slot, the best fits are obtained at dinner time. The different OLS models mainly include the variables of commercial area, bars and restaurants, check-ins, and the presence of population on weekends (BalanceWE), but they also show notable differences. Thus, for example, in the evening model, commercial area is highly significant, as expected, but the bars and restaurants variable is left out of the model (although the number of terraces is in it), suggesting that spending in stores (which are still open) is much more important than consumption in bars and restaurants at that time of day. In contrast, at Dinner time and Late night, both the number of bars and restaurants and the number of check-ins have highly significant coefficients, suggesting that consumers in that time slot go to the most popular bars, located in the nightlife areas of the city center.

Estimating the models for weekdays and weekends separately (Table 7) shows that the coefficients of determination are similar to those of the overall model (Table 6), although the late-night model has a better fit on weekends than on weekdays. This is consistent with the higher spending on weekends in this time slot, resulting in more defined patterns. In general, both models include the same explanatory variables, although, as expected, the weekday and weekend models incorporate the weekday and weekend population balance variables, respectively. Residential area is only significant on weekday evenings, which corresponds to consumption activities, especially shopping, in areas close to home.

Fig. 4 shows the importance of the explanatory variables in the RF model, taking into account all-night spending. The mean squared error (%IncMSE) measures the average decrease in prediction accuracy over the OOB samples when the given variable is excluded from the model. The larger the increase in %IncMSE, the more important the variable.

Table 5
Bivariate relationships (r Pearson).

Bars-Rest	1												
Bar terrace	0.87***	1											
Commerce (m ²)	0.62***	0.58***	1										
Check-ins	0.69***	0.6***	0.48***	1									
Distance	-0.51***	-0.51***	-0.35***	-0.37***	1								
Offices (m ²)	0.35***	0.37***	0.27***	0.37***	-0.18***	1							
Residential (m ²)	0.70***	0.79***	0.54***	0.33***	-0.51***	0.29***	1						
Industry (m ²)	0.04	0.05	0.07	0.18***	-0.07*	0.3***	0.05	1					
BalanceWD	0.34***	0.28***	0.23***	0.61***	-0.17***	0.31***	0.02	0	1				
BalanceWE	0.45***	0.33***	0.28***	0.69***	-0.19***	0.3***	0.06	0	0.97***	1			
Income	0.11**	0.18***	0.04	0.18***	-0.13***	0.13***	0.15***	-0.11**	0.3***	0.26***	1		
Airbnb	0.81***	0.63***	0.49***	0.75***	-0.4***	0.23***	0.45***	0.02	0.46***	0.58***	0.06*	1	
Total night-time	0.81***	0.75***	0.61***	0.77***	-0.4***	0.38***	0.52***	0.05	0.52***	0.6***	0.17***	0.74	
- Evening	0.66***	0.65***	0.62***	0.67***	-0.35***	0.36***	0.5***	0.06	0.55***	0.5***	0.14***	0.59	
- Dinner	0.85***	0.77***	0.56***	0.79***	-0.39***	0.35***	0.49***	0.03	0.56***	0.66***	0.17***	0.79	
- Late night	0.7***	0.59***	0.39***	0.62***	-0.32***	0.31***	0.39***	0.02	0.39***	0.49***	0.15***	0.64	
	Bars-Rest	Bar terrace	Commerce (m ²)	Check ins	Distance	Offices (m ²)	Residential (m ²)	Industry (m ²)	BalanceWD	BalanceWE	Income	Airbnb	

*** p < 0.01; ** p < 0.05. * p < 0.1.

Table 6
Model assessment metrics. Total.

	OLS		Random Forest	
	R ²		R ²	OOB R ²
All night-time	0.78 (1)		0.84	0.77
Evening	0.63 (2)		0.70	0.59
Dinner time	0.84 (3)		0.80	0.84
Late night	0.56 (4)		0.64	0.34

OLS variables:

- (1) + C** + Ch*** + BWE*** + BR***.
- (2) + C*** + Ch** + BT*** + BWE**.
- (3) -R*** + Ch*** + BT*** + BWE*** + BR***.
- (4) + Ch** + BWE*** + BR***.

*** p < 0.01; ** p < 0.05, * p < 0.1.

Table 7
Model assessment metrics. Weekdays and weekends.

	Weekdays			Weekends		
	OLS		Random Forest	OLS		Random Forest
	R ²		R ²	OOB R ²	R ²	R ²
All night-time	0.75 (1)	0.73	0.75	0.79(1)	0.75	0.79
Evening	0.62 (2)	0.64	0.58	0.62(2)	0.79	0.48
Dinner time	0.83 (3)	0.90	0.81	0.84(3)	0.90	0.79
Late night	0.42 (4)	0.29	0.36	0.60(4)	0.46	0.59

OLS variables:

- (1) + C*** + Ch*** + BT*** + BR** (1) + C** + Ch*** + BWE*** + BR***.
- (2) + R** + C*** + Ch*** + BT** + BWD*** (2) + C*** + Ch*** + BT*** + BWE**.
- (3) + Ch*** + BWD*** + BR*** (3) -R + Ch*** + BWE*** + BR***.
- (4) -R + Ch** + BWD*** + BR*** (4) + Ch* + BWE*** + BR***.

*** p < 0.01; ** p < 0.05, * p < 0.1.

The number of bars and restaurants is the most important variable in the model. It is followed in importance by the presence of terraces, the commercial area, the number of tourist accommodations on Airbnb, and the activity on Foursquare (check-ins). Other variables, such as the balance between present and resident population, and above all industrial area, office space, and average income, are of less importance in the model.

The results according to weekends and weekdays show some specific

characteristics that are worth commenting on (Fig. 4). Office space, for example, is much less important on weekends than on weekdays, while the opposite is true for check-ins, indicating that on weekdays the workplace is of some importance in explaining spending, while on weekends it is the “more popular” leisure venues that help to better explain the distribution of spending.

If we look at the results by night-time slot (Fig. 5), we see that commercial area is the most important variable in the evening, but its importance decreases notably during dinner time and, above all, in the late night. In contrast, in these last two time slots, and especially at dinner time, the variables most related to restaurants and nightlife stand out. Residential area is also more important in the more nocturnal time slots, but in general with a negative correlation, as shown by the partial dependence plots.

Partial dependence plots were constructed to characterize the type of relationship between factors and spending for the night-time as a whole (Fig. 6). The results show that most factors are not linearly associated with spending. The presence of bars and restaurants increases spending significantly, but above 200 bars the increase in spending is marginal. This situation also occurs with the variables of commercial area, terraces, and check-ins, where, once a certain value is reached, their effect on spending is very weak. Distance to the city center shows a negative curve, with a very pronounced drop in spending in the first 2 km, but after 2.5 km the effects of distance are also marginal, which is consistent with the strong concentration of night-time spending in the city center. Interestingly, the relationship between population balances and spending, both on weekdays and weekends, is positive when the population present exceeds the resident population, while in the other cases the effect is marginal.

6. Discussion

Since the mid-1970s, when some governments began to promote the night-time economy to revitalize urban centers (Heath, 1997; Lovatt & O’Connor, 1995), its importance has continued to grow, becoming a fundamental part of city life (Hollands & Chatterton, 2003). The expansion of concepts such as the 24-h city (Heath, 1997), nightlife promotion campaigns, or the creation of figures such as night mayors (O’Sullivan, 2016) are examples of the efforts made by cities to expand and promote their night-time economy. This interest has also extended to the academic world, whose concerns have expanded beyond

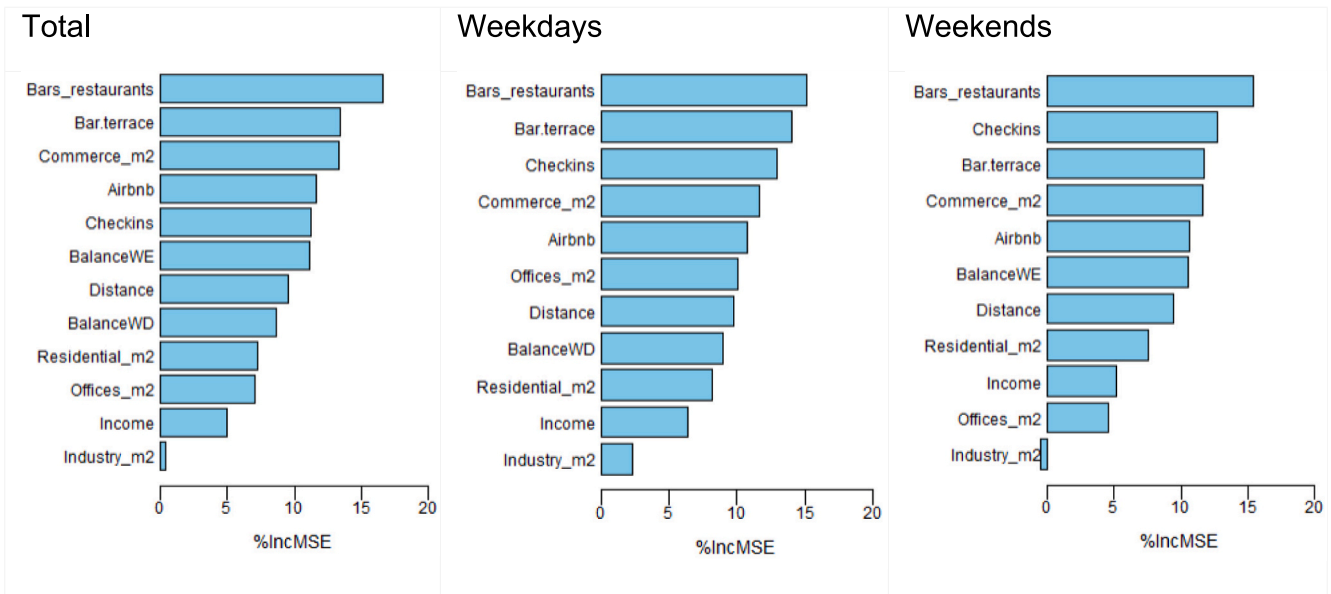


Fig. 4. RF variable importance (%IncMSE)*. * A higher percentage increase in mean squared error (%IncMSE) corresponds to higher importance.

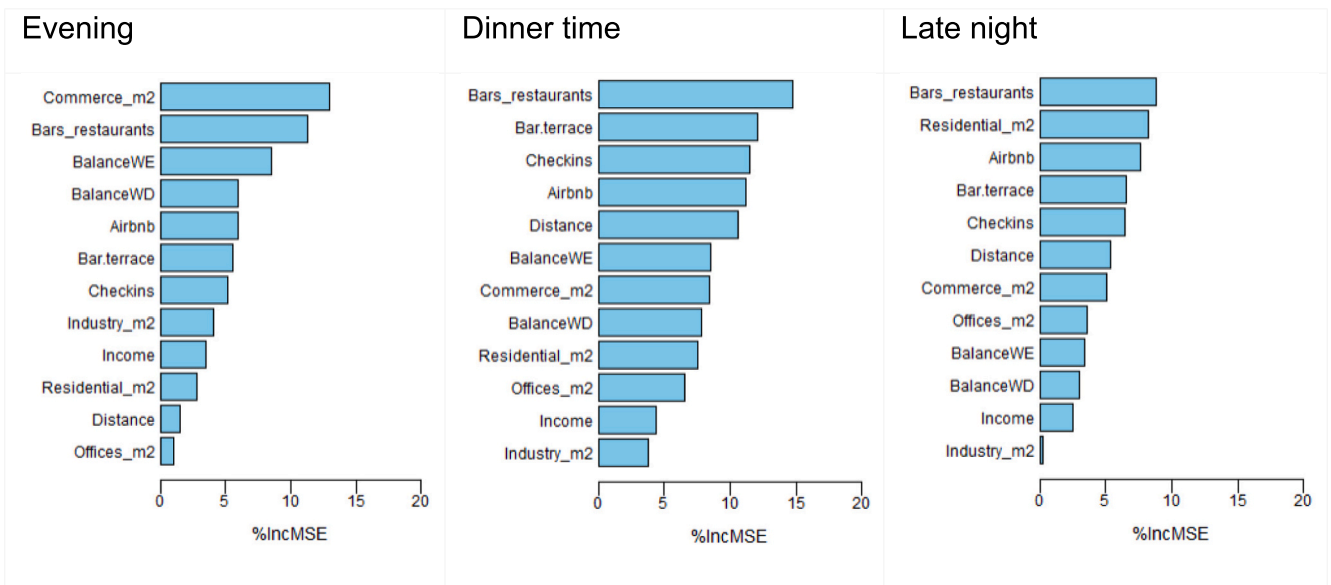


Fig. 5. RF variable importance (%IncMSE)* by time slot.

traditional topics such as planning or regulation (Yeo & Heng, 2014). Several authors have studied the characteristics of the night-time economy in cities, based on different proxy indicators such as night-time light intensity, mobile phone data or social media data.

New data sources have enabled new approaches, for example, the identification of busy and vibrant spaces (Kim, 2020; Li et al., 2022, 2024) and attractive hotspots (Lee & Lee, 2024). However, consumption related issues have hardly been studied. In this sense, bank card data offers a great opportunity to quantify at the intra-urban scale the night-time economy in terms of consumption, by analyzing its spatiotemporal patterns. This work has measured the important weight of the night-time economy in total spending in Madrid (30 %), showing differences in the amount of spending according to the categories of the commercial sector and in three time slots. The disaggregation into time slots and spending categories provides a more precise understanding of how night-time spending patterns change as the night progresses, an aspect that had not been addressed in the literature.

Another contribution of this article is the combination of bank card transaction data with other data sources, such as mobile phone data, social media data, cadastral records, etc. In this way, it has been possible to study the importance of different variables in urban night-time spending and to analyze the relationship of these variables with night-time consumption using partial dependence plots (Fig. 6). These datasets have also allowed us to examine the appropriateness of proxy variables commonly used in the literature to study nightlife. The results are consistent with those of previous studies that highlighted the importance of the presence of bars and restaurants (Capponi et al., 2019) and the amount of residential floor space (Li et al., 2022) in the night-time economy. The positive relationship between spending and the number of Airbnb accommodations confirms the close connection between nightlife and tourism, highlighted in previous research (Eldridge & Smith, 2019). Distance to the city center has also been identified as an important variable in predicting night-time spending, due to the propensity of night-time spending to concentrate in city centers, as

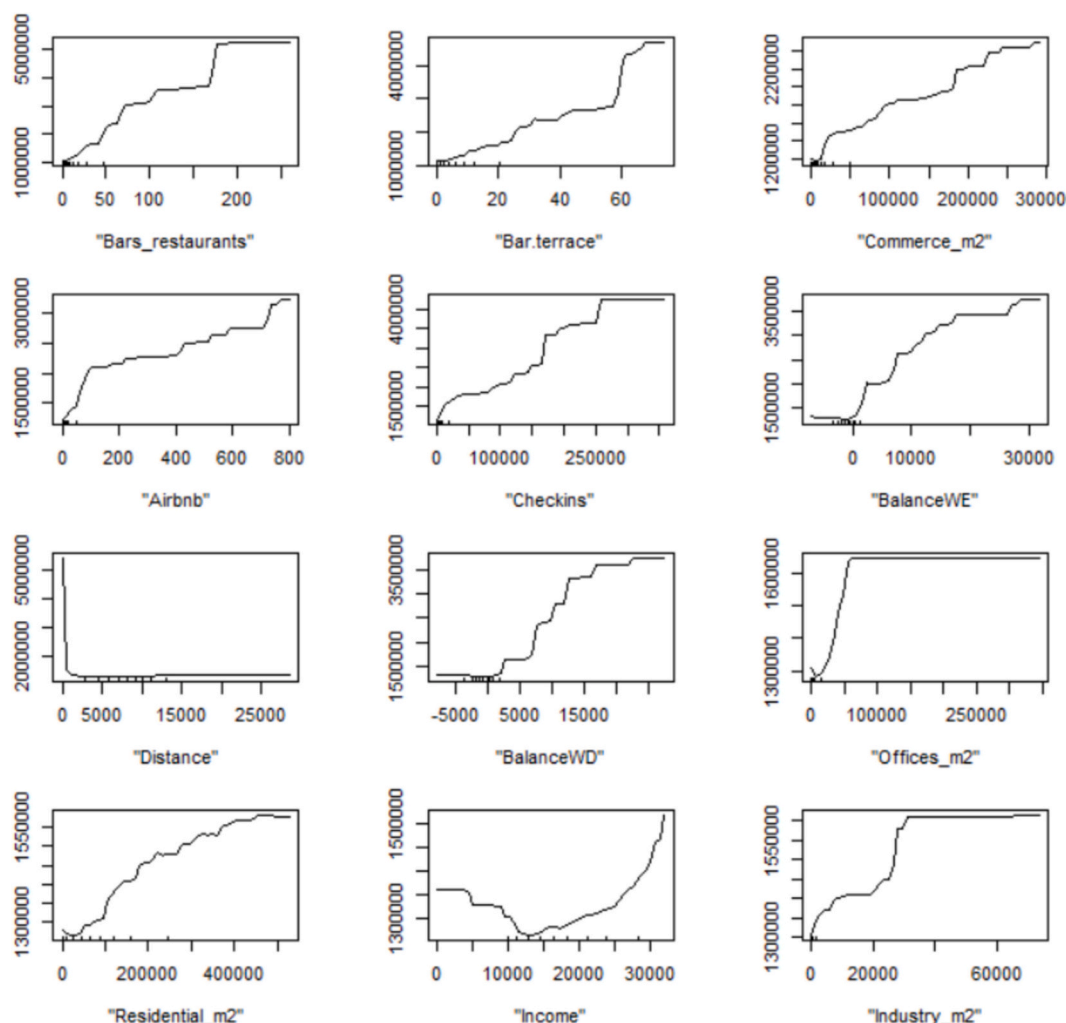


Fig. 6. Partial dependence plots. Total night.

suggested by Wu et al. (2023).

One of the most interesting results of our research is that the floating population variable, used as a proxy variable for the night-time economy in several studies (for example, Kim, 2020; Li et al., 2022), is not as closely related to consumption as expected, although it does increase spending. Interestingly, variables such as the popularity of establishments (check-ins on Foursquare) and the number of Airbnb accommodations show a higher correlation with night-time spending than the floating population. Therefore, floating population does not appear to be a good proxy for night-time spending, without questioning whether it adequately reflects the city’s nightlife areas (Wu et al., 2023). Future research should combine night-time vitality and consumption to better understand night-time geographies.

These inputs have important implications for planners and decision-makers. The identification of night-time consumption zones provides highly relevant information for city managers to strengthen services such as transportation, safety, street cleaning, and control of business licenses and noise. Likewise, this article demonstrates that the 24-h city concept only becomes a reality in the city center, at least in Madrid. The identification and characterization of night-time consumption zones provide useful information to city managers in case they want to promote new areas of night-time economy areas. Also, the areas of the city most dependent on night-time consumption will be the most vulnerable in case of pandemics such as COVID-19 (Santiago-Iglesias, Romanillos, Carpio-Pinedo, et al., 2024), so measures can be proposed to prevent city centers from becoming hyperspecialized in night-time activities.

This research has some limitations. Some of them are related to the characteristics of the dataset. To preserve the anonymity of bank card users and establishments, the expenditure data are provided aggregated in a grid of cells of 500 × 500 m, so the scale for the analysis cannot be chosen by the researcher. Also, the difficulty in accessing this type of data may make it difficult to replicate this study in other cities. Furthermore, these results cannot be extrapolated directly to other cities without considering the specific characteristics of each one. Factors such as the importance of terraces in sociocultural life (Frago, 2020), the social and functional mix of cities (Koch, 2015) or the different rhythms of urban life may influence the results, which requires the selection of the most appropriate variables in each case. Finally, the Foursquare dataset used is not recent, as this social network is less and less used. It would be preferable to use data from a social network with similar characteristics to Foursquare, but from the same date as the rest of the variables.

For future research, it would be interesting to carry out longitudinal studies to analyze the evolution of night-time spending in cities, and to use spatial statistical tools to identify spatial clusters and outliers, as well as their evolution over time. Another line of research could be to further explore the relationships and synergies between night-time vitality and night-time spending. In addition, it would be interesting to compare the results obtained in Madrid with those of other cities in different contexts and cultures to improve our understanding of night-time spending. It would also be worthwhile to further investigate the social and economic implications of the night-time economy for residents and the local

economy.

7. Conclusions

The importance of the night-time economy lies in its ability to boost local employment, stimulate economic growth, and enhance a city's attractiveness. Moreover, a vibrant night economy can attract tourists, generating additional revenue for businesses and local governments. However, it can also cause inconvenience to the local population, for example through noise and disorder.

To date, studies on the night-time economy have focused on its social effects, often relegating the economic perspective. The latter has only been analyzed indirectly through indirect indicators, such as the balance between present and resident population, or night-time lighting. The availability of bank card transaction data opens new avenues for research on the night-time economy. This article uses this new data source to perform a spatiotemporal analysis of night-time spending in Madrid, a city with a vibrant nightlife.

The results obtained indicate that night-time spending (from 7 p.m. to 7 a.m.) accounts for approximately 30 % of direct spending in the city's establishments. As the night progresses, spending decreases and its structure also changes. In the evening, shopping is very important, but at dinner time restaurants gain relative importance, and at late night the main protagonists of spending are bars. From a spatial point of view, night-time spending is concentrated in the city center, where there is a wide range of establishments. As expected, the concentration of night-time spending in the city center increases as the night progresses.

The article combines bank card transaction data and other data sources (new and old) to study the geography of the night-time economy. The variable most correlated with total night-time spending is Bars/restaurants, followed by variables expressing the popularity of establishments (check-ins on Foursquare), and the presence of tourists (Airbnb). In contrast, variables reflecting excess population (balance between present and resident population) show a moderate correlation with spending, which means that they are not the best proxies to explain the spatial distribution of spending, at least in Madrid. In the evening, several variables stand out for their high correlation coefficient with spending, which is indicative of the greater diversity of activities in that time slot, while at dinner time and late night, the Bars/restaurants variable is by far the one with the greatest explanatory power.

The OLS models obtained show that a small number of independent variables have a high explanatory power on the spatial distribution of night-time spending. In the general model (all night), variables related to the popularity of establishments (check-ins on Foursquare), presence of population (excess population on weekends), hospitality establishments (bars/restaurants), and retail (commercial area) are significant. The first two (popularity of establishments and excess population on weekends) are included in the models for all three night-time slots, while

retail only appears in the evening time slot and bars and restaurants only appear in the dinner and late night slots. Likewise, the results of the Random Forest models also indicate that the most important variables in explaining the distribution of night-time spending are those related to hospitality (Bars/restaurants, Terraces), commercial area and environments with tourist accommodations (Airbnb), followed by popularity (Check-ins), and although the presence of population has an impact, it is not as important.

The results obtained could be useful for urban managers and planners, providing them with information for decision-making on the spatiotemporal patterns of night-time spending and the variables that most influence these patterns. However, these results cannot be directly extrapolated to other cities, since cities with different cultures may present different patterns both in the temporal and spatial distribution of night-time spending, and in the structure of spending by category. Future studies on night-time spending in other cities may provide interesting results to establish comparisons, identify characteristics common to several cities and those that differ among them, and reinforce the relationship between night-time economy and vitality.

CRedit authorship contribution statement

Julia de las Obras-Loscertales Sampérix: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Conceptualization. **Juan Carlos García-Palomares:** Writing – original draft, Supervision, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Diego Ramiro-Fariñas:** Writing – original draft, Supervision, Methodology, Conceptualization. **María Soledad Hernández Martín-Caro:** Resources, Methodology, Funding acquisition. **Javier Gutiérrez:** Writing – original draft, Supervision, Methodology, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

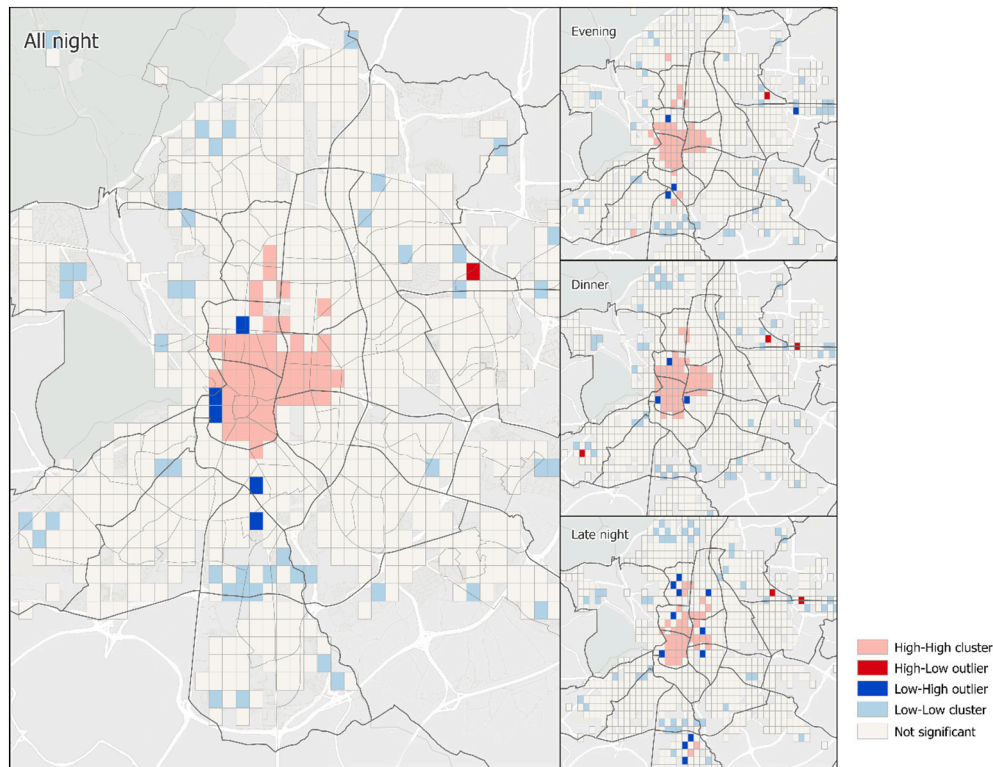
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix 1

Anselin Local Moran's Index of night-time spending in Madrid



Data availability

The authors do not have permission to share data.

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