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Tourism, neighbouring unemployment and street crime in Spanish provinces: beyond the denominator problem

Ángel Manzanares Gutiérrez

amanzanares@unex.es

Universidad de Extremadura

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Abstract

Crime in tourist areas is expressed per capita. However, tourists are both victims and perpetrators. This paper examines whether the higher amount of urban crime in Spanish provinces with high tourism could be explained by just a mechanical increase in population. A balanced panel dataset is constructed with data for 50 provinces between 2016 and 2025. Police data on urban property crime and data on the number of overnight stays from four official accommodation surveys were used. We demonstrate that if crime increases proportionally with population, the elasticity relating crime to tourism intensity should equal the percentage of the population who are tourists, which averages around 0.02. Specification tests indicated that a Spatial Lag of X model should be used with provincial and year fixed effects, and standard errors clustered at the provincial level. Outside the pandemic years, the association between tourist intensity and street crime is between 0.18 and 0.31 (direct and total effects), an order of magnitude above the proportional benchmark, although its precision is moderate and it weakens in dynamic and other demanding specifications. Unemployment in neighbouring provinces is positively associated with local street crime in almost every specification, whereas own unemployment is not. A shift-share instrument based on source markets proves weak, so the results are interpreted as conditional associations.

Keywords: tourism; street crime; ambient population; spatial lag of X; spillovers; Spain.

JEL classification: K42; R12; Z32; C23.

1. Introduction

Official crime rates in Spain are computed per 1,000 residents, yet a sizeable share of the people present in many provinces are not residents. In 2025 the Balearic Islands, Barcelona and Girona recorded the highest crime rates in the country, and two of them, the Balearic Islands and Girona, are among the provinces with the most overnight stays per inhabitant. There are two potential interpretations of this. Firstly, visitor numbers increase the population within a region and so increase the number of crimes. This would cause the crime rate per resident to increase purely due to the absence of tourists in the denominator of the equation. Secondly, tourism can increase the risk per individual by creating concentrated opportunities for crime and a dilution of protection, as predicted by routine activity theory.

The former interpretation provides an exact quantitative result that has not been used in previous literature. If there is a direct proportional relationship between the crime rate per resident and the tourist intensity then the elasticity of the crime rate per resident with respect to the tourist intensity equals the proportion of the population present that are tourists. In Spain this equates to approximately 2% of the sample mean and 14% in the most tourist province. If the elasticity is much greater than this then this shows that there is an increased risk.

Since the 1980's there have been studies into the relationship between tourism and crime. In Spain it was found that there was a positive impact from tourism arrivals on crime in different provinces between 2000 and 2008 (Montolio and Planells-Struse, 2016). Biagi and Detotto (2014) also included spatial components to the relationship between tourism and crime in Italy using a single cross-section. Dynamic spatial durbin models have been carried out on spatial panels for other countries such as China (Zhang and Xiang, 2022) however none have been done for Spain. Three aspects remain open. First, the denominator problem has been acknowledged in criminology (Andresen, 2006; Stults and Hasbrouck, 2015) but has not been confronted with a comprehensive measure of regulated tourist accommodation and an explicit benchmark. Second, the contribution of conditions in neighbouring provinces has not been estimated for Spain with a spatial panel. And third, the composition of recorded crime has changed radically since 2020, with fraud, largely online, displacing street property crime as the main growth component.

The main objective of this research is to determine whether tourist intensity is associated with street crime in Spanish provinces beyond the proportional effect of a larger population present. First, we seek to derive and quantify the proportional benchmark and to compare it with the estimated elasticities. Second, the research aims to estimate direct and indirect (spillover) associations of tourism and unemployment through spatial panel models selected by formal specification tests. Finally, it attempts to offer evidence useful for the allocation of police resources and for supra-provincial coordination of crime prevention.

Two hypotheses are tested:

H1: The elasticity of street crime with respect to tourist intensity exceeds the visitor share of the population present, so that tourism is associated with a higher risk per person present and not only with a larger number of people.

H2: Street crime in a province is associated with conditions in neighbouring provinces, both tourist intensity (target availability within reach of offenders) and unemployment (the pool of potential offenders within commuting distance).

The confirmation of H1 is a necessary condition to treat tourist crime as an excess risk that deserves specific attention, rather than as a by-product of the size of the population present. The second hypothesis states that the province is not a closed unit. Offenders travel, and both the opportunities and the motivations for crime may cross provincial borders, although regional economic cycles can generate similar patterns without any mobility of offenders.

This article contributes in four ways. First, we derive an intuitive benchmark that identifies the pure mechanical denominator effect from excess risk. Second, we construct an equivalent population based on the four official accommodation surveys to distinguish between street crime and fraud. Third, we estimate spatial panel models for 2016-2025 with a formal model selection process and clustered inference. Fourth, we report on our transparent attempt to identify causal effects using a shift-share instrument, which was not strong enough.

Section 2 presents a brief review of the literature regarding the economics of crime, tourism, vulnerable population and spatial spillovers. Section 3 describes data and creation of an equivalent population. Section 4 details the empirical methodology including the proportional benchmark, model selection and shift-share approach. Section 5 presents the results. Section 6 investigates the robustness of the results and attempts to identify the causal

mechanism. Finally Section 7 concludes with implications for policy makers as well as a summary of findings and limitations of the study.

2. Literature review

2.1. The economics of crime and its territorial dimension

This approach was first introduced by Becker (1968) who assumes that the criminal will act rationally and consider the expected benefit against the likelihood and severity of punishment. Ehrlich (1973) extended the model to the allocation of time between legal and illegal activities, introducing labour market conditions as determinants of crime. Cohen and Felson (1979) proposed the routine activity theory: a crime requires the convergence in space and time of a motivated offender, a suitable target and the absence of a capable guardian. The first framework explains who decides to commit crimes; the second, where and when crimes occur.

The evidence on unemployment and crime is mixed. Raphael and Winter-Ebmer (2001) find a positive effect of unemployment on property crime across United States states, and Gould, Weinberg and Mustard (2002) show that wages and unemployment of low-skilled men explain a considerable part of crime trends. For Spain, Buonanno and Montolio (2008) identify the socio-economic and demographic determinants of crime across provinces, and Alonso-Borrego, Garoupa and Vázquez (2012) analyse the relationship between immigration and crime. Several of these studies report strong persistence of crime over time, which motivates the dynamic specifications considered in section 6.

2.2. Tourism and crime

Fujii and Mak (1980) were among the first to relate tourism and crime in a regional context. Pizam (1982) reached less conclusive results, which suggests that the relationship depends on the type of destination and offence. Since then, the literature has converged on the idea that tourists act both as victims and as offenders, and that tourism alters the three elements of the routine activity triangle.

Biagi and Detotto (2014) use spatial lag and spatial error models to examine 103 Italian provinces for the year 2005 concluding that tourist visits increase certain crimes particularly theft and robbery. However, their cross-sectional design cannot control for unobserved provincial characteristics that attract both tourists and crime. Recher and Rubil (2020) exploit variation over time in Croatia and find that more tourism implies more property crime. Zhang and Xiang (2022), by contrast, estimate a dynamic spatial Durbin model for 21 cities in Sichuan and find a negative association between tourism and crime, with negative spillovers to neighbouring cities. The sign of the relationship, therefore, is not universal.

For Spain, Montolio and Planells-Struse (2016) estimate the impact of tourist arrivals on crime in Spanish provinces during 2000–2008 with panel data and find a positive and significant effect on property crimes and crimes against the person. Nevertheless, their analysis precedes the tourist expansion of the last decade, does not incorporate spatial dependence and measures crime per resident. For this reason it is worth revisiting the question with recent data, with a population at risk that includes visitors and with an explicit benchmark for the denominator effect.

2.3. The denominator problem

The choice of the population at risk is not neutral. Andresen (2006) shows that the spatial pattern of crime changes when rates are calculated with the ambient population instead of the resident population. The influx of commuters increases crime rates in US cites (Stults and Hasbrouck, 2015), while the influx of visitors contributes significantly to crime in Montreal's neighbourhoods (Boivin and Felson, 2018).

This can be interpreted to mean that more people in an area will increase the total number of offences, even if the likelihood of committing an offence remains unchanged. This alone will provide an increased amount of police resources. However, a higher crime rate per person indicates that tourism increases the risk an individual faces. This supports routine activity theory as tourists are either more likely targets or guardians have been weakened. To distinguish between these two factors, a benchmark must be found. This is derived in section 4.

2.4. Spatial spillovers of crime

Crime does not occur within administrative boundaries. There are two theoretical reasons that we would expect crime to spill over from one province to another. Firstly there may be an opportunity effect. Offenders in a province may travel to an adjacent tourist area to commit more crimes as there are more opportunities for targets. Secondly there may be a motivation effect. If there is a high level of unemployment in a province then there will be a greater pool of potential offenders. These may commit crimes within reach, including adjacent provinces. Spatial econometric methods can be used to capture these two effects (Anselin, 1988; Elhorst, 2014). Both the Spatial Lag of X (SLX) and Spatial Durbin (SDM) models can be used to allow the explanatory variables in adjacent units to influence each unit. The coefficients can also be interpreted as direct or indirect effects (LeSage and Pace, 2009). The SLX model is often the most appropriate model to begin with if we want to look at local spillover effects from the explanatory variables (Halleck Vega and Elhorst, 2015). For Spanish territories, previous work by the author has applied these techniques to unemployment in local labour markets (Manzanares and Riquelme, 2017), showing that labour market phenomena present spatial autocorrelation that administrative boundaries do not capture.

3. Data

The sample comprises the 50 Spanish provinces for 2016–2025, a balanced panel of 500 observations. Ceuta and Melilla are excluded because of their small size, their geographical position and the peculiarity of their crime figures.

3.1. Crime

Crime data come from the annual series of known offences (*hechos conocidos*) of the Crime Statistics Portal of the Ministry of the Interior, which gathers records of the National Police, the Guardia Civil, the regional police forces and the local police forces that report to the Crime Statistical System. Known offences are used instead of cleared offences because the latter depend on police effectiveness.

Street crime is the sum of four indicators of the portal: 5.1 *Hurtos* (thefts), 5.2 *Robos con fuerza en las cosas* (burglaries), 5.3 *Robos con violencia o intimidación* (robberies) and 5.4

Sustracción de vehículos (vehicle theft), that is, the property offences that require the physical presence of offender and victim. *Fraud* is indicator 5.5 *Estafas*, which in the annual series includes both conventional and computer fraud. *Total offences* is used as a contrast. At the national level, the share of fraud in total offences grew from 4.2% in 2011 to 21.7% in 2025, while that of street crime fell from 59.4% to 39.5%; these national figures are the only use made of the 2011–2015 data.

The panel starts in 2016 for two reasons. Local police forces were progressively incorporated into the Crime Statistical System from 2013 onwards, which generates an uneven break across provinces. And the tourist apartment survey covers only 28 provinces until 2013, so tourist intensity would show artificial jumps in the early years.

3.2. Population and equivalent population

The resident population is taken from the homogeneous series of the Continuous Population Statistics of INE (table 59589), on 1 January of years t and $t+1$, whose mean approximates the mid-year population. Using a single homogeneous series avoids any break in the denominator. Tourist presence is measured by overnight stays in the four occupancy surveys of INE: hotels (EOH, table 67190), tourist apartments (EOAP, table 2063), campsites (EOAC, table 2062) and rural tourism accommodation (EOTR, table 2073). In 2019 hotels account for 74% of the overnight stays, apartments for 15%, campsites for 9% and rural accommodation for 2%.

The equivalent population of province i in year t is calculated as:

$$P_{it}^{eq} = P_{it} + \frac{N_{it}}{365} = P_{it}\left(1 + \frac{T_{it}}{365}\right) \qquad (1)$$

where P_{it} is the mid-year resident population, N_{it} the total number of overnight stays in the four types of accommodation and $T_{it} = N_{it}/P_{it}$ the tourist intensity, that is, overnight stays per resident. The quotient $N_{it}/365$ is the average number of visitors present on any given day.

Three data gaps require treatment, documented in the appendix. Campsite stays are published for only 33 provinces until 2023; to keep the series homogeneous they are used only for those provinces, and in 2024 campsites represent a median of 2.9% of total stays in the other 17.

Some monthly cells of the apartment and rural surveys are suppressed in 2020 and 2021, and hotel data are missing for May and June 2020 in Ávila, León, Palencia, Segovia and Zamora; these cells, which coincide with lockdown closures or statistical confidentiality, are set to zero. Finally, the surveys do not cover dwellings rented through digital platforms, second homes or stays with relatives, so the equivalent population is a lower bound of the people actually present.

3.3. Control variables

The unemployment rate is the annual average of the four quarters of the Labour Force Survey (EPA, table 65349). The share of the population aged 15–29 and the share of foreigners within that age group come from the municipal register until 2020 and from the Continuous Population Statistics (table 60129) from 2021, on 1 January and averaged to mid-year; the 2020 mid-year value therefore combines both sources. The share of foreigners is measured within the 15–29 group because it is the age group most relevant for crime and can be calculated with both sources. GDP per capita in current euros comes from the Regional Accounts of Spain; the 2025 provincial value, not yet published, is extrapolated with the nominal growth of GDP per capita of the corresponding autonomous community.

3.4. Descriptive statistics

Table 1 summarises the variables. Street crime averages 15.12 offences per 1,000 residents and 14.72 per 1,000 equivalent inhabitants. The average difference is small, but tourist intensity ranges from 0.74 to 62.27 overnight stays per resident, the maximum corresponding to the Balearic Islands.

TABLE 1. DESCRIPTIVE STATISTICS, 50 PROVINCES, 2016–2025 (N = 500)

Variable	Mean	Std. dev.	Min.	Max.
Street crime per 1,000 residents	15.12	6.81	3.57	44.59
Street crime per 1,000 equivalent population	14.72	6.43	3.52	43.77
Total offences per 1,000 residents	37.98	10.27	17.60	68.21
Fraud per 1,000 residents	7.09	2.97	1.16	14.53
Overnight stays per resident (T)	8.34	10.91	0.74	62.27
Unemployment rate (%)	14.21	5.37	5.20	34.39
Population aged 15–29 (%)	15.02	1.63	11.32	18.14
Foreigners among population aged 15–29 (%)	13.74	5.92	2.76	27.39

Variable	Mean	Std. dev.	Min.	Max.
GDP per capita (EUR)	26,161	6,044	16,418	47,220

Source: Own elaboration based on the Ministry of the Interior (Crime Statistics Portal) and INE.

In 2019 the street crime rate falls by 13.8% in the Balearic Islands, 12.5% in Las Palmas and 9.0% in Santa Cruz de Tenerife when the equivalent population is used, and by 6–8% in Girona and Tarragona. In the median province the reduction is only 1.3%, and the ranking of provinces barely changes.

4. Empirical strategy

4.1. The proportional benchmark

Let C_{it} denote street offences. Taking logarithms of the crime rate per equivalent population and using equation (1):

$$\ln \frac{C_{it}}{P_{it}^{eq}} = \ln \frac{C_{it}}{P_{it}} - \ln\left(1 + \frac{T_{it}}{365}\right) \qquad (2)$$

Suppose that offences grow exactly in proportion to the population present, so that the rate per equivalent inhabitant does not depend on T_{it}. Differentiating (2), the elasticity of the rate per resident with respect to tourist intensity is then:

$$\frac{\partial \ln(C_{it}/P_{it})}{\partial \ln T_{it}} = \frac{T_{it}/365}{1 + T_{it}/365} \equiv v_{it} \qquad (3)$$

where v_{it} is the share of visitors in the equivalent population. The value of equals 0.022 at the sample mean (T=8.34) and 0.138 in the Balearic Islands for 2019. This is the level that would be achieved under a pure denominator effect. If the elasticity of the rate per resident exceeds then there is excess risk per person present (H1). Equations in (2) imply that the estimates for elasticity per resident and per equivalent population are not independent. The difference between the two is approximately equal to by construction. The equivalent population specification is presented because it can be seen to be equivalent to an elasticity of excess risk and because it accounts for the nonlinear nature of the benchmark across provinces.

Secondly, because overnight stays are included in the denominator of the equivalent population rate and the numerator of tourist intensity, any measurement error in will cause a negative bias in the equivalent population specification (division bias).

For this reason, section 6 also estimates a model for the logarithm of the number of offences with the logarithms of tourist intensity and resident population as separate regressors.

4.2. Spatial weights and exploratory analysis

The spatial structure is represented by a first-order queen contiguity matrix W. The binary matrix is symmetric before row-standardisation. Island provinces lack physical neighbours: the Balearic Islands are connected to Barcelona and Valencia, their main ferry links, and Las Palmas and Santa Cruz de Tenerife to each other. The latter choice creates a two-province component separated from the rest; section 6 checks the sensitivity of the results to connecting the Canary Islands with Cádiz, Huelva and Seville, their main maritime and air links to the mainland, and to excluding the three island provinces. Global spatial autocorrelation is measured with Moran's I:

$$I = \frac{N}{S_0} \cdot \frac{\sum_i \sum_j w_{ij} z_i z_j}{\sum_i z_i^2} \qquad (4)$$

where N is the number of provinces, w_{ij} the elements of W, z_i the deviation of the crime rate of province i from the mean, and S_0 the sum of all weights, which equals N for a row-standardised matrix. The null hypothesis of spatial randomness ($H_0: I = 0$) is contrasted through 999 random permutations. Local clusters are identified with the LISA statistics of Anselin (1995).

4.3. Spatial panel models and model selection

The general specification is the Spatial Durbin Model (SDM) with province and year fixed effects:

$$\ln y_{it} = \rho \sum_j w_{ij} \ln y_{jt} + x_{it}\beta + \sum_j w_{ij} x_{jt}\theta + \mu_i + \nu_t + \varepsilon_{it} \qquad (5)$$

where y_{it} is the street crime rate (per resident or per equivalent population), ρ the spatial autoregressive parameter, x_{it} the $1 \times K$ row vector of explanatory variables (logarithm of

tourist intensity, unemployment rate, share of population aged 15–29 and share of foreigners in that group), β and θ the $K \times 1$ vectors of coefficients of the own and spatially lagged explanatory variables, μ_i the province fixed effects, ν_t the year fixed effects and ε_{it} the error term.

The SDM nests three simpler models: the Spatial Lag of X (SLX, $H_0: \rho = 0$), the spatial autoregressive model (SAR, $H_0: \theta = 0$) and the spatial error model (SEM, $H_0: \theta + \rho\beta = 0$). We contrast these restrictions through likelihood ratio (LR) tests, following Elhorst (2014). When the SLX is not rejected, its coefficients are directly interpretable: β is the direct effect, θ the indirect effect and $\beta + \theta$ the total effect (Halleck Vega and Elhorst, 2015).

The SLX is estimated by two-way within least squares with standard errors clustered by province, which are robust to heteroskedasticity and to serial correlation within each province. This choice matters. Maximum likelihood standard errors of the SDM assume serially independent errors, and in this panel they are around 35% smaller than clustered ones. The SDM is reported as a robustness check, estimated by maximum likelihood with the Lee and Yu (2010) correction using the *splm* package in R (Millo and Piras, 2012), with effects computed following LeSage and Pace (2009).

The province fixed effects absorb every time-invariant characteristic, such as being a coastal, island or metropolitan province, and the year fixed effects absorb shocks common to all provinces, such as legislative changes or the national growth of online fraud. Identification comes only from changes within each province relative to the national trend. The reference sample excludes 2020 and 2021, years in which border closures and mobility restrictions broke the usual relationship between tourism and crime; the full sample is also reported.

4.4. Shift-share instrument

The fixed effects do not eliminate time-varying factors correlated with tourism, nor reverse causality, since crime may deter visitors. To address these threats, we test a shift-share instrument (Bartik, 1991) in the spirit of Goldsmith-Pinkham, Sorkin and Swift (2020) and Borusyak, Hull and Jaravel (2022). The predicted growth of hotel overnight stays in province i between 2015 and year t is:

$$\hat{g}_{it} = \ln\left(\sum_{c} s_{ic,2015} \cdot \frac{N_{c,t}^{-i}}{N_{c,2015}^{-i}}\right) \qquad (6)$$

where $s_{ic,2015}$ is the share of source market c in the hotel overnight stays of province i in 2015, with shares summing to one in each province, and $N_{c,t}^{-i}$ the overnight stays of market c in Spain excluding province i (leave-one-out). Twenty-five markets are used: residents in Spain as a single market, 23 countries or groups of countries listed in the appendix, and a residual category. The data come from the EOH tables of overnight stays by province and country of residence for 2015, 2019 and 2025.

The instrument requires two mechanical preconditions: that provinces differ in their market composition and that markets evolve unevenly. Its validity then requires relevance, that is, that predicted growth explains actual growth, and exclusion, that is, that the 2015 market composition is not related to provincial crime trends other than through tourism. Because only three years of country-level data were assembled, relevance is evaluated in long differences across provinces, which is a necessary condition for the instrument to be useful in the annual panel.

5. Results

5.1. Exploratory spatial analysis

Table 2 shows that street crime presents positive and significant spatial autocorrelation in every year. The null hypothesis of spatial randomness is rejected at the 1% level, and Moran's I rises from 0.386 in 2016 to 0.504 in 2025. The correction of the denominator reduces the statistic by only 0.03–0.04 points. Fraud, by contrast, shows weaker and unstable dependence, and in 2022 it is not significant at the 5% level.

TABLE 2. MORAN'S I OF CRIME RATES BY TYPE OF OFFENCE AND DENOMINATOR

Year	Street crime, residents	Street crime, equivalent pop.	Total offences, residents	Fraud, residents
2016	0.386***	0.349***	0.383***	0.359***
2019	0.415***	0.376***	0.418***	0.236***

Year	Street crime, residents	Street crime, equivalent pop.	Total offences, residents	Fraud, residents
2022	0.462***	0.426***	0.406***	0.127*
2025	0.504***	0.475***	0.478***	0.362***

Note: Pseudo-significance from 999 permutations. *** $p < 0.01$; * $p < 0.10$.

Source: Own elaboration.

The LISA analysis for 2019 identifies two types of significant clusters at the 5% level: a) High-High clusters (hot spots) in the Balearic Islands, Barcelona, Girona and Lleida, that is, the north-eastern axis formed by Catalonia and the Balearic Islands; b) Low-Low clusters (cold spots) in León, Lugo, Ourense, Pontevedra, Salamanca and Valladolid, in the north-west of the peninsula; c) no significant High-Low outliers; and d) no significant Low-High outliers. With the equivalent population the High-High cluster is identical and the Low-Low cluster loses only Ourense.

5.2. Model selection

Table 3 reports the LR tests of the SDM against its nested alternatives. The restriction $\rho = 0$ cannot be rejected in any specification (p between 0.23 and 0.57), whereas the SAR and SEM restrictions are rejected at the 1% level. Spatial dependence therefore operates through the explanatory variables of the neighbours and not through neighbouring crime, and the SLX is retained as the main model.

TABLE 3. LIKELIHOOD RATIO TESTS OF THE SDM AGAINST NESTED MODELS (STREET CRIME)

Specification	SLX ($\rho = 0$), df = 1	SAR ($\theta = 0$), df = 4	SEM ($\theta + \rho\beta = 0$), df = 4
Residents, 2016–2025	0.38 (p = 0.538)	22.88 (p < 0.001)	24.47 (p < 0.001)
Equivalent pop., 2016–2025	0.32 (p = 0.574)	23.21 (p < 0.001)	24.59 (p < 0.001)
Residents, excl. 2020–2021	1.46 (p = 0.226)	20.08 (p < 0.001)	22.71 (p < 0.001)
Equivalent pop., excl. 2020–2021	1.37 (p = 0.243)	20.33 (p < 0.001)	22.84 (p < 0.001)

Source: Own elaboration.

5.3. SLX estimates

Table 4 presents the SLX estimates. In the reference sample, excluding 2020 and 2021, the direct elasticity of street crime per resident with respect to tourist intensity is 0.200 and the total elasticity 0.310. Both are about one order of magnitude above the proportional benchmark of equation (3), which is 0.022 at the sample mean. The difference between the

direct elasticity and the benchmark is significant at the 5% level in a one-sided test (t = 1.68), and that of the total elasticity at the 5% level in a two-sided test (t = 2.04). With the equivalent population, the direct and total elasticities are 0.181 and 0.278, as expected from equation (2). The precision, however, is moderate: with clustered errors the direct effect is significant only at the 10% level, and the indirect effect of tourism is positive but not significant.

TABLE 4. SLX MODEL WITH TWO-WAY FIXED EFFECTS. DEPENDENT VARIABLE: LOG OF STREET CRIME RATE

	(1) Residents 2016–25	(2) Equivalent 2016–25	(3) Residents excl. 2020–21	(4) Equivalent excl. 2020–21
ln overnight stays per resident				
Direct (β)	0.070 (0.053)	0.027 (0.049)	0.200* (0.106)	0.181* (0.106)
Indirect (θ)	0.131 (0.102)	0.097 (0.101)	0.110 (0.152)	0.097 (0.152)
Total (β + θ)	0.201** (0.097)	0.124 (0.094)	0.310** (0.141)	0.278* (0.142)
Unemployment rate (percentage points)				
Direct	0.000 (0.004)	0.001 (0.004)	0.001 (0.004)	0.001 (0.004)
Indirect	0.015** (0.006)	0.017*** (0.006)	0.017** (0.007)	0.017** (0.007)
Total	0.015** (0.007)	0.017*** (0.007)	0.018** (0.008)	0.018** (0.008)
Population aged 15–29 (%)				
Direct	−0.003 (0.024)	−0.005 (0.024)	0.000 (0.024)	−0.001 (0.024)
Indirect	0.035 (0.036)	0.030 (0.036)	0.025 (0.037)	0.024 (0.037)
Foreigners among population aged 15–29 (%)				
Direct	0.006 (0.007)	0.005 (0.007)	0.006 (0.008)	0.006 (0.008)
Indirect	−0.007 (0.014)	−0.007 (0.014)	−0.011 (0.015)	−0.011 (0.015)
Province and year fixed effects	Yes	Yes	Yes	Yes
Observations	500	500	400	400

Note: Standard errors clustered by province (50 clusters) in parentheses. In the SLX model the direct, indirect and total effects equal β, θ and β + θ. *** p < 0.01; ** p < 0.05; * p < 0.10.

Source: Own elaboration.

Unemployment behaves differently. Its direct effect is nil in every specification, whereas its indirect effect is positive and significant at the 5% level: an increase of one percentage point in the unemployment rate of neighbouring provinces is associated with 1.5–1.7% more street crime in the province. Neither the share of young people nor the share of foreigners among them is significant.

When the pandemic years are included, the direct association of tourism falls to 0.070 per resident and to 0.027 per equivalent population. In 2020 and 2021 tourism collapsed while

crime fell much less, and these years dominate the within-province variation. For this reason specifications (3) and (4) are taken as the reference, although the total effect per resident remains significant at the 5% level in the full sample.

6. Robustness and identification

6.1. Alternative specifications

Table 5 summarises the associations of tourism and neighbouring unemployment under alternative specifications, all for street crime per resident and excluding 2020–2021 unless otherwise stated. The results can be grouped into three blocks.

First, the tourism association is robust to the choice of controls, of accommodation surveys and of spatial weights. Including GDP per capita (in logarithms, with its spatial lag), removing the demographic controls, restricting overnight stays to the three surveys available for all provinces, connecting the Canary Islands to Andalusia or excluding the three island provinces leaves the direct elasticity between 0.15 and 0.21 and the total between 0.26 and 0.40, although several estimates are significant only at the 10% level or not significant. The SDM gives almost identical point estimates. A non-spatial fixed-effects model, which assigns to own tourism the association that the SLX splits between own and neighbouring tourism, yields 0.274, significant at the 1% level.

Second, the tourism association weakens in the most demanding specifications. Street crime is highly persistent: in a dynamic SLX with the lagged dependent variable and its spatial lag, the autoregressive coefficient is 0.59. The short-run direct elasticity falls to 0.082 and is not significant, although the implied long-run elasticity, $0.082/(1-0.590)=0.20$, coincides with the static estimate. These dynamic estimates are subject to Nickell bias, which with ten years is downward for the autoregressive coefficient. In the model for the number of offences, which avoids division bias, the direct and total elasticities are 0.106 and 0.229, positive but imprecise. And when province fixed effects are allowed to differ before and after 2021, which removes any level break due to the change of source of the demographic controls but also most of the within-province variation in tourism, the association disappears.

Third, the indirect association of neighbouring unemployment is the most stable result. It remains between 0.012 and 0.020 and significant in almost every specification, including the dynamic one and the one with province-specific breaks in 2021. It is reduced to 0.010 and loses significance at the 5% level when linear trends by autonomous community are included, which suggests that part of this association reflects regional economic cycles rather than the mobility of offenders. In a non-spatial model, own unemployment is positive (0.008) but not significant at the 5% level.

TABLE 5. ROBUSTNESS: STREET CRIME PER RESIDENT, EXCLUDING 2020–2021 UNLESS STATED

Specification	Tourism, direct	Tourism, total	Neighbouring unemployment
SLX, reference (Table 4, col. 3)	0.200* (0.106)	0.310** (0.141)	0.017** (0.007)
SDM, maximum likelihood (a)	0.202*** (0.067)	0.321*** (0.107)	0.018*** (0.005)
Non-spatial fixed effects (b)	0.274*** (0.094)	—	—
+ GDP per capita	0.176* (0.099)	0.318** (0.143)	0.016** (0.006)
+ GDP per capita, equivalent population	0.157 (0.099)	0.289** (0.143)	0.016** (0.006)
Without demographic controls	0.205** (0.098)	0.266** (0.126)	0.020*** (0.005)
Three surveys (without campsites)	0.152 (0.097)	0.258* (0.144)	0.016** (0.007)
W with Canary Islands linked to Cádiz, Huelva and Seville	0.185* (0.096)	0.395* (0.213)	0.015** (0.007)
Excluding the three island provinces	0.181 (0.113)	0.328 (0.204)	0.015* (0.009)
Dynamic SLX (lagged dependent variable 0.590***)	0.082 (0.064)	0.091 (0.088)	0.012*** (0.004)
Log number of offences, controlling for log population	0.106 (0.096)	0.229 (0.164)	—
Province × post-2021 fixed effects	0.077 (0.101)	−0.059 (0.210)	0.014** (0.006)
Linear trends by autonomous community	0.165 (0.115)	0.393** (0.198)	0.010 (0.006)
Total offences	0.216** (0.104)	0.366*** (0.141)	0.015** (0.007)
Fraud	0.107 (0.208)	−0.011 (0.310)	−0.007 (0.014)

Note: Standard errors clustered by province in parentheses, except (a), maximum likelihood with the Lee and Yu (2010) correction and effects simulated with 2,000 draws, and (b), where own unemployment is 0.008 (0.005). *** p < 0.01; ** p < 0.05; * p < 0.10.

Source: Own elaboration.

The estimates for total offences and fraud explain why street crime is analysed separately. In the fraud model, the share of young people has a negative direct effect (−0.107, standard error 0.044) and the share of young foreigners a positive indirect effect (0.060, standard error 0.026), whereas tourism is not associated with fraud. In total offences, the share of young people has a negative direct effect (−0.063, standard error 0.022). Neither appears in street

crime, so mixing both types of offence would lead to erroneous conclusions on the demographic determinants of crime.

6.2. The pandemic as a natural experiment

The collapse of tourism in 2020 could, in principle, act as a natural experiment. An event-study specification is estimated in which the logarithm of tourist intensity of each province in 2019, standardised, interacts with year dummies, with 2019 as the reference year, province and year fixed effects, the unemployment rate as control and standard errors clustered by province. Table 6 shows that the pre-pandemic coefficients for crime are close to zero, but the experiment is uninformative for H1. In logarithmic terms, the fall of tourism was fairly similar across provinces: one standard deviation of exposure implies an additional drop of only 14% in 2020. Street crime per resident fell 2.9% more per standard deviation in 2020, but 2.0 points of that difference correspond to the mechanical fall of the population present, reported in the last column. With the equivalent population the differential is −0.9% and not significant.

TABLE 6. EVENT STUDY: INTERACTION OF STANDARDISED 2019 LOG TOURIST INTENSITY WITH YEAR DUMMIES

Year	ln tourist intensity	ln street crime, residents	ln street crime, equivalent pop.	ln (P^eq / P)
2016	0.041 (0.008)	0.002 (0.014)	0.001 (0.014)	0.001 (0.001)
2017	0.032 (0.007)	0.013 (0.011)	0.011 (0.011)	0.002 (0.001)
2018	0.012 (0.004)	0.006 (0.006)	0.005 (0.006)	0.001 (0.000)
2019	reference	reference	reference	reference
2020	−0.139 (0.052)	−0.029 (0.016)	−0.009 (0.015)	−0.020 (0.004)
2021	−0.090 (0.021)	−0.030 (0.015)	−0.017 (0.015)	−0.013 (0.003)
2022	−0.021 (0.006)	−0.014 (0.012)	−0.012 (0.012)	−0.002 (0.000)
2023	−0.029 (0.006)	−0.016 (0.016)	−0.015 (0.016)	−0.001 (0.000)
2024	−0.031 (0.008)	0.003 (0.014)	0.003 (0.014)	0.000 (0.000)
2025	−0.038 (0.010)	0.009 (0.015)	0.010 (0.015)	0.000 (0.000)

Note: Standard errors clustered by province in parentheses.

Source: Own elaboration.

6.3. The shift-share instrument

The mechanical preconditions of the instrument hold. Source markets evolved very unevenly: between 2015 and 2025 hotel overnight stays of residents in Ireland, Poland and the United States grew by 70–90% in logarithmic terms, whereas those of Germany, Sweden and Japan fell. Market composition also differs strongly across provinces: British visitors exceed 50% of foreign stays in Alicante, Portuguese visitors reach 45% in Huelva and French visitors 33% in Lleida.

However, the relevance condition is not satisfied. Table 7 shows that the correlation between predicted and actual growth of hotel overnight stays is 0.11 for 2015–2019 and 0.12 for 2015–2025, and the heteroskedasticity-robust first-stage F statistic, equal to the square of the robust t, is close to 1, far below the conventional threshold of 10 (Staiger and Stock, 1997). Provincial tourism growth is explained by local factors, such as the supply of accommodation, destination policies or substitution between hotels and tourist apartments, rather than by the composition of source markets. Cádiz, for example, should have grown by 10% according to its market mix and grew by 24%; Barcelona should have grown by 30% and grew by 17%, probably because of the limits imposed on the hotel supply.

TABLE 7. FIRST STAGE OF THE SHIFT-SHARE INSTRUMENT (LONG DIFFERENCES, 50 PROVINCES)

Period	Coefficient	Robust t	Robust F	Correlation
2015–2019	0.30	1.00	1.0	0.11
2015–2025	0.31	0.94	0.9	0.12

Note: Dependent variable: log change in total hotel overnight stays. Predicted change built with 2015 shares and leave-one-out national growth of 25 markets.

Source: Own elaboration based on INE (EOH).

The design has limitations that may contribute to its weakness. This covers only hotels (74% of overnight stays) and assumes that domestic tourism is an undifferentiated market growing at nearly the same rate across all provinces. This is a long difference specification with no controls. A different instrument focusing on international markets or splitting up domestic tourism by source region may have done better. However for this specification, with a weak instrument second stage results would be biased. Therefore, instrument variable estimates are not presented and results from section 5 can be interpreted as conditional relationships.7.

7. Discussion and conclusions

Crime measurement affects diagnosis and therefore public resource allocation. If a province is visited by many people there will be more crimes committed, even if the risk per person is constant. Police resources should be scaled in proportion to the actual number of people present. Whether the risk per person increases due to tourism is another question. This research has isolated the two factors by using a benchmark. If there is not a proportional relationship then the elasticity of the crime rate per person with respect to tourist intensity will equal the proportion of people present who are tourists. On average this figure is 0.02.

Results align with H1. For non-pandemic years, within-province elasticity of street crime to tourism intensity is around 0.18-0.20, whilst including neighbour tourism this increases to 0.28-0.31. This is roughly an order of magnitude greater than a proportional relationship. Thus, the presence of tourist crime in Spain is not a denominator problem. The adjustment for visitors only matters in the islands and a handful of Mediterranean provinces and accounts for a small amount of the relationship. The sign of the coefficient is also in line with Montolio and Planells-Struse (2016) findings during 2000-2008, however the negative coefficient is in contrast to Zhang and Xiang (2022) who find a negative relationship in Chinese cities. However, it should be noted that with province-level clustering, the raw relationship is only significant at the 10% level. The relationship is reduced in both the dynamic specification and count specification and becomes insignificant when allowing province effects to vary in 2021.They are robust conditional associations, not causal effects.

H2 is partly confirmed. Neighbouring tourism is positively associated with local crime, but imprecisely. Neighbouring unemployment, by contrast, is associated with local street crime in almost every specification, while own unemployment is not. This pattern is compatible with offenders who reside where labour conditions are worse and act in adjacent provinces. Yet it is also compatible with regional economic cycles captured more precisely by the average unemployment of several neighbours than by the noisier provincial estimate of the EPA, and the association indeed weakens with trends by autonomous community. Both mechanisms cannot be separated with the present data. Fraud, finally, presents a weaker

spatial structure than street crime, and its growth since 2020 distorts any analysis based on total offences.

The implications for public policy differ in their evidential basis. Two follow directly from the accounting results and do not require a causal interpretation: police resources in tourist provinces should be sized according to the population actually present, which in the Balearic Islands exceeded the resident population by 16% on average in 2019 and by considerably more in summer; and official statistics would gain in usefulness if they published, alongside the rate per resident, a rate per equivalent population and a separate series of street crime. A further implication may be that if the relationship with neighbouring unemployment is due to offender mobility then there could be benefits in coordinating crime prevention efforts between adjacent provinces and relating these to supra-provincial employment policies.

The three main limitations of this research are, that there was no credible identification strategy, that it does not fully account for the population and also that it is limited to a provincial level. To address the first issue, a monthly/quarterly approach could be taken with data to take advantage of the seasonal nature of tourism. This would also mean a narrower identification strategy could be used, perhaps only looking at the international market. Alternatively, shocks could be identified for specific destinations.The second limitation is that the accommodation surveys omit dwellings rented through platforms, second homes and stays with relatives. The experimental statistics of INE on tourist dwellings and on population movements measured with mobile phones, available only from 2019–2020, could provide a fuller measure in a shorter panel. The third limitation is related to the scale. The province aggregates very different municipalities, and tourist crime probably concentrates in specific neighbourhoods and resorts.

Finally, it should be noted that the spatial concentration of street crime has increased since 2022, a trend that deserves specific attention. Future lines of research include analysing the spatial structure of fraud with data on the residence of victims and offenders and extending the analysis to the municipal scale. In short, this article shows that the higher street crime of Spanish tourist provinces is not explained by the omission of visitors from the denominator, and that part of the conditions associated with crime lie beyond provincial borders.

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Appendix: data sources and treatment

Crime. Ministry of the Interior, Crime Statistics Portal, annual series of known offences by province, 2011–2025. Indicators: 5.1 *Hurtos*, 5.2 *Robos con fuerza en las cosas*, 5.3 *Robos con violencia o intimidación*, 5.4 *Sustracción de vehículos* (street crime); 5.5 *Estafas* (fraud); total criminal offences.

Population. INE, Continuous Population Statistics, homogeneous series by province, 1 January 2016–2026 (table 59589). Population aged 15–29 and foreigners aged 15–29: municipal register by five-year age groups and nationality, 2016–2020 (table 03002), and Continuous Population Statistics, 2021–2026 (table 60129).

Tourism. INE occupancy surveys, monthly overnight stays by province: hotels (EOH, table 67190), tourist apartments (EOAP, table 2063), campsites (EOAC, table 2062) and rural tourism accommodation (EOTR, table 2073). Hotel overnight stays by province and country of residence for 2015, 2019 and 2025 (EOH annual tables, including table 67182).

Controls. INE, Labour Force Survey, unemployment rate by province, quarterly (table 65349). INE, Regional Accounts of Spain, GDP per capita by province and autonomous community in current euros (table 80110).

Provinces without campsite data until 2023 (17): Araba/Álava, Badajoz, Bizkaia, Cáceres, Ciudad Real, Cuenca, Guadalajara, Lugo, Ourense, Palencia, Las Palmas, Santa Cruz de Tenerife, Segovia, Soria, Toledo, Valladolid and Zamora.

Missing monthly cells set to zero. Hotels: May and June 2020 in Ávila, León, Palencia, Segovia and Zamora. Rural accommodation: April, May and November 2020 in all provinces (closures). Tourist apartments: suppressed cells concentrated in 2020 and 2021.

Source markets of the shift-share instrument (25). Residents in Spain; Germany, Austria, Belgium, Denmark, Finland, France, Greece, Ireland, Italy, Luxembourg, Netherlands, Poland, Portugal, Czech Republic, Sweden, Norway, United Kingdom, Switzerland, rest of Europe outside the EU (including Russia), Japan, United States, rest of America and African countries; and a residual category.