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Deserts and hotspots: the evolution of centrality, accessibility, and socio-economic impacts in bar and restaurant location patterns

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ABSTRACT

The literature of bar and restaurant location patterns does not account sufficiently for temporal dynamics and the role of urban spatial. We address these gaps by developing a novel urban economic framework with a two-fold empirical approach: a) dynamic longitudinal Poisson models that incorporate socio-economics, demographics and accessibility to analyse temporal shifts in the concentration of bar and restaurants, or 'hotspots'; and b) a longitudinal logit approach that models the determinants of bar and restaurant 'deserts'. We compile a unique dataset of more than 1100 small areas over a 17-year period (2002–2019) across two carefully selected UK city-regions, Greater Manchester and Nottingham. The key findings reflect a fundamental shift in consumer preference over time. During the study period, the probability of bar 'desert' formation increased almost 20-fold along with the reduction in bar counts by around 35 percent in both study-areas. Conversely, restaurant numbers have increased by almost 35 percent and the probability of restaurant 'deserts' reduced by at least a factor of 5. While, the Poisson specification provides evidence of positive path dependence in areas with an established bar and restaurant 'ecosystem', both approaches show significant accessibility, agglomeration, and socioeconomic sorting effects.

1. Introduction

Location patterns of bars and restaurants play a key role in the urban environment, influencing public health outcomes but also economic growth through 'urban buzz' (Arribas-Bel et al., 2016). Such location patterns are path dependent on existing urban forms and are continuously shaped by a complex interplay of socioeconomic conditions, population movements and local economic forces (McCann & van Oort, 2019). Over at least the last 5 years, an alleged mass closure of bars and pubs has often been featuring in UK news stories (Heward, 2019; Newman, 2024) and started to concern policymakers (Foley, 2021; HM Treasury, 2024). We are motivated by this coverage in seeking to analyse the determinants, magnitude and evolution of any such phenomenon.

There is a substantial body of research on location patterns of bars and restaurants, but it is situated in disparate literature strands. It majorly comes from epidemiological approaches (Foster et al., 2017; Morrison et al., 2015) that model the count of bars and restaurants and focus on socioeconomics and ethnic-minorities, but typically adopt a cross-sectional framework that does not account for the temporal dynamics of location patterns.[1] Research on bar and restaurant location patterns is also prominent in the hospitality literature (Prayag et al., 2012; Jung & Jang, 2019) that offers insights on agglomeration and connectivity through clustering approaches. However, we identify gaps in accounting for the temporal dynamics, accessibility and the role of urban spatial structure. Our paper specifies a novel approach by harnessing the strengths of these disparate fields into an urban economic framework to provide a two-fold empirical approach: a) dynamic longitudinal Poisson models that incorporate ethno-demographic, socio-economic and accessibility variables to analyse temporal shifts in bar and restaurant location patterns; and b) longitudinal logit models that analyse the determinants, trend and spatial structure of bar and restaurant 'deserts'.

The paper contributes to the literature by offering a nuanced

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[1] To our knowledge, Jin et al. (2018) is the only epidemiological study to adopt a longitudinal approach. The strong assumption of the constant rate of venue number increases each period (linear trend) and the lack of economic activity and accessibility characteristics leave significant room for improvement.

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Table 1
Summary of epidemiological count model papers examining bar-restaurants location patterns.

Author(s)	Study Period	Statistical Approach	Dependent Variable (counts)	Key Explanatory Variables
Livingston (2012)	2006	Poisson regression	Separate for bars and restaurants	Deprivation index, population, area, male population, median age, proportion of visitors.
Morrison et al., 2015	2011	Poisson regression	Separate for bars and restaurants	Population, commuter change in population, income.
Morrison et al. (2015)	2011	Poisson regression	Separate for bars and restaurants	Population age, male population, education level, unemployment, marital status, language spoken at home, household income, retail zoning.
Morrison et al. (2016)	2009	Negative binomial regression	Separate for bars and restaurants	Population, area, male population, population age, education level, household income, race/ethnic composition (Black, Asian, Hispanic).
Snowden (2016)	2013	Negative binomial regression	All on-premises alcohol outlets	Population, area, population age 15–24, racial/ethnic composition (Black, Hispanic, Asian), poverty matrix, residential instability, single parent households.
Foster et al. (2017)	2012	Negative binomial regression	Separate for bars and restaurants	Population, area, deprivation index, male population, median population age, proportion of visitors, retail density.
Jin et al. (2018)	2001–2013	Poisson regression	Separate for bars and restaurants	Population, area, median household income, racial/ethnic composition (Black, Hispanic, Asian), male population, percentage aged 15–24, average household size, unemployment rate, US federal poverty level, presence of major highway.

understanding of bar and restaurant 'hotspot' and 'desert' evolution. To achieve this, we carefully select, in terms of socio-economic and demographic diversity, two key UK urban areas, Greater Manchester and Nottingham. We compile a unique dataset of bar and restaurant counts for more than 1100 small areas between 2002 and 2019, incorporating time-variant socio-economic, demographic and accessibility information. The key findings indicate a non-linear trend in bar 'desert' formation and count reductions, as well as path dependence, all of which push towards bar centralisation. Conversely, we observe non-linear restaurant 'desert' reduction and count increases, which are suggestive of increasing sprawl but with a weak path dependence pushing towards restaurant 'hotspots'. Accessibility by public transport to urban centres is found to be a key disruptor of 'deserts' and force for centralisation across all venue types and study areas. The results imply major generational shifts in consumer preferences away from venues primarily centred on alcohol consumption, or bars, and towards venues more focused on food consumption, or restaurants, which is consistent with recent UK press coverage (Heward, 2019; Newman, 2024) and previous literature (Oldham et al., 2018; Dunphy et al., 2025).

The structure of the paper is as follows. Section 2 presents the background and research context. Section 3 provides theoretical and methodological considerations. Section 4 presents the study area and the data. Section 5 provides the empirical approach and model selection process. Section 6 presents and discusses the results of the econometric models. Section 7 draws conclusions.

2. Background

For bars and restaurants, we also use the overarching term alcohol venues that constitute any hospitality venue licensed for the on-premises sale of alcohol. Research on alcohol venue locations draws predominantly from two academic fields, each offering distinct analytical approaches to spatial distribution patterns. Epidemiological studies analyse venue locations through population health impacts and socio-economic characteristics, while hospitality management literature examines economic clustering mechanisms and firm strategic behaviour.

Epidemiological analyses primarily employ Poisson and negative binomial regression models estimating venue counts through socioeconomic and demographic variables (Morrison et al., 2015; Morrison et al., 2015; Snowden, 2016; Jin et al., 2018). Socioeconomic deprivation correlates positively with alcohol venue concentration (Pearce & Day, 2008; Livingston, 2012; Morrison et al., 2015; Snowden, 2016; Foster et al., 2017; Jin et al., 2018), with bars demonstrating stronger associations than restaurants (Hay et al., 2009; Jin et al., 2018), while Livingston (2012) found higher restaurant concentrations in less deprived areas. Ethnic-minority population density initially correlates with elevated venue densities (Romley, 2007; Trangenstein et al., 2020; Jin et al., 2018), though this relationship diminishes when controlling for socioeconomic deprivation (Morrison et al., 2016; Snowden, 2016). This suggests omitted variable bias unless economic factors are included that fundamentally drive spatial distribution patterns.

Table 1 provides and overview of all papers that employ count models. Almost all epidemiological studies failed to consider the temporal dimension employing cross-sectional approaches that cannot account for the dynamic and shifting patterns of bars and restaurants in continuously evolving urban environments. This literature also omits core urban economic factors such as agglomeration and accessibility with the following two papers the only exceptions: Morrison et al. (2015) who find that areas zoned for retail activity tend to have higher concentrations of bars and restaurants; and Foster et al. (2017) who observe a positive association between the number of retail units and the concentration of on-premise outlets.

The hospitality literature employs spatial clustering techniques to examine how factors such as agglomeration and centrality influence the spatial clustering of bars and restaurants (Jung & Jang, 2019; Smith, 1985). Sevtsuk (2014) observed that the presence of a bar or restaurant elevates the likelihood of similar establishments opening in proximity, indicating that spatial clustering generates positive externalities that reinforce the attractiveness of these locations for both consumers and firms. Picone et al. (2009) observed spatial clustering among both bars and restaurants, with bars exhibiting the highest degree of clustering. Similarly, Jung and Jang (2019) showed that restaurants benefit from agglomeration, with more intense clustering in central business districts (CBDs), where both competition and demand are higher. Mossay et al. (2022) also demonstrated that restaurants in city centres cluster more tightly, benefiting from proximity and enhanced spillover effects. These findings illustrate the role of agglomeration in driving location patterns in urban environments, as bars and restaurants cluster to capitalise on shared economic benefits.

The hospitality literature highlights that restaurants in central, accessible areas benefit from proximity to complementary commercial activities that drive consumer demand (Smith, 1985; Sevtsuk, 2014). Central business districts are particularly attractive, where higher consumer exposure and foot traffic leads to enhanced business performance. Centrality not only amplifies agglomeration effects but also attracts businesses seeking to leverage the accessibility and convenience of these prime urban locations (Prayag et al., 2012; Jung & Jang, 2019). While cluster and nearest neighbour analysis employed in the hospitality literature effectively highlights spatial groupings (Smith, 1983), it does not directly model the determinants of establishment counts, as opposed to count models that they allow for direct analysis of the number of bars and restaurants in relation to socio-economic, demographic, and accessibility variables.

Urban economic research has increasingly emphasised the role of consumption-driven mechanisms in shaping intra-urban spatial structure. A key concept within this shift is urban buzz (Arribas-Bel et al., 2016), referring to the growth of dense, interaction-rich environments enabled by concentrations of consumption amenities such as restaurants and bars (Glaeser & Gottlieb, 2006). Rather than traditional production-oriented explanations based on wage gradients or firm productivity, recent studies highlight the role of consumption experiences in driving urban revival (Couture & Handbury, 2020). The resurgence of inner-city living, especially among young, college-educated individuals, is strongly associated with access to non-tradable service amenities including the presence of restaurants and nightlife (Couture & Handbury, 2020). These amenities form an increasingly foundational component of residential choice. Changes in household expenditure patterns further reinforce this, with younger, higher-income cohorts allocating an increasing share of spending and travel to food and drink establishments (Couture & Handbury, 2020). These findings indicate that the spatial distribution of bars and restaurants reflects broader transformations in urban economic functioning. As consumption amenities become key determinants of locational desirability, their concentration in accessible, central areas reinforces agglomeration effects and alters traditional urban hierarchies. The clustering of alcohol venues in central accessible areas generates demand externalities and reduces consumer search costs, strengthening the feedback loop between consumer preference and venue concentration (Jung & Jang, 2019; Sevtsuk, 2014).

The urban economics literature predominantly treats service amenities, including bars and restaurants, as explanatory variables when examining residential location preferences and demographic restructuring in literature focused on patterns of gentrification, urban revival, and spatial sorting (Baum-Snow & Hartley, 2020; Couture & Handbury, 2020). This positions venues in urban economic literature to be primarily examined as elements within larger urban transformation processes rather than being the focus of the analysis.

The epidemiological and hospitality literature provide valuable but incomplete insights into the factors influencing bar and restaurant distribution. The epidemiological strand overlooks urban economic dynamics and temporal evolution (Morrison et al., 2016; Snowden, 2016), while the hospitality literature neglects socio-economic and ethnic-minority dimensions (Mossay et al., 2022; Sevtsuk, 2014). Urban economics typically treats venues as amenity inputs into housing or labour market models (Baum-Snow & Hartley, 2020; Couture & Handbury, 2020). There is a clear gap in these disparate strands of literature for directly examining the location patterns of bars and restaurants. These establishments operate as profit-maximising entities responding to complex spatial economic incentives including rent gradients, agglomeration benefits, and demographic composition. Location decisions reflect strategic positioning within competitive landscapes. Examining how alcohol venues interpret and capitalise on urban economic signals provides insights into the role of venue location patters.

3. Theoretical considerations and methodological framework

The spatial distribution of alcohol venues reflects fundamental economic mechanisms that determine both area viability, or 'desert' creation, and venue concentration, or 'hotspots'. The theoretical framework in Appendix 1 establishes two distinct processes that are briefly illustrated in this section. First, a minimum viability threshold establishes the formation of venue 'deserts' based on consumer choice of potential consumption destinations. Second, the aggregation of individual venue profit-maximising decisions generates equilibrium venue counts.

Consumer choice of areas as potential locations for consumption draws from maximising utility, which is a function of service variety and quantity, subject to accessibility constraints (Athey et al., 2018; Jung & Jang, 2019). For area j to be viable for venue location it must pass a minimum viability threshold of expected patronage, otherwise it becomes a venue dessert:

$$E[Pj, t] > \overline{P} \quad (1)$$

where $\overline{P}$ represents the probability threshold that determines whether an area j within the choice set $j \in J$ can support venues. Areas falling below this threshold become venue 'deserts' due to insufficient potential patronage relative to alternative locations.

Venue 'deserts' are analysed through a conditional logit specification:

$$P(Dj,t = 1) = \exp(\gamma Xj,t) / (1 + \exp(\gamma Xj,t)) \quad (2)$$

Where Dj,t indicates a venue 'desert' in area j at time t, and Xj,t represents area characteristics. The choice of a conditional logit specification for venue 'desert' analysis is supported by theoretical foundations in random utility maximization (Guimarães et al., 2003). The assumption that the stochastic component of utility follows an extreme value type 1 (EV1) distribution yields the tractable closed-form logit probability formulation shown in equation (2) (Schmidheiny & Brülhart, 2009).

Equation (2) allows for the examination of spatial patterns in venue location by capturing changes in the distribution of viable areas and potential identification of time patterns that suggest trends of increasing or decreasing venue centrality. This specification accounts for a fundamental asymmetry in market dynamics addressing a common limitation of spatial equilibrium models (Stammann, 2023). 'Deserts' or areas without venues forgo any agglomeration effects, breaking the simultaneity between venue presence and area attractiveness. This distributional assumption is particularly valuable for modelling spatial choice scenarios with numerous alternatives, as it produces mathematically convenient choice probabilities while maintaining consistency with economic theory of profit/utility maximization (Schmidheiny & Brülhart, 2009). When applied to venue 'desert' analysis, this specification effectively captures the threshold effects in market viability conditions across geographic space, allowing us to model the discrete nature of the participation decision regarding whether venues consider an area to be a viable market location.

The next step is an equilibrium venue count emerging from individual firm profit-maximising location decisions. The optimal location condition incorporates both firm profits and agglomeration effects as shown in equation (3):

$$L^*i, t = \operatorname{argmax}(j \in J)\{\pi i, j, t + A(n, t) \mid E[Pj, t] > \overline{P}\} \quad (3)$$

where L*i,t denotes the optimal location for firm i at time t chosen from the set of all possible areas $j \in J$, πi,j,t represents venue-specific profits for venue i in area j, and A (n,t) comprising the count of venues (n) and time (t) captures agglomeration benefits through demand externalities and reduced consumer search costs. (Deng & Picone, 2019; Jung & Jang, 2019).

Sequential entry decisions generate equilibrium venue counts in area j, with firms entering until the marginal profit falls below a minimum threshold in equation (4):

Enter area j if: $\pi j,t(nj,t) > \pi$

Do not enter if: $\pi j,t(nj,t+1) \le \pi$ (4)

Where πj,t (nj,t) denotes profit for a venue in area j with existing venue count nj,t, and π represents the minimum profit threshold.

Equations (3) and (4) allow, as shown in Appendix 1, the specification of a dynamic conditional fixed effects (FEs) Poisson model that takes the form of equation (5):

$$Yj,t = \exp(\beta Xj,t + \phi Yj,t\text{-}1 + \delta t + \alpha j) \quad (5)$$

Where Yj,t represents the expected venue count in area j at time t. The parameter vector β quantifies the effect of area characteristics Xj,t. Equation (5) accommodates two key dynamic elements: The autoregressive parameter ϕ captures temporal dependence through the lagged dependent variable Yj,t-1, reflecting the impact of existing venue density on area attractiveness. Time-specific effects δt control for systematic evolution of market conditions exogenous to specific areas, capturing national trends in venue numbers across periods. Small area FEs αj account for time-invariant unobserved spatial heterogeneity and provide spatial omitted variable bias (OVB) treatment (Kuminoff et al., 2010). These area FEs also address overdispersion through heterogeneity capture forgoing the need for explicit overdispersion parameter and a negative binomial specification (Wooldridge, 2010) and circumventing the incidental parameter problem common in non-linear FEs models (Cameron & Trivedi, 2014, chap. 9).

Equation (5) enables a nuanced analysis of firm location decisions by allowing for positive-sum outcomes in capturing simultaneous expansion or contraction of firm counts across locations. This flexibility is beneficial for accurately modelling dynamic patterns of firm entry and exit and particularly open systems where firms may consider alternatives beyond the primary study area (Schmidheiny & Brülhart, 2009).

4. Study areas and data

The urban areas in Greater Manchester and Nottingham were selected for their socio-economic and demographic diversity, which constitute key factors in bar and restaurant location patterns (Foster et al., 2017; Morrison et al., 2016). Greater Manchester, the UK's second-largest urban conurbation, contains areas in the bottom and 95th percentile of socioeconomic deprivation across an entirely urban context (Hay et al., 2009; Livingston, 2012). Nottingham, as a regional city distinct from other major conurbations, provides comparison across different urban economic contexts, enabling analysis of distinct spatial and market dynamics.

The study areas encompass 627 contiguous urban Lower Layer Super Output Areas (LSOA) in Greater Manchester and 492 in Nottingham, covering a 17-year period (2002–2019) with observations at three-year intervals. LSOAs, hereafter referred to as "areas", represent small scale census statistical areas containing between 1000 and 3000 residents, comparable to US Census Blocks. Statistical output areas constitute the standard unit of analysis in the epidemiological alcohol venue location literature due to comprehensive socioeconomic data availability at this scale (Livingston, 2012; Morrison et al., 2015, 2016). Studies of alcohol venue location benefit from smaller study areas to avoid aggregation bias and better capture local spatial dynamics influenced by varying population structure and geographical stratification (Larsson & Öner, 2014; Livingston, 2012; Morrison et al., 2015, 2016). The selection of 2019 over 2020 is to eliminate any bias resulting from Covid-19 lockdown measures.

Counts of venues were obtained from CGA Nielsen, an industry leading on-premises venues market research company. Classification of on-premises venues as bars or restaurants represent industry standard classifications derived from their main revenue source of either alcohol or food sales. For clarity UK pubs are categorised as either bars or restaurants depending on proportion of revenue derived from alcohol or food sales. Figs. 1 and 2 are maps of the Manchester and Nottingham study areas respectively, showing comparison of the distribution of bars and restaurants between 2002 and 2019. Both Figures exhibit a high rate of areas with no venues. At the start of the study period 43.06 % and 47.15 % of areas contained no bars, while 74.16 % and 77.40 % of areas contained no restaurants in Manchester and Nottingham respectively. These figures are important in highlighting the predominance of 'deserts' and that the restaurant locational patterns exhibit substantially more centralised baseline. Figs. 3 and 4 display the temporal trend and demonstrate that the count of bars decreases in both study areas over the study period, while the restaurant counts increase.

Variable selection was informed by review of previous research applying epidemiological modelling in Table 1. Table 2 shows the full list of variables and data sources. Table 3 shows the full descriptive statistics for each variable by study area. Data on ethnic-minority populations was obtained from the Consumer Centre Research Centre (CDRC). Deprivation was captured using the UK Index of Multiple Deprivation (IMD). Both the total IMD index and the income deprivation specific domain were tested with the income domain providing the best fit. The income domain is an appropriate measure directly capturing key deprivation measures seen in the literature, including unemployment (Jin et al., 2018; Morrison et al., 2015). The IMD is not published on an annual basis and was adjusted to align with the count data.[2]

Centrality to urban centres was incorporated using Journey Time Statistics (JTS) from the UK Department for Transport that measures the travel time to the nearest urban centre by foot or public transport. The 2009 JTS data was used for the 2002, 2005, and 2008 study periods, while other periods used data from the corresponding years. The number of retail employees per area was included as a measure of commercial activity. Variables were included to account for key population characteristics drawing on insights from previous studies on socio-economic and demographic factors (Jin et al., 2018; Morrison et al., 2016). Population density, the proportion of the population between the ages of 18–24, and the proportion of male population were gathered from the ONS Nomis data repository.

5. Empirical approach

This section outlines our empirical strategy based on the methodological framework outlined in section 3. Two complementary approaches are employed to capture different dimensions of venue distribution. First, count modelling is employed to quantify how area characteristics influence venue concentrations, which is then complemented with logit regressions to identify factors determining venue 'desert' formation. These complementary methods allow us to understand both the intensity of venue presence, or 'hotspots', and the threshold conditions leading to venue absence, or 'deserts'.

We start by running a panel regression in Table 4 that establishes baseline estimates and allows testing for different specification options. Hausman tests show that FEs are appropriate over random effects. Wooldridge test results indicate significant temporal autocorrelation, supporting the importance of temporal dynamics in venue location patterns. We do not find any significant presence of unit root issues across the board. The coefficients are according to the expectations from the literature and economic theory regarding accessibility, deprivation, and agglomeration, with the exception of ethnic-minority effects that are discussed in the next section. The time FEs show a clear and highly statistically significant pattern of substantial reductions in bar and increases in restaurant especially after 2014. This provides evidence on the importance of accounting for temporal patterns in the preferred specifications.

To demonstrate the shortcomings of typical cross-sectional count models (Livingston, 2012; Morrison et al., 2015; Snowden, 2016), we present the results of a naive pooled cross-sectional Poisson regression in Table 4. The coefficients of the Poisson models are reported as incident rate ratios (IRR) for ease of interpretation.[3] IRR measures the relative difference in the rate at which events are experienced by two groups. IRR accounts for the time each individual is at risk, which is useful in our case. Beyond almost everything appearing to be statistically significant, the results contradict expectations and economic theory at places, for example population density reduces the incidents of bars and restaurant

[2] IMD year 2004 was used for study years 2002 and 2005, IMD year 2007 for study year 2008, 2010 was used for 2011, 2015 for 2014 and 2019 for 2017 and 2019.

[3] Poisson coefficients are reported as incident rate ratios (IRR) and interpreted as a percentage change for a unit increase in the dependent variable. An IRR above 1 indicates increased higher expected counts of venues, while values below 1 indicate lower expected counts, for each unit change in explanatory variables.

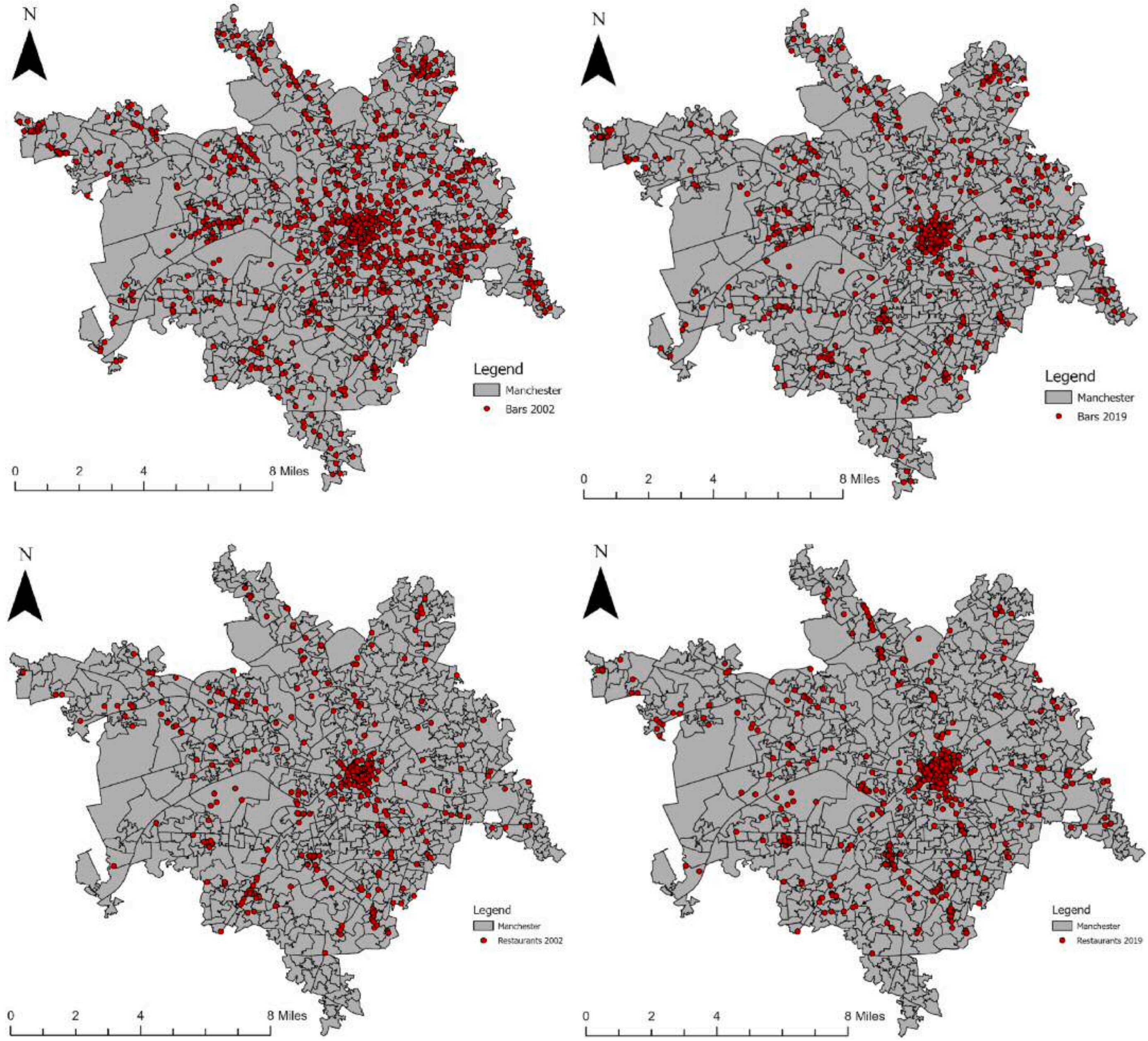

Fig. 1. Distribution of bars and restaurants in Manchester. Moving Clockwise from top left: Distribution of bars in Manchester in 2002; distribution of bars in Manchester in 2019; distribution of restaurants in Manchester in 2019; distribution of restaurants in Manchester in 2002.

instead of increasing it.

Even this naive Poisson with no FEs seems to be fitting the data better than the FE panel models in most cases, if we were to believe adjusted R^2 to pseudo R^2 comparison, or only in 'Nottingham Bars' case through a proper AIC/BIC comparison. By assuming a continuous dependent variable, the panel OLS lacks the flexibility of accurately modelling patterns of firm entry and exit and particularly open systems where firms may consider alternatives beyond the primary study area (Schmidheiny & Brülhart, 2009). Conversely, the naive Poisson cannot account for temporal trends and shocks or unobserved spatial heterogeneity, which are picked up by the coefficients. Hence, the statistical tests and comparisons in Table 4 point us toward a dynamic temporal and area FEs count model.

The logit model in equation (2) provides distinct spatial insights through its treatment of geographic and temporal variation in market viability conditions. The binary nature of 'desert' classification or 'state' enables identification of critical thresholds in market conditions across urban space, offering analytical advantages over continuous spatial measures. We can include time FEs to capture temporal shocks. If indicated by a Hausman test, conditional area FEs are introduced to account for spatial heterogeneity and treat OVB. The conditional FE specification has the additional advantage of removing invariant areas[4] from estimation and isolating the determinants of the transition, instead of assuming that relevant information can be provided by the vast majority of areas fixed in a single 'state'. This specification enables efficient estimation of 'desert' formation determinants whilst controlling for unobserved heterogeneity in local market conditions. The Logit

[4] LSOA areas that do not change 'state' from or to 'desert' across the study period.

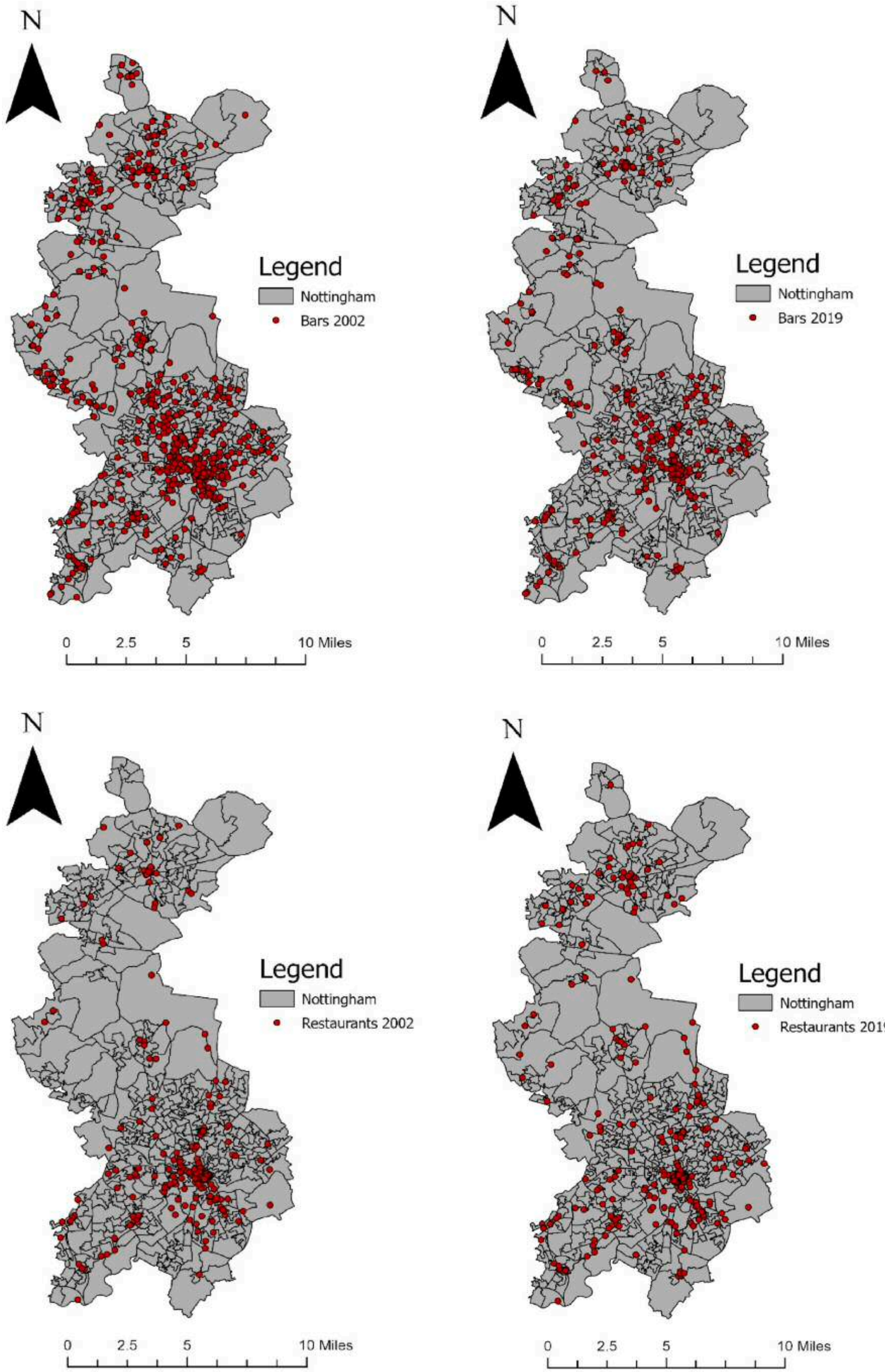

Fig. 2. Distribution of bars and restaurants in Nottingham. Moving Clockwise from top left: Distribution of bars in Nottingham in 2002; distribution of bars in Nottingham in 2019; distribution of restaurants in Nottingham in 2019; distribution of restaurants in Nottingham in 2002.

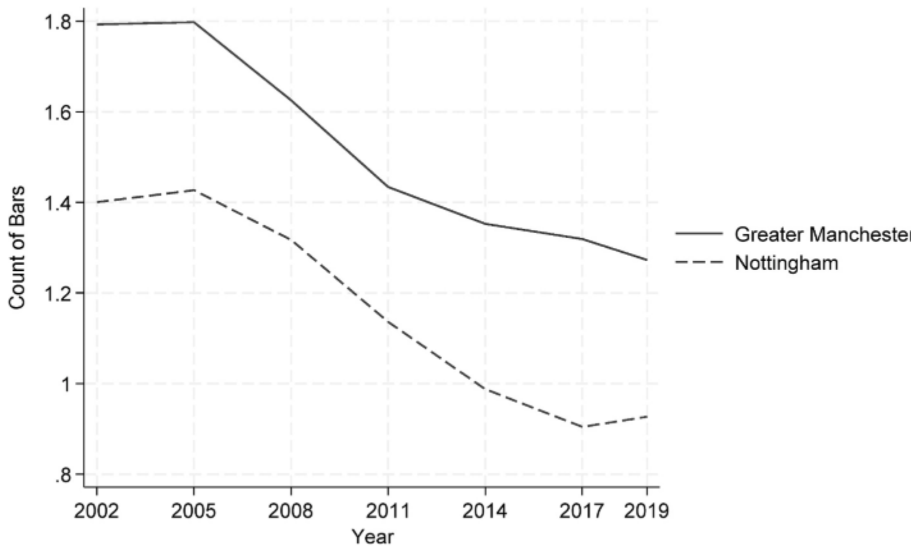

Fig. 3. Change in mean count of bars (LSOA).

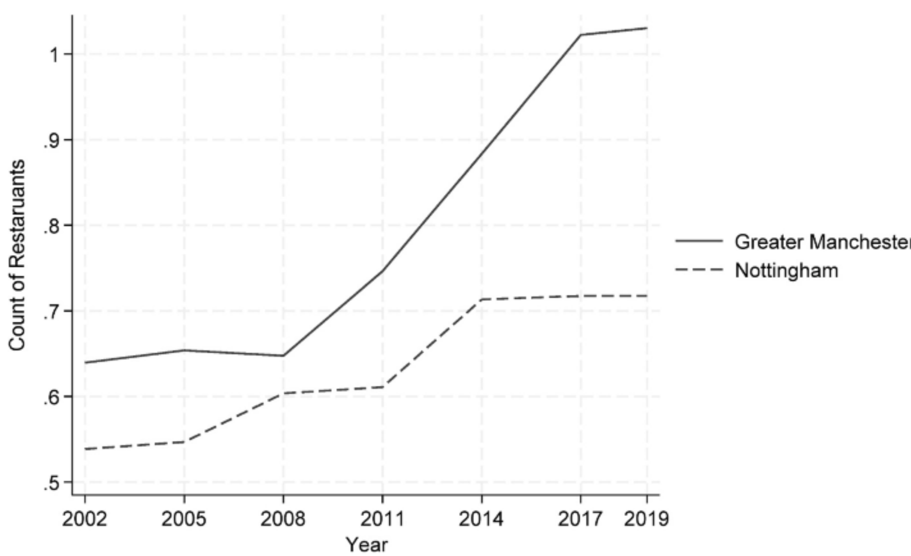

Fig. 4. Change in mean count of restaurants (LSOA).

coefficients are presented as odds ratios (ORs).[5]

6. Results

This section provides the results of the models set up in sections 3 and 5. The logit model results are presented on the formation of venue 'deserts'. The results for the preferred Poisson models are then discussed, with comparison between the pooled cross-sectional and longitudinal approaches.

6.1. Bar and restaurant 'deserts'

Following equation (2), the results of the longitudinal logit models on consumer choice of areas as potential locations for consumption are presented in Table 5. The Hausman tests indicate the fixed effects specification to be appropriate across the board, which includes only time-variant data and areas transitioning between 'desert' and non-'desert' state within the study period. The time FEs exhibit statistically significant coefficients and improved goodness of fit significantly across all models. The pseudo-R^2 values for the logit models for bars show a very good model fit[6] in both study areas and models, while only the preferred logit model of Nottingham restaurants achieves a good fit. This suggests that venue 'desert' formation is more critical for bars.

The magnitude of the time FEs indicates a non-linear trend of bar 'desert' formation especially after 2011 suggesting significant bar centralisation. The formation likelihood increased markedly between 2002

[5] Logit coefficients are expressed as odds ratios (OR) and measure proportional changes in 'desert' likelihood relative to a baseline OR of 1. Coefficients above 1 indicate increased 'desert' probability, while values below 1 indicate decreased probability, for each unit change in explanatory variables.

[6] The interpretation of McFadden's pseudo- R^2 for logit regression varies depending on the sample characteristics. Our bar data represents large samples (>200) with symmetric distribution (38–62 %), values of 0.15–0.32 therefore indicate good fit. Our restaurant data represents a large sample with asymmetric distributions (<38 %or >62 %) with values of 0.11–0.20 indicating good fit (Hemmert et al., 2018).

Table 2
Description and justification of variables.

Variable	Variable description	Source
Spatial unit	Lower Layer Super Output Area (LSOA) for 2011 census	Office for National Statistics (2016)
Manchester City	Study area consisting of Manchester LSOAs.	Office for National Statistics (2016)
Nottingham City	Study area consisting of Nottingham LSOAs.	Office for National Statistics (2016)
Year	Factor variable for the identification of year in the study period: 2002, 2005, 2008, 2011, 2014, 2017, 2019.	NA
Bar	Count of bars	CGA Nielsen
Bar deserts	LSOA without bar observations	Authors own
Restaurant	Count of restaurants	CGA Nielsen
Restaurant deserts	LSAO without restaurant observations	Authors own
Population Density	Population density as usual residents per square kilometre scaled to 1000	Nomis (2024)
Age 18-24	Proportion of population aged between 18 and 24	Nomis (2024)
Male Population	Proportion of male population	Nomis (2024)
Asian	Proportion of Asian residents	CDRC (2024a)
Black	Proportion of Black population	CDRC (2024a)
Income Deprivation	National percentile ranking of income deprivation on the Indices of Multiple Deprivation. Factors considered in income deprivation are: Adults and children in Income Support families; adults and children in income-based Jobseekers Allowance families; adults and children in income-based Employment and Support Allowance families; adults and children in Pension Credit (Guarantee) families; adults and children in Working Tax Credit and Child Tax Credit families below 60 % median income not already counted; asylum seekers in England in receipt of subsistence support, accommodation support, or both; adults and children in Universal Credit families where no adult is working	CDRC (2024b)
Retail	Count of employees that work in retail by place of work scaled to 100	Nomis (2024)
Accessibility	Travel time in minutes to nearest urban centre by foot or public transport	Department for Transport (2021)

Table 3
Descriptive statistics.

Variable	Manchester				Nottingham			
	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max
Bar	1.5133	3.5829	0.0000	53.0000	1.1571	2.9620	0.0000	48.0000
Bar deserts	0.5040	0.5000	0.0000	1.0000	0.5545	0.4971	0.0000	1.0000
Restaurant	0.8034	3.6204	0.0000	86.0000	0.6355	2.1451	0.0000	36.0000
Restaurant deserts	0.7443	0.4363	0.0000	1.0000	0.7357	0.4410	0.0000	1.0000
Population density	5.1944	3.0348	0.1697	42.3810	4.5212	2.9302	0.0985	21.1190
Retail	0.8503	3.7820	0.0000	81.4000	0.8418	3.7786	0.0000	101.1500
Accessibility	13.6579	5.0644	3.3286	36.8654	15.4689	6.1519	3.3284	54.0662
Income	21.1416	13.9894	0.4000	96.0000	16.7574	11.4538	1.0000	66.0000
Aged 18–24 (%)	11.7367	10.2580	2.7484	88.0000	11.1706	10.7441	3.2129	81.0000
Male (%)	49.8525	3.4168	41.0000	93.0000	49.5422	2.6848	42.0000	67.0000
Asian (%)	8.9810	12.6895	0.0000	100.0000	5.3509	7.4600	0.0000	55.5000
Black (%)	2.6106	3.6679	0.0000	31.0000	1.3315	1.9201	0.0000	14.5000

and 2019, rising 26-fold for Manchester and 19-fold for Nottingham bars. Restaurants exhibit the reverse pattern suggestive of sprawl, which was more pronounced in Nottingham with a 'desert' formation likelihood reducing 11-fold, while Manchester 'deserts' formation dropped 4-fold during the study period. In interpreting these result we need to remember that the restaurant locational patterns exhibit substantially more centralised baseline. In 2002, 74.16 % and 77.44 % of areas were in the restaurant 'desert' state compared to just over 43.06 % and 47.15 % in the bar 'desert' state for Manchester and Nottingham. These contrasting spatial evolution patterns reveal distinct geographical restructuring processes unobservable in static frameworks (Morrison et al., 2016; Snowden, 2016). More importantly, this evidence suggests a major generational shift in consumer preferences and behaviour, which is consistent with the press coverage (Heward, 2019; Newman, 2024) and potentially has major policy implications. This is also consistent with literature that find a shift in the drinking preferences and habits of generation z (Dunphy et al., 2025; Oldham et al., 2018). If we were to look only at 'Aged 18–24', which in 2002 included a combination of generation x and y, such a shift in behaviour is not discernible. 'Aged 18–24' is associated with 12.3 % increase restaurant 'deserts' in Nottingham and a 6.36 % decrease in restaurant 'deserts' in Manchester.

Accessibility by public transport is expected to be a key disruptor of 'deserts', given the potential alcohol consumption, and an indication of centralisation pressures. We find as 1-min increase in travel time to the nearest urban centre increased restaurant 'desert' formation by 22 % in Manchester, and bar and restaurant 'deserts' by 10 % and 7 % respectively in Nottingham. Surprisingly, the travel time effect on Manchester bar 'deserts' was not statistically significant. Retail activity only decreased the likelihood of restaurant 'deserts' in Nottingham, by 44 %. Together with the findings for time FEs these results indicate a dramatic shift towards centralisation of venue locations in line with previous findings that alcohol venues, particularly for bars, locate in central well connected areas where agglomeration economies from reduced consumer search time and demand externalities from complementary commercial activity support venue presence (Jung & Jang, 2019; Prayag et al., 2012; Sevtsuk, 2014). Figs. 1 and 2 highlight the extent of venue centralisation and the significant increase in bar 'deserts' between 2002 and 2019 is quite noticeable.

Our results show income deprivation to reduce bar and restaurant 'deserts' only in Nottingham, which is consistent with the literature

Table 4
Poisson base model results.

	Longitudinal OLS				Pooled Poisson			
	Bars		Restaurants		Bars		Restaurants	
	Manchester	Nottingham	Manchester	Nottingham	Manchester	Nottingham	Manchester	Nottingham
Population density	0.0125	−0.0118	0.0448***	0.0032	0.9883***	0.9677***	0.9699***	0.9657***
	(0.0091)	(0.0093)	(0.0172)	(0.0067)	(0.0044)	(0.0053)	(0.0057)	(0.0068)
Retail	0.1620***	0.0153	0.3865***	−0.0000	1.0387***	1.0200***	1.0456***	1.0198***
	(0.0094)	(0.0122)	(0.1251)	(0.0101)	(0.0009)	(0.0014)	(0.0008)	(0.0016)
Accessibility	−0.0060	−0.0188**	−0.0205*	−0.0123*	0.9195***	0.8951***	0.8912***	0.9018***
	(0.0070)	(0.0075)	(0.0114)	(0.0072)	(0.0029)	(0.0034)	(0.0042)	(0.0046)
Income Deprivation	0.0231***	0.0479***	−0.0043	−0.0209	0.9966***	1.0204***	0.9466***	0.9894***
	(0.0038)	(0.0098)	(0.0056)	(0.0147)	(0.0011)	(0.0015)	(0.0020)	(0.0022)
Aged 18–24 (%)	0.0049	−0.0218	0.0150	0.0145	1.0215***	1.0261***	1.0139***	1.0248***
	(0.0056)	(0.0150)	(0.0195)	(0.0275)	(0.0010)	(0.0013)	(0.0013)	(0.0017)
Male (%)	−0.0139	−0.0005	−0.0275	0.0035	1.0737***	1.1106***	1.0935***	1.1544***
	(0.0105)	(0.0162)	(0.0254)	(0.0144)	(0.0022)	(0.0047)	(0.0037)	(0.0065)
Asian (%)	−0.0126**	0.0183	−0.0161	0.0050	0.9888***	0.9765***	1.0147***	0.9788***
	(0.0064)	(0.0131)	(0.0101)	(0.0110)	(0.0013)	(0.0032)	(0.0014)	(0.0044)
Black (%)	−0.0781***	−0.0224	−0.0442***	−0.0858**	1.0052	0.9733**	1.0007	0.9773
	(0.0140)	(0.0332)	(0.0166)	(0.0346)	(0.0049)	(0.0106)	(0.0094)	(0.0162)
2002	base	base	base	base				
2005	0.0707	0.0393	0.0467	0.0129				
	(0.0544)	(0.0298)	(0.0443)	(0.0313)				
2008	−0.0639	−0.0880**	0.0793	0.0950**				
	(0.0572)	(0.0353)	(0.0666)	(0.0395)				
2011	−0.1743***	−0.2109***	0.1692**	0.0790				
	(0.0598)	(0.0435)	(0.0833)	(0.0481)				
2014	−0.1957***	−0.3357***	0.3918***	0.2445***				
	(0.0646)	(0.0519)	(0.1044)	(0.0513)				
2017	−0.2037***	−0.3221***	0.4742***	0.2236***				
	(0.0659)	(0.0547)	(0.1077)	(0.0492)				
2019	−0.2240***	−0.3008***	0.5180***	0.2360***				
	(0.0660)	(0.0667)	(0.1162)	(0.0570)				
Cons	1.9704***	1.0554	1.8274	0.7845	0.0997***	0.0163***	0.0586***	0.0019***
	(0.5414)	(0.8311)	(1.2820)	(0.7509)	(0.0113)	(0.0037)	(0.0108)	(0.0006)
Area FEs	yes	yes	yes	yes	no	no	no	no
Adj R sq	0.1439	0.1992	0.3201	0.0473	0.3809	0.2157	0.2714	0.2913
IPS unit-root test, H0: unit-root	−5.29***	−11.00***	−10.62***	−10.56***	0.0997***	0.0163***	0.0586***	0.0019***
Hausman test, H0: random effects	244.68***	159.11***	105.33***	&				
Wooldridge, H0: no autocorrelation	83.90***	133.37***	35.04***	7.26***				
LL (Model)	−5574.3218	−2830.3461	−5800.7398	−2676.8835	−8771.5441	−5559.3867	−5132.2793	−3767.2312
AIC/BIC	11,179/ 11,274	5689/5775	11,629/ 11,719	5382/5468	17,561/ 17,619	11,194/ 11,137	10,283/ 10,338	7552/7608

Notes: * significant at $p < 0.10$; **significant at $p < 0.05$; ***significant at $p < 0.01$; Poisson coefficients presented as IRRs;˜ denotes Pseudo-R^2. Pseudo-R^2 should be interpreted with caution as it fails to account for the inherent discreteness of count data and does not fully represent proportion of explained variance (Cameron and Trivedi, 2014); & Hausman test for Nottingham restaurants failed the asymptotic assumptions, this may indicate issues with the continuous specification but does not indicate that random effects are appropriate.

findings of alcohol venues concentrating in deprived areas with lower rent structures (Morrison et al., 2015). We find some evidence of Black populations sorting in areas with no restaurants in Nottingham and no bars in Manchester. We discuss this divergence to the US literature in section 6.3 that brings in the count model results as well. It is noted that the Asian population effect on dessert formation are subsumed in the time FEs of our preferred models, suggesting that some temporal trends or shocks in the data were initially falsely attributed to Asian population sorting. Population density was not associated with a significant effect on the likelihood of venue 'deserts' for either venue type, which is not surprising since we are looking at predominantly dense urban areas. Males were associated with an 18.19 % increase in the likelihood of restaurant 'deserts' in Manchester per one percent increase in male population.

6.2. Bar and restaurant 'hotspots'

The conditional FEs Poisson specification enables efficient estimation for panel count data and controls for time-invariant spatial heterogeneity through conditional FEs (Cameron & Trivedi, 2014, chap. 9; Jin et al., 2020). The area FEs absorb persistent spatial patterns without explicit spatial dependence structures (Balia et al., 2016; Billé et al., 2023). This means that the model coefficients are not affected by other context specific unobservables in either the spatial or temporal dimension. The difference these FEs make to coefficients is obvious from a quick comparison between the naïve Poisson models in Table 4 and the results for the dynamic longitudinal Poisson models in Table 6. The AIC and BIC across all models in Table 6 also show substantially superior goodness of fit compared with the equivalent models in Table 4.

Across all models, there are positive and significant autoregressive (Yj,t-1) effects of 3.57 % and 3.92 % for bars and 1.75 % and 5.80 % for restaurants in Manchester and Nottingham, respectively. This finding highlights a weak in magnitude but inherent positive path dependence in areas with an established bar and restaurant 'ecosystem'. It is also consistent with the hospitality literature on spatial clustering, where existing establishments increase likelihood of similar venues opening nearby (Sevtsuk, 2014). Even though there is some path dependence, or 'hotspots', as areas with many bars attract new bars, bar counts declined consistently across both cities in a non-linear pattern, as shown by the time FEs. Manchester and Nottingham respectively experienced 24.35 % and 27.60 % reductions between 2005 and 2019. Restaurants demonstrate the reverse trend with substantial growth of 35 % for both Manchester and Nottingham.

Accessibility by public transport emerges as a key positive

Table 5
Logit model results.

	Logit Model No time FEs				Preferred Logit Model			
	Bars		Restaurants		Bar		Restaurant	
	Manchester	Nottingham	Manchester	Nottingham	Manchester	Nottingham	Manchester	Nottingham
Population density	0.9660	1.0412	0.9640	0.9254	0.9618	0.9903	0.9408	0.9777
	(0.0494)	(0.0500)	(0.0356)	(0.0485)	(0.0561)	(0.0537)	(0.0357)	(0.0538)
Retail	1.3772**	0.7541	0.9804	0.7177	1.2984	0.6943	0.9968	0.5600***
	(0.2244)	(0.1590)	(0.0667)	(0.1501)	(0.2257)	(0.1976)	(0.0730)	(0.1240)
Accessibility	1.1866***	1.3337***	0.9604	0.9827	1.0515	1.2158***	1.0990***	1.0663*
	(0.0384)	(0.0504)	(0.0245)	(0.0252)	(0.0480)	(0.0686)	(0.0379)	(0.0402)
Income	0.9464**	0.8300***	1.0252	0.8986***	0.9848	0.8480***	1.0036	0.8843***
	(0.0204)	(0.0361)	(0.0156)	(0.0319)	(0.0206)	(0.0490)	(0.0160)	(0.0325)
Aged 18–24 (%)	0.9384**	0.9314	0.9807	1.1049**	1.0279	0.9613	0.9364***	1.1230**
	(0.0295)	(0.0479)	(0.0220)	(0.0547)	(0.0370)	(0.0588)	(0.0236)	(0.0576)
Male (%)	1.0012	0.9375	1.1338**	0.9812	0.9884	0.9803	1.1819***	1.1133
	(0.0728)	(0.0838)	(0.0587)	(0.0817)	(0.0711)	(0.1072)	(0.0636)	(0.0979)
Asian (%)	1.1450***	1.3957***	1.0442	0.8386***	1.0065	0.9829	1.0601	0.9838
	(0.0485)	(0.1307)	(0.0335)	(0.0504)	(0.0449)	(0.0984)	(0.0386)	(0.0608)
Black (%)	1.6945***	1.7593***	1.1068*	1.6685***	1.3641***	1.0886	1.1134*	2.6493***
	(0.1732)	(0.3265)	(0.0599)	(0.2978)	(0.1445)	(0.2452)	(0.0668)	(0.5442)
2002					base	base	base	base
2005					0.9044	1.4487	1.0157	0.5255**
					(0.2959)	(0.5656)	(0.2529)	(0.1661)
2008					1.7415*	2.2273**	1.5133	0.2940***
					(0.5696)	(0.8961)	(0.4134)	(0.1007)
2011					3.7202***	9.2163***	1.4043	0.1619***
					(1.2716)	(4.1165)	(0.4088)	(0.0603)
2014					5.9309***	16.8974***	0.5342**	0.1256***
					(2.3170)	(7.8255)	(0.1622)	(0.0497)
2017					10.1942***	29.0634***	0.2802***	0.0756***
					(4.1986)	(13.2148)	(0.0870)	(0.0311)
2019					18.5252***	25.7075***	0.2399***	0.0883***
					(7.8933)	(12.0576)	(0.0759)	(0.0370)
Area FEs	yes	yes	yes	yes	yes	yes	yes	yes
Hausman test, H0: random effects	61.80***	38.52***	90.79***	50.44***				
Pseudo R Squared	0.2521	0.2842	0.0197	0.0640	0.3383	0.4516	0.0770	0.1627
LL (Model)	−342.9017	−265.8902	−457.0847	−283.4224	−303.3944	−203.7063	−430.3746	−253.5114
AIC/BIC	702/742	548/586	930/970	583/620	635/705	435/502	889/959	535/599

Notes: * significant at $p < 0.10$; **significant at $p < 0.05$; ***significant at $p < 0.01$; the Logit coefficients are presented as ORs.

determinant of bar 'hotspots' in both Manchester and Nottingham. An additional minute of travel time to the urban centre decreases counts by 1.36 % and 3.95 %, respectively. Retail is associated positively with bars in Manchester, with 100 additional retail employees corresponding to a 0.37 % increase in counts. This finding supports observations that retail areas support higher bar concentrations through demand externalities (Morrison et al., 2015; Sevtsuk, 2014). Conversely, there is a weak negative effect of retail on restaurant 'hotspots'.

Income deprivation exhibits no significant effects in Nottingham and differentiated effects across venue type in Manchester. 1 % deprivation increase is associated with 0.88 % increase in bar counts and a 1.15 % decrease in restaurant concentrations. These results support previous findings that bars demonstrate stronger associations with deprivation while restaurants concentrate in less deprived areas (Livingston, 2012). Consistent to section 6.1 results, we find evidence of Black populations sorting to negatively affect bar counts in Manchester and restaurant counts in both study areas. Male population correlates positively with bars in Nottingham while reverse emerges for Manchester restaurants. Population density significantly associates with bar establishments in Manchester only, with each unit increase corresponding to a 1.94 % increase in bar counts. The proportion of population aged 18–24 shows no significant associations with venue counts across any model.

6.3. Discussion

In bringing together the results of the preferred Poisson and logit models, the combination of FEs across two specification and the autoregressive count coefficients provide a nuanced picture of bar and restaurant 'hotspot' and 'desert' evolution. Time FEs indicate a non-linear trend in restaurant 'desert' reduction and count increases, which is suggestive of increasing sprawl but from a quite centralised and concentrated baseline. However, there is a weak path dependence pushing the other way and new restaurant attracted in restaurant 'hotspots'. Conversely, a non-linear trend of bar 'desert' formation as well as count reductions suggests significant bar centralisation from a more sprawling baseline than restaurants. The autoregressive bar path dependence seems to be pushing towards 'hotspots'. Travel time to central locations by public transport also pushes towards to centralisation in bar counts and in 'desert' formation for both venue types. The combination of this evidence reinforces the idea of a major generational shift in consumer preferences affecting bars and restaurant in a nuanced but reversed way, which is consistent with the press coverage (Heward, 2019; Newman, 2024) and previous literature (Dunphy et al., 2025), and will have long term implications for policy maker and local economies.

Income deprivation decreased the likelihood of venue 'deserts' for both venue types in Nottingham and associated with an increase in bar numbers and a decrease in restaurant numbers. These findings show context depended deprivation effects and reflect results in the literature (Hay et al., 2009; Jin et al., 2018; Livingston, 2012). Lower rent structures in deprived areas appear to benefit both bars and restaurants potentially through increased area viability. Bars capitalise more effectively on these lower rents as consumers demonstrate greater willingness to travel access bars, particularly when visiting multiple

Table 6
Dynamic longitudinal Poisson model results.

	Bars		Restaurants	
	Manchester	Nottingham	Manchester	Nottingham
Population density	1.0194**	1.0077	1.0059	1.0100
	(0.0081)	(0.0065)	(0.0103)	(0.0082)
Retail	1.0037**	1.0042	0.9941*	0.9972**
	(0.0018)	(0.0031)	(0.0036)	(0.0014)
Accessibility	0.9864**	0.9605***	1.0048	0.9937
	(0.0062)	(0.0065)	(0.0104)	(0.0100)
Income	1.0088***	0.9988	0.9865**	1.0055
	(0.0031)	(0.0028)	(0.0063)	(0.0056)
Aged 18–24 (%)	0.9990	1.0029	1.0054	0.9941
	(0.0026)	(0.0024)	(0.0039)	(0.0044)
Male (%)	0.9992	1.0289**	0.9632**	1.0091
	(0.0070)	(0.0116)	(0.0144)	(0.0144)
Asian (%)	0.9892	0.9943	0.9844	1.0154
	(0.0084)	(0.0059)	(0.0122)	(0.0108)
Black (%)	0.9375***	0.9976	0.9354*	0.8643***
	(0.0125)	(0.0266)	(0.0339)	(0.0347)
2005	base	base	base	base
2008	0.9259***	0.9047***	0.9391	1.1417***
	(0.0229)	(0.0190)	(0.0453)	(0.0570)
2011	0.8762***	0.7653***	1.1041	1.1472**
	(0.0261)	(0.0256)	(0.0782)	(0.0705)
2014	0.8945***	0.7649***	1.2569***	1.4362***
	(0.0367)	(0.0350)	(0.0806)	(0.1021)
2017	0.8378***	0.7137***	1.4347***	1.3734***
	(0.0391)	(0.0321)	(0.0990)	(0.1058)
2019	0.7565***	0.7240***	1.3539***	1.3547***
	(0.0369)	(0.0370)	(0.1116)	(0.1027)
Yj,t-1 (Lag)	1.0392***	1.0357*	1.0175**	1.0580**
	(0.0138)	(0.0192)	(0.0077)	(0.0240)
Conditional FEs	yes	yes	yes	yes
LL (Model)	−2053.5523	−1336.6253	−1188.9127	−843.2924
AIC/BIC	4135/4215	2701/2777	2406/2480	1715/1784

Notes: * significant at $p < 0.10$; **significant at $p < 0.05$; ***significant at $p < 0.01$; Poisson coefficients presented as IRRs; The constant term omitted in FEs Poisson models (Wooldridge, 2010); AIC/BIC shows better overall fit of the preferred Poisson models in Table 5 when compared to the identical regressions with the depended variables assumed to be continuous instead of count.

establishments during a single outing (Deng & Picone, 2019; Picone et al., 2009).

The US literature shows higher venue densities in areas with higher black populations (Romley, 2007; Trangenstein et al., 2020; Jin et al., 2018), but this relationship weakens after controlling for socioeconomic deprivation (Morrison et al., 2016; Snowden, 2016). The US literature typically shows 30–50 % Black populations in their data (Jin et al., 2018; Snowden, 2016; Trangenstein et al., 2020), compared to our study sample of 1.3 %–2.6 % predominantly African/Caribbean Black populations and Asian populations of 5.3–9 %. Nevertheless, there is substantial spatial sorting of ethnic-minority populations in our data with many neighbourhoods reaching 15 %–30 % and 55 %–100 % Black and Asian populations in Nottingham and Manchester, respectively. We provide evidence that Black population sorting has substantial effect on increasing desert formation and lower venue counts in most cases. We cannot be clear on the direction of the effect, whether populations sort in areas with less/no alcohol venues or alcohol venues are reduced in these areas due to lower customer base. We are confident that the divergence of our results to the US literature is because the UK's Black populations have distinct cultural and religious backgrounds (Office for National Statistics, 2023) that differ markedly from the US Black populations.

7. Conclusion

This paper combines epidemiological and hospitality literature insights in developing an urban economic framework that provides a two-fold empirical approach. Dynamic longitudinal Poisson models incorporate ethno-demographic, socio-economic and accessibility variables to analyse concentrations, or 'hotspots' and temporal shifts in bar and restaurant location patterns. Longitudinal logit models analyse the determinants, trend and spatial structure of bar and restaurant 'deserts'. Two key UK urban areas, Greater Manchester and Nottingham, are selected in term of socio-economic and demographic diversity, compiling a unique dataset of bar and restaurant counts for more than 1100 small areas between 2002 and 2019. Our two-fold empirical approach not only addresses limitations and gaps stemming from cross-sectional data (Morrison et al., 2016; Snowden, 2016) or static approaches (Jin et al., 2018) but offers a nuanced understanding of bar and restaurant 'hotspot' and 'desert' evolution that implies major generational shifts in consumer preferences consistent with recent UK press coverage (Heward, 2019; Newman, 2024) and previous literature (Dunphy et al., 2025; Oldham et al., 2018).

During our study period, the Poisson and logit time fixed effects and the autoregressive count coefficients show over 19-fold increase in bar 'desert' formation and 24 % reductions in count, as well as a weak in magnitude path dependence, all of which push towards 'hotspots' and bar centralisation. Conversely, we observe up to 11-fold restaurant 'desert' reduction and 35 % count increases, which are suggestive of increasing sprawl but with a weak path dependence pushing towards restaurant 'hotspots'. Given the potential for alcohol consumption, accessibility by public transport to urban centres is, as expected, a key disruptor of 'deserts' and force for centralisation across all venue types and study areas. Our results show context-depended deprivation effects broadly consistent with the literature (Hay et al., 2009; Jin et al., 2018; Livingston, 2012). We find evidence of Black population sorting effect on increasing 'desert' formation and lowering venue counts, which diverges from the US literature (Romley, 2007; Trangenstein et al., 2020; Jin et al., 2018) because of distinct cultural and religious backgrounds of UK's Black populations.

We did not explicitly model spatial dependence, as some studies do (Jin et al., 2018; Morrison et al., 2016), but we account for spatial heterogeneity and spatial OVB non-parametrically. An important avenue of future research is the development of a new methodological framework for the introduction of a spatial econometric data generating process into venue count models and for the empirical strategies of combining spatial and temporal dependence into spatiotemporal models (Thanos et al., 2018). Covid-19 lockdowns had significant and potentially long-lasting impacts for the industry, exposing it to structural risks. A potentially valuable extension for the industry would be to model the risk of closure by specifying Hazard models (Cissé & Dubé, 2024) for bar and restaurant location patterns. Another future research avenue is to employ quasi-experimental approaches in order to capture impacts of significant policy changes or infrastructure improvements (Dubé et al., 2024).

CRediT authorship contribution statement

Jonathan Wood: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Sotirios Thanos:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization. **Anupam Nanda:** Writing – review & editing, Supervision, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Jonathan Wood reports financial support was provided by ESRC (grant number ES/P000655/1). Jonathan Wood reports equipment, drugs, or supplies was provided by Consumer Data Research Centre (under project ID CDRC 1035, ES/L011840/1; ES/L011891/1). Anupam Nanda is a board member (non-paid) of the European Real Estate Society which is a learned society in real estate research and education. If there are other

and consumer utility effects, explaining the persistence of venue clusters despite evolving market conditions.

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