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Spatial dynamics of long-term urban retail decline in three transatlantic cities

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ABSTRACT

This paper studies the effects of the centrality, connectivity and agglomeration of retail establishments on their long-term viability in three cities in the United States, United Kingdom and The Netherlands. As retail is declining in all three markets, there is a dearth of knowledge on the spatial patterns of this decline. This obstructs the substantiation of development decisions and public policy on urban retail retention and growth. Without knowing where stores are most at risk of closing, where can we decide to invest or divest? This paper uses a self-built dataset of store locations and store closures over the span of more than a century in the urban cores of Detroit, Michigan; Birmingham, England; and The Hague, The Netherlands. While taking different paths, all three cities have experienced significant retail decline over the past century. The probability of store closure over time is compared to the metric distance of stores to the retail center of gravity (centrality), store location along well-used streets as measured by their Choice value (connectivity), and the number of surrounding stores (agglomeration). These three comparisons are statistically analyzed using simple line regression, panel regression, and spatial autoregressive probit models. Across these models, store closure is most significantly affected by agglomeration, then by centrality, followed by connectivity. The significance of all three measures is strongest in The Hague, followed by Birmingham and Detroit – two cities that experienced large-scale urban renewal and socio-economic decline.

1. Introduction

Many cities in the Western Hemisphere are experiencing a significant loss of street-level commercial activity in their urban cores. At a seemingly daily pace, high-profile retailers announce urban store closures in what has been dubbed the ‘retail apocalypse’ (Helm et al., 2020; Townsend et al., 2017), which has only been exacerbated by the COVID-19 crisis at the time of writing. Especially e-commerce is ascribed to disrupting the current retail market, most notable in durable goods sectors where physical stores cannot add consumer experiential value or convenience (Christensen & Raynor, 2015; Lipsman et al., 2018; Verhoef et al., 2015). Besides affecting suburban and regional retail centers, the resulting loss of physical retail stores strongly impacts the urban experience, as retailers form the cornerstone of vibrant and walkable environments (Jacobs, 1961; Leinberger & Alfonzo, 2012; Mehta & Bosson, 2010). As a result, urban retail erosion elicits significant scholarly, professional and public debate. For example, the rapid rise of storefront vacancies along British High Streets incites national inquiries on their revitalization, often focusing on preparing for life after retail (Burt et al., 2016; Carmona, 2016; Portas, 2011). New York vigorously debates the culprits for its growing vacant storefront “gaps in an otherwise welcoming smile” (Kilgannon, 2018), ranging from greedy landlords, burdensome regulation, retail gentrification, or the rise of e-commerce – and debates policy to save small businesses (Kasinitz et al., 2015; Surico, 2018).

Two perspectives are notably absent from the current scholarly and professional debate on retail decline, which obstructs the ability to predict and mitigate future trends. Firstly, there is a dearth of research on where retail decline takes place within cities. This is partly due to the schism between the academic fields that study retail. Many current studies on retail dynamics yield from economics and marketing fields, and focus on organizational, economic, political and technological aspects (e.g. Evans, 2011; Grewal et al., 2017). Organizational retail change is often conceptualized in environmental, cyclical and conflictual terms (Brown, 1987b; 1993b). Furthermore, many studies of retail change focus on the operations of larger retailers, which are often...
located outside of cities, especially in North America (Dawson et al., 2008; Grewal et al., 2017; Kent & Omar, 2003). Studies in retail geography and change tend to focus on citywide or regional trade area analysis, a resolution that is too coarse to understand change at the micro scale of the retail cluster, its streets and its storefronts—where retail dynamics most affect the experience of citizens (Birkin et al., 2002; Stephen Brown, 1994). Fortunately, a growing urban planning and design canon has focused on the spatial dynamics of retail at the micro-scale over the past decades (Hillier, 1996; Hillier & Hanson, 1984; Van Nes & López, 2007), and the American urban planning and design scholarship on urban retail at the micro-scale has increased over recent years (Hidalgo & Castañer, 2015; Sevtsuk, 2014, 2020).

Nevertheless, the vast majority of these recent studies do not focus on long-term patterns of retail change. The seemingly unique and pressing circumstances of contemporary retail decline—and the natural inclination of retail marketing, development and planning scholars and professionals to focus on the future—forgo the lessons on how retail has declined in the past. An unfortunate omission, as the current retail apocalypse shows strong similarities with past retail revolutions, such as the rise of the department store in the late 19th century, chain retailers in the early 20th century, car-based suburban retail in the mid-20th century, and self-service stores and discounters in the late 20th century (Davis, 1966; Miellet & Voorn, 2001; Stobart, 2010). Historiographies of retail change have often focused on organizational and cultural processes (e.g. Coleman, 2006; Davis, 1966; Longstreth, 1997), case study businesses (e.g. Longstreth, 2010; Miellet, 1992), case study streets (Duren, 1995), or narrative descriptions of spatial change supported by cartography (Lesger, 2013). The current body of work lacks a quantitative focus on the spatial structure of retail transformation in entire urban districts, which limits their capacity to foresee future transformation trends. Furthermore, studies focus on retail change in specific national contexts, which depend on unique regulatory and cultural processes (e.g. Coleman, 2006; Davis, 1966; Longstreth, 1997), case study businesses (e.g. Longstreth, 2010; Miellet, 1992), case study streets (Duren, 1995), or narrative descriptions of spatial change supported by cartography (Lesger, 2013). The current body of work lacks a quantitative focus on the spatial structure of retail transformation in entire urban districts, which limits their capacity to foresee future transformation trends. Furthermore, studies focus on retail change in specific national contexts, which depend on unique regulatory and cultural processes (e.g. Coleman, 2006; Davis, 1966; Longstreth, 1997), case study businesses (e.g. Longstreth, 2010; Miellet, 1992), case study streets (Duren, 1995), or narrative descriptions of spatial change supported by cartography (Lesger, 2013). The current body of work lacks a quantitative focus on the spatial structure of retail transformation in entire urban districts, which limits their capacity to foresee future transformation trends. Furthermore, studies focus on retail change in specific national contexts, which depend on unique regulatory and cultural processes (e.g. Coleman, 2006; Davis, 1966; Longstreth, 1997), case study businesses (e.g. Longstreth, 2010; Miellet, 1992), case study streets (Duren, 1995), or narrative descriptions of spatial change supported by cartography (Lesger, 2013). The current body of work lacks a quantitative focus on the spatial structure of retail transformation in entire urban districts, which limits their capacity to foresee future transformation trends. Furthermore, studies focus on retail change in specific national contexts, which depend on unique regulatory and cultural processes (e.g. Coleman, 2006; Davis, 1966; Longstreth, 1997), case study businesses (e.g. Longstreth, 2010; Miellet, 1992), case study streets (Duren, 1995), or narrative descriptions of spatial change supported by cartography (Lesger, 2013).

By studying retail transformation from an urban, spatial and long-term perspective, this paper will demonstrate how and where retail decline has impacted the urban retail landscape at this microscale, complementing the current body of knowledge on why the market is transforming. More specifically, this paper will demonstrate the spatial dynamics of long-term urban retail decline in urban cores, yielding a detailed distribution pattern of retail closures that will enable urban stakeholders to forecast the risk of further decline for specific urban locations. In hence fills the knowledge gap on the probability of retail decline in specific locations, augmenting the significant body of scholarly and professional work on mitigating urban retail decline in Western markets (Abbott, 1993; Evers et al., 2011; Gratz & Mintz, 1998; Leinberger, 2005; Portas, 2011).

2. Theoretical perspectives

The research in this paper will benchmark and expand the current body of knowledge on retail decline, specifically focusing on the underexplored microlevel spatial dynamics of this decline. Spatial models have mostly focused on the location of (urban) retail success, by modeling supply and demand-side dynamics of retail establishments. These models and theories distinguish three main spatial elements of retail success: agglomeration, centrality and accessibility. Early-20th century models focused on the advantages of retail merchandise agglomeration for the hierarchical position of retail clusters in the economic region (Christaller, 1933; Reilly, 1929; Reilly, 1931), based on the notion of the rational consumer and its minimization of travel and risk to obtain goods, a premise which has been challenged in subsequent years (Brown, 1993; Kooijman, 2000). The advantage of retailer agglomeration is also a risk minimization strategy on the supply side, as shops cluster to sell complementary goods, but also take market share from competitors and to enable customers to compare goods (Brown, 1989; Hotelling, 1929). At the micro scale of the retail street, the benefits of agglomeration prompt retailers to cluster with compatible peers and close to anchor stores (Hernández & Bennison, 2000; Nelson, 1958; Sevtsuk, 2020), which has been demonstrated to reduce their chance of failure over longer spans of time (Kickert and vom Hofe, 2018).

These three models result in a pattern of retail clusters and streets, in which retailers co-locate with compatible competitors in the most accessible, visible and well-connected location that they can afford (Garner, 1966; Kivell & Shaw, 2012). The resulting hub-and-spoke pattern is the spatial expression of the three benefits of agglomeration, centrality and connectivity (Fig. 1).

This tripartite model of retail location represents neoclassical economic theory, as it presumes retailers’ ability to make discrete location decisions with full knowledge of spatial conditions, regardless of organizational structure (e.g. of chain retailers), suburban advantages, or operational, social, topographic and regulatory externalities (Hernández & Bennison, 2000). Despite these (potentially growing) theoretical shortcomings, the presumption of retailers’ discrete decision making to seek locational advantages along lines of agglomeration, centrality and connectivity still holds. Over the past decades, studies continue to demonstrate the correlation between retail location and street centrality and connectivity, either through the Space Syntax definition of the ‘movement economy’ (Hillier, 1996; Hillier & Hanson, 1984), or other methods that define the propensity of streets and street segments to attract (pedestrian) traffic, hence retail land use (Marcus et al., 2018; Porta et al., 2006a, 2006b; Stahle et al., 2003). While most of these models have been applied to cities in Europe, Asia and South America, urban scholar Andres Sevtsuk (2014) recently demonstrated that American locations with better accessibility, traffic, and clustering attract more retailers through a self-created land use dataset and street accessibility metrics.

However, these studies only focus on snapshots of current retail distribution within cities, limiting their ability to recognize trends. Furthermore, their focus on currently operating retailers prevents an understanding on retail closure. As the urban retail landscape is accelerated decline in the era of e-commerce and health crises, where can

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1 On the other hand, retail scholar Stephen Brown argues that public policy frameworks and risk-averse retailer have actually turned the aforementioned retail models into a self-fulfilling prophecy (Brown, 1987a, 1987b; Brown, 1994).
cities expect retail establishment closures to happen? Are establish-
ments more likely to close in dispersed locations along peripheral,
poorly connected streets, therefore amplifying the theorized pattern of
retailers locating in clusters along the most central and well-connected
streets? Alternatively, are retail closures more randomly distributed
throughout urban areas, making targeted planning for decline more
difficult?

3. Methodology

This paper assesses the influence of agglomeration, centrality and
connectivity on the risk of retail closure, at the scale of the urban core –
measuring between one and three miles in diameter. This paper will
focus on urban cores, as they contain the largest and most dynamic
stock of retail premises within most cities. Furthermore, urban cores
continue to serve as foci of culture, socialization and identity for urban
regions – with retail playing a strong but henceforth uncertain role
(Gehl, 2010; Rypkema, 2003). Lastly, the meso-scale of urban cores
presents a comprehensive area to demonstrate spatial patterns of de-
cline beyond the micro-scale of the singular street, and the macro-scale
of the trade area. Retail establishments are defined as street-facing re-
tail shops, bars, restaurants, coffeehouses, and lunchrooms (also known
as Food & Beverage establishments). Establishments on upper floors
and inside enclosed shopping malls are not counted, except if the latter
malls are part of the urban pedestrian network beyond business hours.
Retail closure is defined as a retail function disappearing from a
building, rather than the replacement of a retail tenant with another
tenant (known as churn). This is due to the limitations of our long-term
data set, which measures retail closures in four roughly quarter-cen-
turies between 1911 and 2018. This long time span allows for mea-
surement of retail change through a series of retail revolutions over the
past century, including the suburbanization of retail, and the rise of
self-service, chain and discounter retail. As a result, the number of retail
establishments in Western markets have been in decline more or less
constantly, since national statistics began in most countries about
90 years ago. The decline ranges from over 50% in the United States, to
over 80% in the United Kingdom over the past 90 years alone. In other
words, the current retail apocalypse is but an extension of a much
longer pattern of establishment decline.

3.1. Case study selection, data collection, and research hypotheses

This paper studies the spatial patterns of retail decline in three
urban cores: Detroit in the United States, Birmingham in the United
Kingdom, and The Hague in The Netherlands. These urban cores were
selected to represent prevalent Western planning paradigms such as
traffic interventions in the early 20th century, mid-20th century
Modern renewal, and late 20th century public space improvements.
Each also represents their own national urban dynamics, which differ
significantly. Detroit and Birmingham are known for their post-
industrial decline (Flattman, 2008; Galster, 2012; Hubbard, 1996;
Vergara, 1995); both cities have indeed suffered from significant losses in
urban employment and economic activity, which reflects in the loss of
vibrancy in their urban cores. Conversely, the center of The Hague
has won awards for its high quality public space and complete and
diverse retail offering. While these three case studies seem very dif-
ferent at first sight, they actually contain a range of similarities and
differences, which allow for literal and theoretical replication (Yin,
1994). Firstly, all three urban cores have actually suffered from sig-
nificant decline in the number of retail establishments since 1911,
ranging from 50% in The Hague to 68% in Birmingham and 87% in

Detroit. The annual chance of retail disappearing from a location (the
core measure this paper will study) has decreased by over 50% in
Birmingham and The Hague, but it has remained high in Detroit (Table 1).
Retail decline has been the result of suburbanization of the retail
offer into new neighborhoods and planned shopping malls in all
three cities, but to different extents. Downtown Detroit counts less than
2% of its region’s retail and food & beverage establishments; The Ha-
gue’s popular downtown has less than 20% of the regional establish-
ments. Similarly, all three cores have seen a significant decline in their
downtown residents, jobs and visitors, followed by a recent upswing in
all cores. Conversely, the very different social, economic and cultural
context of the three cores would enable the discovery of similar spatial
decline dynamics to signify theoretical replicability, hence general-
izability (Kickert and vom Hofe, 2018; Yin, 1994).

The three urban cores are broadly defined to study core and per-
ipheral effects of retail decline; each core matches the size of its trade
area’s population. Detroit’s larger metropolitan population make its
1510 acre downtown roughly twice as large as Birmingham’s city center
at 745 acres, and three times larger than The Hague’s inner city at 570
acres (Fig. 2). Several data sources have been combined to create a
reliable longitudinal dataset of store closures. The location of street-
level retail establishments has been determined by combining historical
maps from various sources at the plot level, with business directories
and government databases for both cities in 1911, 1937, 1961, 1988
and 2017. The x-y coordinates of each business establishment has been
denoted in a comparable format for all cities, and entered into a GIS
database. Wholesalers and automotive businesses are excluded from the
inventory, except if they also sold to pedestrian consumers. Store clo-
sures are defined by comparing store locations between datasets; if a
location is no longer present in a next era, it is marked as “to be closed.”
The final dataset therefore contains attributes on the location of a re-
tailer, and whether it will be closed in the next era or not.

The maps from the GIS database show a clear visual pattern of retail
frontage contraction into the hub-and-spoke system that the economic
models in Section 2 would predict. The maps demonstrate the pro-
longevity of stores to close along lines of centrality (as they contract to-
ward the heart of the urban core) and connectivity (as they contract
toward a set of radial streets). While The Hague and Birmingham retain a
consistent retail core with radiating commercial corridors, Detroit’s
downtown retail has nearly disappeared altogether after 1961, leaving
only a dispersed pattern of singular survivors (Fig. 3). The visual pat-
terns from the maps lead to the following hypotheses, which this paper
will corroborate through statistical methods in the following sections:

1. The chance of a store closure is influenced by the metric distance to
the heart of downtown, i.e., centrality.
2. The chance of a store closure is influenced by the connectivity of the
street segment it is located on.
3. The chance of a store closure is influenced by the number of sur-
rounding retailers within 50 m, i.e., agglomeration (expanding on
previous work by the paper authors).

These numbers are derived from the United States Census of Retail Trade
and County Business Patterns, and from the United Kingdom Census of
Distribution, as well as Eurostat Enterprise Statistics.
3.2. Research design

To corroborate the three hypotheses of centrality, connectivity and agglomeration, retail establishments receive further characteristics. To connect stores to the first two metrics of centrality and connectivity, stores are assigned to the street segments (between intersections to other streets) that they are located along. These segments are distilled for each city and each time period from street and topographic maps. For each street segment, centrality and connectivity characteristics are calculated, and these calculated segment characteristics are then assigned to all stores along that segment. After this, a series of statistical calculations study the relationship between store closure, street centrality (CENT; hypothesis 1) and street connectivity (CONN; hypothesis 2). To connect stores to agglomeration (AGGL; hypothesis 3), the number of other stores is calculated within 50 m. This distance allows for measurements of stores across the street, but within viewing distance.

The calculation of the centrality and connectivity characteristics of street segments is conducted in DepthmapX, an open-source software developed by the Space Syntax community (Al-Sayed et al., 2018; Turner, 2001). For decades, this community has studied the relationship between street configuration and land use, finding correlations between the integration of streets in the urban network and the amount of retail stores located along this street in the aforementioned “movement economy” (Hillier, 1996; Hillier & Hanson, 1984). While original studies focus on street integration as an indicator for pedestrian activity and hence retail land use, more recent work demonstrates that retailers locate along street segments that are used en route to other streets – the “Choice” variable in Space Syntax terminology (Omer & Goldblatt, 2016; Vaughan et al., 2013; Vaughan et al., 2010). Choice is calculated as the cumulative amount a street segment is chosen as a least-angle route between all other street segments within a set radius. Pilot studies for the three cities in this paper demonstrate that Choice most strongly correlates with retail distribution at the 5000-meter radius of measurement; hence this value is calculated through angular analysis for each segment – which is drawn by the authors on topographical mapping. The Choice values are weighted by segment length, and they have been normalized to allow cross-city-and-era comparisons (Hillier et al., 2012). The specific segment normalized Choice value is then attributed to the retailers located along this segment.

Depthmap is also used to calculate the influence of centrality on this decline (hypothesis 1). This is defined as distance from the most high-performing retail location in the city, known as the “100% corner” in the United States and the “A1 corner” in Europe. This retail center of gravity has remained stable over the past century due to continued private and public investments to maintain it; it hence serves as the base point from which distance is measured for all time periods. Depthmap calculates the metric, on-the-ground distance to the main corner as a value for the entire street segment, which is subsequently attributed to the retail properties along that street segment. Fig. 4 gives examples of the 1911 and 2017 street layouts for each city, as well as the retail center of gravity. The maps demonstrate the transformation of downtown street patterns in all three cities.

The database of open/closed stores is then compared to their centrality, connectivity and agglomeration values through three statistical analyses, each with their own benefits and drawbacks.

| Year          | Detroit | The Hague | Birmingham |
|---------------|---------|-----------|------------|
| 1911-1936     | 2418    | 2925      | 3129       |
| 1937-1960     | 2.46%   | 2.15%     | 1.67%      |
| 1961-1987     | 2.99%   | 1.78%     | 2.16%      |
| 1988-2017     | 5.03%   | 1.37%     | 1.33%      |
| 2017          | 32.9%   | 0.72%     | 0.60%      |

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4. Analysis

4.1. Data processing

Each retail establishment is attributed with its potential closure in the next era (0 or 1), its centrality characteristic (distance from the retail center of gravity between 0 and 1100 m), its normalized street connectivity value (mostly between 1.23 and 1.56), and the number of its surrounding retailers within 50 m (between 1 and 40). Two statistical measures then calculate the overall probability of closure for each store, dependent on the centrality, connectivity and agglomeration characteristics.
Fig. 3. Retail frontages in The Hague, Detroit and Birmingham 1911–2011/2017.
DETOUR
1911

2017

BIRMINGHAM
1911

2017

THE HAGUE
1911

2017

Street connectivity (Normalized angular choice at R = 5000m)
★ Center of retail gravity

(caption on next page)
Characteristics. This requires ‘binning’ stores into bandwidths of connectivity and centrality that contain a sufficient number of stores to calculate the probability of closure. The probability of a store closing at 682 m from the retail center of gravity requires comparison with a sufficient number of other stores that did or did not close, none of which are exactly at that distance; this probability can however be defined when comparing to all stores within 600–700 m of the retail center of gravity. For agglomeration effects, there is a sufficient sample size for each discrete number of surrounding stores, hence binning is not necessary for this measure. Within each connectivity and centrality bin, and for each number of surrounding stores, the average annual probability of store closure is calculated using Eq. (1):

\[
\text{Chance of business closure: } P_t(B_x) = \frac{B_x(\text{closed})}{B_x(\text{total})} \tag{1}
\]

This equation defines the probability of a store within the bin with characteristics \( x \) closing within a certain time interval as \( P_t(B_x) \). The equation calculates this definition through dividing \( B_x(\text{closed}) \), the number of stores within this characteristics bin that closed, by \( B_x(\text{total}) \), the total number of stores within this characteristics bin. Hence, for each bin of centrality and connectivity characteristics, for each city, and for each time period, the average probability of store closure is calculated. This calculation is then annualized, using Eq. (2).

Annualization of the chance of business closure:

\[
P(B_x) = 1 - (1 - P_t(B_x))^{1/(\Delta t)} \tag{2}
\]

This yields an annual chance of closure for retail establishments with a certain characteristic within a certain time period and city, e.g., stores between 600 and 700 m to the retail center of gravity in The Hague between 1911 and 1936. This calculation is performed for each time period and each of the three characteristics. These values need to be normalized to account for the widely varying downtown-wide chances of retail establishment closure between cities and time periods due to aforementioned citywide market dynamics such as income and population decline, suburban competition, regulatory policies, and the rise of e-commerce. As mentioned for example, Detroit’s average downtown retail establishment decline was almost twice as much as in The Hague over the past century as a result of citywide socio-economic decline and unfettered suburbanization. The annual average values for each retail establishment characteristic and each time period are therefore controlled against the average chance of any establishment closure within that time period in each city. The outcome demonstrates whether establishments with certain characteristics are more or less likely to close versus the average chance of closure in a time period. This control is conducted as a subtraction, to maintain the absolute annual chance of closure (Eq. (3)):

Controlled Mortality Rate (by the average overall chance of business closure):

\[
\text{MR}(B_x) = P(B_x) - P(B_{\text{all}}) \tag{3}
\]

In this equation, \( \text{MR}(B_x) \) is the controlled mortality rate, the higher or lower probability that a business with characteristics \( x \) closes as compared to \( P(B_{\text{all}}) \), the average annual probability that any business closes. Along with the annualization of closure probability, this formula may amplify values for small sample sizes – especially when all or no businesses within a sample close. While space does not permit us to show all resulting data, Table 2 shows an example of the resulting controlled mortality rates (converted to percentages) for The Hague dependent on their distance from the retail center of gravity, per era. Retailers beyond 1100 m from the center of gravity are left out, as they are subject to the gravitational pull of a secondary center, and sample sizes become too small, especially in later eras.

An impression of the overall mortality rate per distance bucket over the full time period between 1911 and 2017 can be given by an average weighted by the number of retail establishments within each era. The weighted averages for the centrality, connectivity and agglomeration effects on retail establishment mortality rate are graphed in Figs. 5, 6 and 7. Due to the outsized effect of outliers, the ranges for each city are different for connectivity and agglomeration. The graphs show that in all three cities, the distance of a retail establishment from the retail center of gravity seems to have an effect on its controlled mortality rate. Connectivity seems to have an effect in all cities but Birmingham, and agglomeration seems to affect mortality in all three cities.

4.2. Independent regressions

While the weighted average graphs indicate effects of centrality, connectivity and agglomeration, they should be considered only exploratory. To delve into these relationships in more detail, this paper presents three statistical methods to study the relationship between the three forces and retail mortality. Firstly, the controlled Mortality Rate (MR) is analyzed by independent regressions for each characteristic, city and era. Thirty-six simple regression models investigate how each of the three selected explanatory variables, namely centrality (CENT), connectivity (CONN), and agglomeration (AGGL) affect businesses’ chance of closure in Detroit, The Hague, and Birmingham, for each era. The general form of the linear regression model is described by Eq. (4).

Simple linear regression model: \( \text{MR}_i = \beta_0 + \beta_1 X_i + \epsilon \) \tag{4}

In this equation, MR is the controlled Mortality Rate and X, the explanatory variable, represents any one of the three factors influencing closure, i.e., centrality, connectivity, and agglomeration. Specific focus is on the parameter \( \beta_1 \) which indicates the strength and the direction of the any of the three characteristics on MR. The remaining parameter \( \beta_0 \) represents the intercept. The error terms \( \epsilon \) have the required ordinary least square properties, i.e., \( \epsilon \sim NID(0, \sigma^2) \). The R², significance and slope results from the 36 independent regressions are outlined in Table 3.

Please note that due to small sample sizes and resultant MR outliers in outer ranges, the ranges per regression vary per year, per measure and per city.

The table demonstrates significant spatial influences on retail mortality, but with different outcomes per city and era. Centrality effects are significant at the 5% level of significance for all three cities until 1988, and for The Hague afterward. The estimated centrality parameter is positive, indicating that with increasing distance from the retail center of gravity, the Mortality Rate of businesses increases. This confirms hypothesis 1 that the metric distance to the retail center of gravity significantly influences the chance of retail closure in all three cities. In Detroit between 1988 and 2017, centrality has lost its significance as the number of remaining retailers has dwindled and reinvestment has followed land ownership patterns rather than spatial logic (Kickert, 2019). In Birmingham, centrality ceased to affect retail closure due to a massive central mall scheme that forced many businesses to relocate (Flatman, 2008).

Connectivity effects are significant for The Hague until 1988, but
only significant for Detroit until 1937, and not at all for Birmingham. For Detroit and The Hague, the significant parameters have the expected negative sign: with increased street connectivity, retail establishment closure risk decreases. The decreasing significance over time in The Hague and Detroit and Birmingham’s insignificant influence can be explained by more drastic changes in the street network over time in recent decades, which strongly affect choice values. Also, Birmingham’s shopping apparatus has been relatively dependent on shopping malls like the Bullring and Grand Central, which do not fully relate to street-level choice values. Both malls have also received significant overhauls over the past century.

Agglomeration effects are significant for all three cities except for Detroit after 1988, due to the aforementioned effects of downtown investment. The difference between the estimated parameters can be explained by the different types of businesses, as The Hague’s urban core contains more comparison shops that are sensitive to agglomeration. Furthermore, the different sensitivities may relate to the greater reliance on car access to stores outside The Netherlands, and the prevalence of shopping malls in Birmingham.

The R^2 values for the significant parameters range from 0.192 (agglomeration effect in Detroit between 1961 and 1987) to 0.901 (centrality effect in Birmingham between 1911 and 1936). All statistically significant estimated parameters have the expected signs.

### 4.3. Pooled cross section analysis

A panel regression with a pooled cross section model combines the individual effects of each force over a longer time period. The pooled cross section framework is deployed with dummy variables due to the small sample size for each time period and characteristic. All nine models (three cities, three characteristics) are rerun in order to determine whether the relationship between the Mortality Rate and the previously defined centrality (CENT), connectivity (CONN), and agglomeration (AGGL) measures is statistically significant. The general form of the pooled model is described by Eq. (5):

\[
\text{MR}_t = \beta_0 + \beta_1 X_{it} + \delta_1 \text{D}37 + \delta_2 \text{D}61 + \delta_3 \text{D}88 + \varepsilon_t
\]

where MR is the mortality rate, X is any one of the three factors
influencing closure, and D37, D61, and D88 are categorical variables (Time Periods) representing the three time periods starting in 1937, 1961, and 1988. To avoid perfect serial collinearity among the categorical variables, the fourth categorical variable D11, representing the time period starting in 1911, was dropped from the model. The parameters to be estimated are $\beta_0$, $\beta_1$, $\delta_1$, $\delta_2$, and $\delta_3$. Following Wooldridge (2002), robust standard error was used to correct for both serial correlation and heteroscedasticity. Using the Cook’s distance measure ($C_i$), highly influential observations from the pooled data set were identified and deleted, i.e., any observation for $C_i > 1$. The results from these individual nine pooled cross section models are outlined in Table 4.

The panel regression results reflect many of the findings from the independent regressions. While agglomeration remains significant for all three cities, centrality is significant in Birmingham, and connectivity only remains significant in The Hague.

Seven of the nine individual models are statistically significant as
### Table 3
Outcomes of the independent regressions: analyzed ranges, correlation, significance and slope.

|                  | Detroit            | The Hague          | Birmingham         |
|------------------|--------------------|--------------------|--------------------|
| **Centrality**   |                    |                    |                    |
| Range            | 0–1100 m           | 0–1100 m           | 0–1100 m           |
| R-squared        | 0.86               | 0.56               | 0.46               |
| p-Value          | < 0.001***         | 0.008<             | 0.022              |
| CENT             | 0.0041             | 0.0035             | 0.0065             |
| Range            | 0–1100 m           | 0–1100 m           | 0–1100 m           |
| R-squared        | 0.77               | 0.71               | 0.62               |
| p-Value          | < 0.001***         | 0.001<             | 0.004              |
| CENT             | 0.0056             | 0.0031             | 0.0050             |
| **Birmingham**   |                    |                    |                    |
| Range            | 0–1100 m           | 0–1100 m           | 0–1100 m           |
| R-squared        | 0.90               | 0.73               | 0.82               |
| p-Value          | < 0.001***         | 0.026              | 0.031              |
| CENT             | 0.0027             | 0.0029             | 0.0052             |
| **Connectivity** |                    |                    |                    |
| Range            | 1.23–1.71          | 1.23–1.71          | 1.23–1.65          |
| R-squared        | 0.42               | 0.01               | 0.03               |
| p-Value          | 0.009<             | 0.799              | 0.543              |
| CENT             | −0.0640            | −0.0045            | 0.0251             |
| **Agglomeration**|                    |                    |                    |
| Range            | 1–40               | 1–38               | 1–32               |
| R-squared        | 0.79               | 0.57               | 0.19               |
| p-Value          | < 0.001***         | < 0.001***         | 0.012              |
| AGGL             | −0.0012            | −0.0009            | −0.0010            |

**Significant at the 95% confidence level.**
**Significant at the 99% confidence level.**
**Significant at the 99.9% confidence level.**

### Table 4
Outcomes of the panel regression.

| City      | Detroit  | Hague  | Birmingham |
|-----------|----------|--------|------------|
|           | Coefficient | p-Value | Coefficient | p-Value | Coefficient | p-Value |
| **Centrality** |          |        |            |        |            |         |
| Intercept  | −0.0203   | 0.003<  | −0.0109    | 0.006<  | −0.0096    | 0.014<  |
| CENT      | 0.0032    | < 0.001*** | 0.0024    | < 0.001*** | 0.0018    | 0.003<  |
| Time Periods | Yes      |        | Yes        |        | Yes        |         |
| R-squared | 0.38      | 0.34   | 0.32       |        |            |         |
| F-value   | 6.48      | < 0.001*** | 5.93      | < 0.001*** | 5.54      | < 0.001*** |
| **Connectivity** |          |        |            |        |            |         |
| Intercept  | 0.0271    | 0.370  | 0.0691     | < 0.001*** | 0.0095    | 0.570   |
| CONN      | −0.0140   | 0.505  | −0.0491    | < 0.001*** | −0.0055   | 0.640   |
| Time Periods | Yes      |        | Yes        |        | Yes        |         |
| R-squared | 0.09      | 0.48   | 0.04       |        |            |         |
| F-value   | 1.01      | 0.412  | 9.78       | < 0.001*** | 0.287    | 884     |
| **Agglomeration** |        |        |            |        |            |         |
| Intercept  | 0.0162    | < 0.001*** | 0.0266    | < 0.001*** | 0.0172    | < 0.001*** |
| AGGL      | −0.0010   | < 0.001*** | −0.0009   | < 0.001*** | −0.0005   | < 0.001*** |
| Time Periods | Yes      |        | Yes        |        | Yes        |         |
| R-squared | 0.39      | 0.64   | 0.43       |        |            |         |
| F-value   | 23.3      | < 0.001*** | 68.2      | < 0.001*** | 28.7      | < 0.001*** |

**Significant at the 95% confidence level.**
**Significant at the 99% confidence level.**
**Significant at the 99.9% confidence level.**
indicated by their F-values (below 0.05). The corresponding $R^2$ values range from 0.04 to 0.64 indicating some moderate model fits at most. Centrality appears to have a higher effect on businesses in Detroit than in the two European cities with estimated parameters of 0.0032 for Detroit, 0.0024 for The Hague and 0.0018 for Birmingham. Thus, for increasing the distance to the retail center of gravity by 100 meter intervals—from one bin to the next—increases a business’s probability of closure, as compared to the average annual probability that any business closes, by 0.32% in Detroit, by 0.24% in The Hague, by 0.18% in Birmingham. Connectivity again is less of importance as indicated by the regression results. Only for The Hague, the CONN parameter is statistically significant with a value of −0.0491. This implies that for every 0.03 increase in connectivity, i.e., from one bin to the next, the mortality rate decreases by $-0.0001 + 3 = 0.0015$, or 0.15%. Finally, the panel regression results indicate a robust agglomeration effect. In Detroit, The Hague, and in Birmingham, the probability of a business closing, decreases by 0.10%, 0.09%, and 0.05% for each additional business within 50 m respectively, again, with respect to the average annual probability that any business closes.

Both of the previously described statistical methods require binning and processing the store closures, which leads to a loss of fidelity. The weighted average of the independent regression models smooth out outliers across the four time periods, especially in later eras with smaller samples sizes and erratic closure patterns. In the pooled cross section analysis, influential observations are identified and deleted according to the Cook’s distance measure. The results confirm the robustness of estimated parameters when comparing the corresponding parameters with one another across the two different modeling approaches, but also leave some room for small differences among them, as the problem of dealing with outliers has been addressed differently.

4.4. Spatial autoregressive probit model

In a third approach, the final statistical method is the spatial autoregressive probit (SAR probit) model. The SAR probit model has the advantage that it uses the raw data collected for each of the four time periods and for each of the three cities. For comparison, the simple regression and pooled cross section regression models use mortality rates calculated from these raw data. In addition, the SAR probit framework allows that all three explanatory variables of interest, i.e., Metric distance, Choice value, and Nearby number of stores, are combined in one model. However, when jointly interpreting the estimated parameters in one model, potential co-variation of the regressors may be present as indicated in Fig. 3. Centrality and agglomeration, for instance, appear to be related over time which is explained by the fact that retail agglomerations seek the most high-performing retail locations in the city. Retail agglomerations are also more present on well-connected streets (Hillier & Hanson, 1984; Sevtsuk, 2014). Lastly, the large number of observations in the raw data sets reduces the impact of a small number of outlying observations, a problem encountered in the two previous described approaches. For using the raw data in a spatial framework, all observations were geocoded. One model is run per city per time period, making a total of twelve individual models. The SAR probit model used in presented research relies heavily on LeSage et al. (2011). The SAR probit model is defined by Eq. (6):

$$y^* = \rho Wy^* + X\beta + \epsilon,$$

where $y^*$ is the $n \times 1$ latent unobservable utility or closed-open status of firms. The spatial lag $Wy^*$ identifies the nearest neighbors of a business by means of a sparse, row stochastic weight matrix $W$. A business’s decision to close, as such, is also influenced by its surrounding businesses’ decision to close or to stay open for business. While the agglomeration effect counts the number of nearby businesses within 50 m, the spatial lag $Wy^*$ variable additionally accounts for the latent unobservable utility of the nearest four neighboring businesses. The spatial parameter $\rho$ measures the strength of the spatial dependence of neighboring businesses ranging between 0 and 1. A $\rho$-value of 0 ($\rho = 0$) indicates no spatial correlation; the elimination of the spatial lag would result in a non-spatial probit model. The $n \times k$ matrix $X$ contains all business-specific explanatory variables as defined above measuring the centrality, connectivity, and agglomeration effects. In addition, we use categorical variables (dummies) to control for different types of business for Detroit and The Hague. In these two cities, our data allows us to differentiate between four retail types of businesses, including run stores (e.g., grocery stores and drugstores), fun stores (e.g., department stores, fashion, leisure goods), destination stores (e.g., home goods, hardware, electronics), and bar/restaurants. The disturbance terms have the desired properties $\sim \mathcal{N}(0, I_n)$. We follow closely the Bayesian estimation process with a Markov chain Monte Carlo (MCMC) algorithm as described in greater detail by LeSage and Pace (2010). The results from these individual twelve SAR probit regressions are summarized in Table 5. Specifically, the coefficients in Table 5 refer to posterior means of the total effects. Though the individual models do contain intercepts, direct, indirect, and total effects are only calculated for the explanatory variables. As such, no results for the intercepts are reported in Table 5. To keep the amount of results reported in Table 5 manageable, it does not report the direct and indirect effects as well as the lower 0.05 and the upper 0.95 boundaries for the marginal estimated effects.

All spatial parameters $\hat{\rho}$ are statistically significant, using a spatial weight matrix of the four nearest neighbors, confirming prior expectations of spatial dependence among businesses. A business’s decision to stay open or to close up shop is influenced by its nearest four businesses and their decisions to stay open or not. As mentioned in the data collection section, changes in business ownership or type are not able to be measured. The number of nearest neighbors was selected based on comparison of log-likelihood values for models with different numbers of nearest neighbors following LeSage et al. (2011). All significant parameters have the correct signs, except two parameters that exhibit a change in sign between time periods. While a higher metric distance (CENT) from a retail center of gravity is expected to positively signal an increasing chance of business closure, in the 1988–2017 period, the opposite effect is present in Detroit and Birmingham. This may indicate a cluster of business closures in the heart of their urban cores, while closures in the periphery have already stabilized in earlier years (Table 5).

The Hague exhibits the most consistent results across the four time periods. Connectivity and agglomeration matter, no matter the time period. The negative parameters indicate that with increases in the value of the CONN variable and the AGGL variable, the chance of a business to close decreases. For example in the 1988–2017 period, CONN exerts a negative total effect on the probability that a store will close. As the Choice variable CONN was scaled by a factor of 100 for better model performance, the probability that a store will close is 41.0% for a change of 1.0 in the CONN variable, or of approximately 4.1% for a change of 0.1 in the CONN variable. For each additional nearby business, the probability that a store will close decreases by 0.71%. Interestingly, connectivity and agglomeration effects have remained an important force for business viability over the 100 year period from 1911 to 2017, though the effects decline slightly over time as indicated by comparing the estimated parameters. Centrality, surprisingly, was important for business in the 1911–1936 period and only of marginal importance in the 1988–2017 period. For the 1988–2017 period, for every 100-meter distance further away from the retail center of gravity, the probability of closure increases by 0.02%.

For Detroit, the street connectivity lost its importance for businesses after the initial 1911–1936 period as, beginning with the 1937–1960
period, all estimated CONN parameters are insignificant at the 5% level. An increase in CONN of 0.1 during the 1911–1936 period reduces business probability to close by approximately 7.9%. The agglomeration effect is present over time, apart from the 1937–1960 period, though it has decreased in magnitude. While an additional nearby business in the 1911–1936 period reduced the probability for a business to close by as much as 2.12%, for the 1988–2017 period the probability to close was significantly less with 0.85%. As previously mentioned, the influence of centrality has changed sign over time. For the 1911–1936 period, the probability of closure increases by 1.48% for every 100 m in addition of Birmingham, England and the changed method to control agglomeration, as the number of nearby businesses significantly and positively impacts store viability in all three cities across almost all periods in time, as found through all three statistical methods. This corroborates the findings of Kickert & vom Hofe in 2018, even with the addition of Birmingham, England and the changed method to control the mortality rate. The consistent effects of agglomeration on retail viability demonstrate generalizability in three very different cultural and socio-economic contexts, confirming Yin’s theoretical replicability (1994).

Centrality (hypothesis 1) seems to be the second best spatial indicator for business viability, holding true in the independent (average) and panel regression models for all cities over the span of a century. The measure only falls short upon closer examination through the independent regression in the most recent era in Detroit and Birmingham, and the Spatial Autoregressive Probit model for three eras in The Hague and two eras in Birmingham. The Probit model inclusion of stores beyond the 1100 meter cutoff for the regressions may partially explain the anomaly for The Hague, as stores are influenced by a nearby retail agglomeration. Birmingham’s non-significant Probit results for 1937–1988 for centrality occurred during a time of significant urban renewal in the urban core, which may skew store closures. In both Detroit and Birmingham, the change in sign over recent decades may reflect either low numbers of remaining retailers (Detroit), or the resurgence of retailers in blossoming downtown-adjacent neighborhoods (Birmingham). Overall, metric distance from the retail center of gravity is a reliable indicator for continued retail viability in areas without external influence from other clusters or urban renewal efforts. This can be explained from the perspective of upward mobility in shifting markets. Central, high-rent retail vacancies prompt property owners to quickly seek a replacement, even with a lower-rent tenant if necessary.

5. Conclusion

As retail shrinks on both sides of the Atlantic, closures relate to the classical models of retail distribution – at least to a certain extent. As stores close, they generally do so in less central, less well-connected and more isolated locations. Hence, this paper’s three hypotheses of centrality, connectivity and agglomerations hold true, but often only for some cities, or for some time periods. The most reliable spatial indicator of long-term business viability remains the third hypothesis of agglomeration, as the number of nearby businesses significantly and positively impacts store viability in all three cities across almost all periods in time, as found through all three statistical methods. This corroborates the findings of Kickert & vom Hofe in 2018, even with the addition of Birmingham, England and the changed method to control the mortality rate. The consistent effects of agglomeration on retail viability demonstrate generalizability in three very different cultural and socio-economic contexts, confirming Yin’s theoretical replicability (1994).
They may in turn move from peripheral locations, where a replacement is more difficult to find in a generally declining market. When rents fall below a certain threshold, peripheral storefront property owners may also gain interest in non-retail replacements such as offices, health services or homes.

Street connectivity (hypothesis 2) only significantly influences retail viability in The Hague, and to a lesser extent, Detroit, holding in all three statistical methods for The Hague, and in Detroit only in the independent regression model. In Birmingham, connectivity only shows significance in the two most recent eras in the spatial probit model. This may reflect the drastic changes in the street network, and hence the connectivity of street segments, for Detroit and Birmingham. While The Hague’s core street network has remained fairly stable, Detroit and Birmingham have undergone large scale urban renewal projects that cut off streets from their surroundings (Flatman, 2008), which may have affected retail closures with a time delay. For example, while the inner ring road construction in Birmingham cut off many smaller streets from the wider urban network, existing retail clusters fought to remain viable for decades after. Finally, street connectivity can change at the stroke of a planner’s pen within a 25-year measuring interval, potentially clouding the findings.

The stronger effect of agglomeration on retail closure over the other two spatial characteristics shows the importance of planning and investing in clusters, even beyond their urban centrality and connectivity; a lesson that shopping malls have taken to heart, often at the expense of their urban context. As this paper demonstrates three spatial influences on retail viability over several retail revolutions in the past century, future work may delve deeper into the most recent revolution using higher-fidelity data. Larger digital retail datasets like the National Establishment Time Series (NETS) in the United States and Locatus in The Netherlands contain more establishments, and within yearly time spans. This can alleviate this study’s relatively small sample sizes and the lack of ability to take drastic spatial change into account. These datasets also provide more detailed information on establishment ownership, allowing for the connection of spatial characteristics to the rate of ownership change, as high churn rates can signal retail failure. The data may also study the spatial effects on retail viability for different types of retailers, for example measuring whether comparison goods stores benefit more from agglomeration than daily goods stores, and the compatibility of store types within an agglomeration (Sevtsuk, 2020). Furthermore, data that includes the size of establishments can establish the role of anchor stores in agglomeration effects – a known factor in retail success. More external variables such as intra-downtown income density changes, land ownership and investment consolidation, transit connectivity, street design, and the role of e-commerce on specific store types can add depth to future research as well. We look forward to future research on the spatial dynamics of urban retail, providing planners, investors and retailers with crucial insights to maintain a key element in the vitality of walkable cities.

CRediT authorship contribution statement

Conrad Kickert: Conceptualization, Methodology, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition
Rainer vom Hofe: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Supervision
Tigran Haas: Conceptualization, Funding acquisition
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Declaration of competing interest

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

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