Neighbourhood attractiveness and residential property prices; the impact of restaurants as local consumer amenities that foster encounters

Empirical evidence from Amsterdam

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Abstract: This paper concerns an empirical exploration of the effect of local restaurants on neighbourhood attractiveness as reflected by residential property prices. Rich restaurant amenity data is created on the basis of consumer generated content on iens.nl (a Dutch restaurant review website) and by using geographical information system techniques. Two methods of spatial data aggregation are considered. A multilevel hedonic pricing methodology is used in combination with a three-staged estimation strategy. The results indicate the presence of substantial neighbourhood price premiums and the importance of the quantitative, qualitative and cuisine diversity aspects of restaurants for local housing prices. Specifically, it is found that only restaurants of the medium to upper segment of the quality spectrum are positively related to residential property prices, although the causality can not be proven on the basis of the cross-sectional dataset. The sensitivity analysis further suggests marginal diminishing returns for the price effect of restaurants and the subordinate importance of cuisine diversity to restaurant presence. Lastly, the partly inconsistent results on the basis of the neighbourhood aggregation and continuous space buffer aggregated restaurant measures indicate the presence of the modifiable areal unit problem.

Key words: Urban economics, intraurban, neighbourhood attractiveness, residential property prices, local consumer amenities, restaurants, iens.nl (TripAdvisor), GIS, spatial econometrics, multilevel analysis, hierarchical hedonic modelling, MAUP.

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1. Introduction

The often cited realtors' phrase "location, location, location" indicates the generally accepted importance of the location of real estate for its success. Within the residential property market, location refers to neighbourhood attractiveness and accessibility, and property success is expressed by its sales price (Dubin, 1991; Visser & van Dam, 2006). Much research is devoted to the question which factors make up an attractive neighbourhood. However, little attention is given to the presence of a rich variety of services and consumer goods, one of the four critical urban amenities identified by Glaeaser, Kolko and Saiz (2001) in the 'producer city' 'consumer city' debate. Therefore, it is interesting to consider this class of urban amenities at the lower, local level of analysis. Aditionally, in the light of today's advanced information and communication technology dominated society, a paradox can be observed where face to face contact and encounter are becoming increasingly important (Storper & Venables, 2004; Vermeulen et al., 2011). A modern interpretation of the well-known realtors' phrase could therefore be "location, place, encounter" (Stroink, 2013). This research is concerned with local consumer amenities that foster encounters and residential property prices at the neighbourhood level.

The characteristic of modern society mentioned above also provides new opportunities for empirical research within the amenities literature. That is, the presence of well-developed GIS (Geographical Information System) packages and publicly available consumer generated content on review websites enable the creation of rich amenity data. A specific consumer amenity that fosters encounters and of which review websites are well-embedded in its industry are restaurants. Therefore, this paper will empirically assess the following central research question: what is the effect of restaurants, as local consumer amenities that foster encounters, on neighbourhood attractiveness as reflected by its residential property prices? Aside from the quantitative aspect of restaurants – i.e. their presence – other aspects are also considered, including their quality and diversity of cuisines. To do so, rich restaurant measures are created on the basis of iens.nl, a Dutch restaurant review website.

For this intraurban analysis, Amsterdam is taken as case study. The capital of the Netherlands is known for having the highest residential property prices of the Netherlands, and is also the most restaurant dense city of the country (OIS, 2008). Together with its metropolitan attractiveness and its 'consumer city' nature, Amsterdam constitutes an interesting case study for this research. A multilevel hedonic pricing methodology is employed that explains residential property prices on the basis of property specific housing attributes (level 1) and neighbourhood specific location attributes (level 2). This technique provides a statistically correct treatment of spatially clustered data, such that the results can be correctly interpreted (Orford, 2000). Furthermore, a specific three-staged estimation strategy is developed that includes an exploratory evaluation of neighbourhood attractiveness, an in-depth analysis on the basis of the self-created restaurant measures, and a sensitivity analysis to assess the robustness of the obtained results. The results reveal the indisputable importance of restaurant presence and quality for residential property prices, in a way that only restaurants of the medium to upper segment of the quality spectrum are positively related to residential property prices. The results for the diversity of cuisines aspect of local restaurants are less unanimous.

The rest of the paper proceeds as follows. The next section reviews relevant literature on intraurban house price differentials and the specific role restaurants could play herein. Section 3 describes the data and created restaurant measures. The methodology and estimation strategy are detailed in section 4 and the results are presented in section 5. Section 6 discusses the finding and section 7 concludes the paper.

2. Neighbourhood attractiveness and house prices

2.1 How the neighbourhood affects house prices

The value of real estate is influenced by macro, meso and micro factors. Within this distinction macro factors refer to social-demographic, economic and monetary market developments; meso factors refer to neighbourhood and location attributes; and micro factors refer to individual structural attributes of the property (van Gool et al., 2013). Moreover, housing can be perceived as a bundled product that is comprised of a reproducible tangible structure and a non-reproducible plot of land, represented by dwelling-specific and location-specific factors respectively (Wilkinson, 1973). Here, the implicit land value capitalizes the market value of all amenities associated with the home's location (Davis & Heathcote, 2007). Among these amenities are neighbourhood characteristics and the classic element of urban economic models; accessibility (Dubin, 1992; Cheshire & Sheppard, 1995). Neighbourhood attractiveness thus concerns the meso layer of residential property valuation and is capitalized in the land component of house prices. Within this research the focus will be on the potential house price driving effect of local amenities that reflect neighbourhood attractiveness.

2.2 The role of amenities

Many empirical studies have aimed to explain intraurban house price differentials caused by variations in amenities (Haurin & Brasington, 1996). Such studies try to identify location-specific factors that influence the attractiveness of an area and thereby the prices of corresponding houses. These amenities can be roughly classified into the four urban critical amenities identified by Glaeser et al. (2001), namely speed or accessibility, good public services, aesthetics and physical setting, and a rich variety of services and consumer goods. Although these have been developed from the urban economics perspective, and are thus identified as factors that cause urban success in terms of population and aggregated housing price growth (Glaeser & Gottlieb, 2006), they also constitute a useful framework for the lower, local level of analysis. Out of the four amenity classes the first three have been extensively considered at the neighbourhood level of analysis, of which the literature is now shortly assessed in chronological order.

Already in the mid-nineteenth century Von Thünen (1842) highlighted the importance of accessibility to the market place in explaining variations in farmland values with similar fertility. In the urban context, the classical urban rent theory as developed by Alonso (1964) and Muth (1969) indicates a negative rent gradient for land values as a function of the distance to the Central Business District (CBD). Accordingly, house prices in centrally located neighbourhoods are predicted to be higher than those in more distant neighbourhoods. This result is derived on the basis of the monocentric city model and is caused by the trade-off between accessibility and transportation costs. Even though the applicability of monocentric models to modern cities has been questioned (e.g. Dubin, 1992), Cheshire and Sheppard (1995, p. 248) show that, if location-specific characteristics of housing are appropriately accounted for, "monocentric models *can* perform well". Furthermore, investments in transport infrastructure can reduce demand frictions around the CBD since fast transport serves as substitute for distance to the CBD (Fejarang, 1994; Debrezion, Pels & Rietveld, 2007). The resulting positive impact of transportation hubs on housing prices is not limited to existing stations but also present for anticipated railway stations, proportional to the expected risk and uncertainties concerning the project's execution (McMillan & McDonald, 2004; Yiu & Wong, 2005; Agostini & Palmucci, 2008).

Considering public services, it has been long recognized that good schools and less crime increase the neighbourhood's attractiveness. Tiebout (1956) identified schools as an important factor for residential location decisions and demand for neighbourhood housing. Subsequent empirical studies of housing values report a positive impact of the quality of local public schools – as measured by expenditures per pupil or student achievement levels – on house prices (Oates, 1969; Kain & Quigley, 1970; Jud & Watts, 1981). Around the same time, Thaler (1978), and Hellman and Naroff (1979) provided early evidence for the negative effect of crime on residential property values. Haurin and Brasington's (1996) constant quality housing price study identifies school quality as the most important cause of residential property value variations, followed by a moderate importance of crime. More recently, distinctions are made between types of schooling and crime (Gibbons & Machin, 2008). It is argued and empirically confirmed that at the neighbourhood level school quality of primary schools is particularly important since they have smaller catchment areas than secondary schools (Gibbons & Machin, 2003; Cheshire & Sheppard, 2004). In addition, violent crime reduces house prices more than property crime since the first is more linked to the perception of safety and harder to prevent by precautions (Lynch & Rasmussen, 2001). Also, highly visible but ostensibly more trivial offences such as criminal damage may be interpreted as signals of community instability and neighbourhood deterioration in general (Gibbons, 2004).

With respect to the physical setting, it is more recently established that the neighbourhood presence of green space and waterfronts influences residential property values (Luttik, 2000; Geoghegan, 2002; Morancho, 2003). These open spaces are often valued for their view or recreational opportunity, however also potential negative externalities – such as nuisance or a sense of insecurity – exist (Bolitzer & Netusil, 2000; Lutzenhiser & Netusil, 2001). Open spaces are particularly valued in urban densely populated areas where open space is more scarce (Anderson & West, 2006). In addition, population density by itself also constitutes a potential physical factor of importance (Visser & van Dam, 2006; Anderson & West, 2006; Koster & Rouwendal, 2012). Another physical location-specific characteristic concerns the aesthetics or visual quality of the neighbourhood and its build environment (Li & Brown, 1980; Baranzini & Schaerer, 2011). This does not only relate to the presence of green and blue, but also to architectural styles and street patterns. In this vein, old city centres are often perceived as being beautiful (Storper & Manville, 2006). Moreover, the presence of listed heritage – urban monuments and historic-cultural sites – are positively related to the value of residential real estate (Lazrak et al., 2011).

From this chronological overview of intraurban housing price studies it becomes clear that for the local amenities considered relevant for neighbourhood attractiveness there is a trend observable similar to that of the shift from 'producer city' to 'consumer city' at the interurban level of analysis (Glaeser et al., 2001; Glaeser & Gottlieb, 2006). In the beginning, it was believed that distance to the CBD and good schools best proxied neighbourhood attractiveness, which both can be perceived as production input variables (Card & Krueger, 1992; van Ham, 2001).[1] Thereafter, crime – that made it difficult for urban residents to enjoy social interactions (Glaeser & Gottlieb, 2006) – received more attention. And more recently, the physical setting that determines the visual quality and recreational opportunities of the surroundings has been extensively analysed. The shift should be understood in the light of the continuously increase in overall education and income levels that raises resident's demand for 'higher needs' and quality of life (Glaeser & Gottlieb, 2006; Clark et al., 2002). "After all, choosing a pleasant place to live is among the most natural ways to spend one's money (Glaeser et al., 2001, p. 28)". However, to date the fourth critical urban amenity class identified by Glaeser et al. (2001) and most obvious consumer amenities, the presence of a rich variety of services and consumer goods, has received considerable less attention at the local level of analysis. Some exceptions are the works of Pope and Pope (2015) and Kuang (2015), who analyse the local house price effects of Walmart stores and restaurants, respectively. Therefore, this study will contribute to the still scarce body of literature around the capitalization of local services and consumer goods in residential property prices from the intraurban perspective.

2.3 Restaurants as local amenities

Glaeser et al. (2001) state that within the services and consumer goods amenity class, "restaurants, theaters and an attractive mix of social partners are hard to transport and are therefore local goods (p. 28)". Also, these are local amenities that stimulate local 'buzz' and an active street life. In the current society dominated by advanced information and communication technologies, a paradox is observed in which such face to face contact and encounter are particularly valuable (Storper & Venables, 2004; Vermeulen et al., 2011). In addition, the advanced information technologies include the presence of well-developed GIS software, and the dominant communication technologies also regard review websites used by consumers to share their experiences. Together, these developments provide new research opportunities within the amenities capitalization literature. Restaurants are eminently such consumer amenities that foster encounters and for which reviews are widely used by potential customers, therefore they constitute the main focus of this research.

[1] Specifically, van Ham (2003) indicates that locations with good job access or faster means of transport increases one's job search area and thereby improves potential career advancement. Card and Krueger (1992) find that school quality is beneficial for returns to schooling in terms of income.

Restaurants are more than pure private goods for those that have dinner there. Their presence redefines the local context and adds liveliness to the urban fabric which is experienced by residents, visitors and passersby (Clark, 2003). Moreover, restaurants can be perceived as proxy for other similar establishments, such as lunch rooms, coffee corners, juice bars and cafés. Arguments in favour of this statement are the complementary nature of restaurants with respect to other amenities (e.g. often a visit to the theatre is combined with a dinner beforehand), and the high correlation between amenity categories. That is, the viability for one amenity often also implies the viability for others (i.e. agglomeration economies), resulting in clusters of amenities (Vermeulen et al., 2011). The 'gestalt-like' reasoning of Clark (2003) communicates a similar argument where amenity indicators signal the overall imagery of urban cultural and social landscapes. Also, restaurants are more suitable than for example theaters to serve as amenity indicator for neighbourhood attractiveness because the willingness to travel for restaurants is relatively low (Clark, 2003; Iacono, Krizek & El-Geneidy, 2008), and because they are more numerous such that a greater variance is expected.

Previous research into the relationship between restaurants and housing prices mainly focussed on the urban level of analysis, where it is found that cities with more and good restaurants, among others, grow faster and experience higher housing prices on the aggregated level (Glaeser et al., 2001; De Groot et al., 2010; Garretsen & Marlet, 2011). Garretsen & Marlet's (2011) study offers preliminary evidence for the relevance of restaurant related amenities at the neighbourhood level as they found a positive effect of the number of cafés within the neighbourhood on housing prices. Also, Vermeulen et al. (2011) examined the effect of the proximity of qualitative culinary offerings on land values and found a positive impact. However, within these studies the restaurant related factors have not been extensively considered as the central theme. One exception is the forthcoming paper by Kuang (2015), who analysed the price effect of restaurants on the basis of Yelp information. She found a positive effect for both low and high quality restaurants on property prices. In addition, she showed that the provision of information on restaurants by Yelp matters, since for the period that Yelp became widely used by the public the positive effect only remained for high quality restaurants.

2.4 Hypotheses

In the previous paragraphs it has been established that the neighbourhood's attractiveness is comprised of a wide variety of location-specific factors that are capitalized in the land value component of residential property prices. In addition, a trend has been observed within the intraurban literature of house price differentials caused by variations in amenities that evolves from production input related amenities towards the more consumer related amenities. This paper aims to extend this trend by covering the next amenity class in line, namely a rich variety of services and consumer goods. More particularly, the paper will focus on local consumer amenities that stimulate face to face contact and encounter, which are increasingly important in the society of today that is dominated by information and communication technologies. To do so, restaurants will be considered as proxy for these specific local amenities.

To analyse whether restaurants, as local consumer amenities that foster encounters, contribute to neighbourhood attractiveness and thereby residential property prices within the neighbourhood, multiple hypotheses will be tested. In principal, all restaurants add to street liveliness and offer the opportunity to consume and socialize. Therefore, the first hypothesis does not distinguish between restaurants and simply regards their presence.

> *Hypothesis 1:* Neighbourhood attractiveness, as reflected by residential property prices, is positively affected by the presence of local restaurants.

From the amenities literature it becomes clear that often it is not just the quantity that matters but also the quality (e.g. school quality). Reflected on restaurants this implies that the benefits of a fast food restaurant are not of equal magnitude as that of a Michelin star restaurant (De Groot et al., 2010). In addition, also the variety of restaurants could potentially be important, as is suggested by the critical urban amenity of Glaeser et al. (2001) considered in this study. For restaurants one can imagine that this mainly refers to a wide diversity of cuisines.[2] This results in two additional hypotheses.

> *Hypothesis 2:* Neighbourhood attractiveness, as reflected by residential property prices, is positively affected by the quality level of local restaurants.

> *Hypothesis 3:* Neighbourhood attractiveness, as reflected by residential property prices, is positively affected by the diversity of cuisines of local restaurants.

[2] Although other diversities, such as diversity in size and price, are also conceivable, these are considered less important and are therefore not studied in this research.

3. Data and measures

3.1 Dataset

The cross sectional dataset underlying the analysis is comprised of three separate datasets that concern restaurants, residential property transactions and neighbourhoods.

In order to utilize the research opportunities provided by advanced GIS software and rich consumer generated content on review websites, the restaurant data is collected from iens.nl and processed into useful restaurant measures with the free software package QGIS. iens.nl, a Dutch equivalent of restaurant review websites like Yelp and TripAdvisor, lets users write a review and grade the overall experience of their restaurant visit. Although restaurants are not obligated to register on iens.nl, it is common practise to do so. Therefore, it is expected that the iens.nl database practically captures the entire restaurant population of Amsterdam.[3] Together with the restaurant name, coordinates and cuisine, the number of reviews and awarded grade are collected for all restaurants in Amsterdam. The data is collected in July 2016 and represents the current restaurant offer. As no information regarding the year of establishment is present, the simplifying assumption must be made that the overall restaurant offer was approximately stable over the period of analysis. The full sample includes 2725 restaurants, whereof subsamples have been created to distinguish between different quality (grade) and credibility (number of reviews) classes of restaurants (see table 1). GIS techniques are used to locate the restaurants (see figure 1), assign them their corresponding neighbourhood and match them to individual residential property transactions. As such, the restaurant dataset is transformed into neighbourhood characteristics as well as property specific locational characteristics. The next paragraph describes the creation of the restaurant measures.

Table 1. Restaurant (sub)samples (Sl)

Restaurant subsample	Name	Grade criteria	Review criteria	Number of restaurants (K)
S1	Full sample	-	-	2725
S2	Graded sample	≠ ?	≥ 2	1925
S3	"Best 1500" sample	≥ 5.5	≥ 5	1463
S4	"Best 1000" sample	≥ 6.5	≥ 10	1061
S5	"Best 500" sample	≥ 7.5	≥ 25	521
S6	"Best 100" sample	≥ 8.5	≥ 50	89

Notes: The review criterion of the graded sample is set by iens.nl itself; restaurants only receive a grade on the website after at least 2 reviews. The criteria for the "best X" sample are set at round numbers such that the number of restaurants (K) approximate the X.

[3] The validity of the iens.nl restaurant sample is assessed in the empirical analysis.

Figure 1. Geographic overview of all restaurants of Amsterdam registered on iens.nl, by quality class

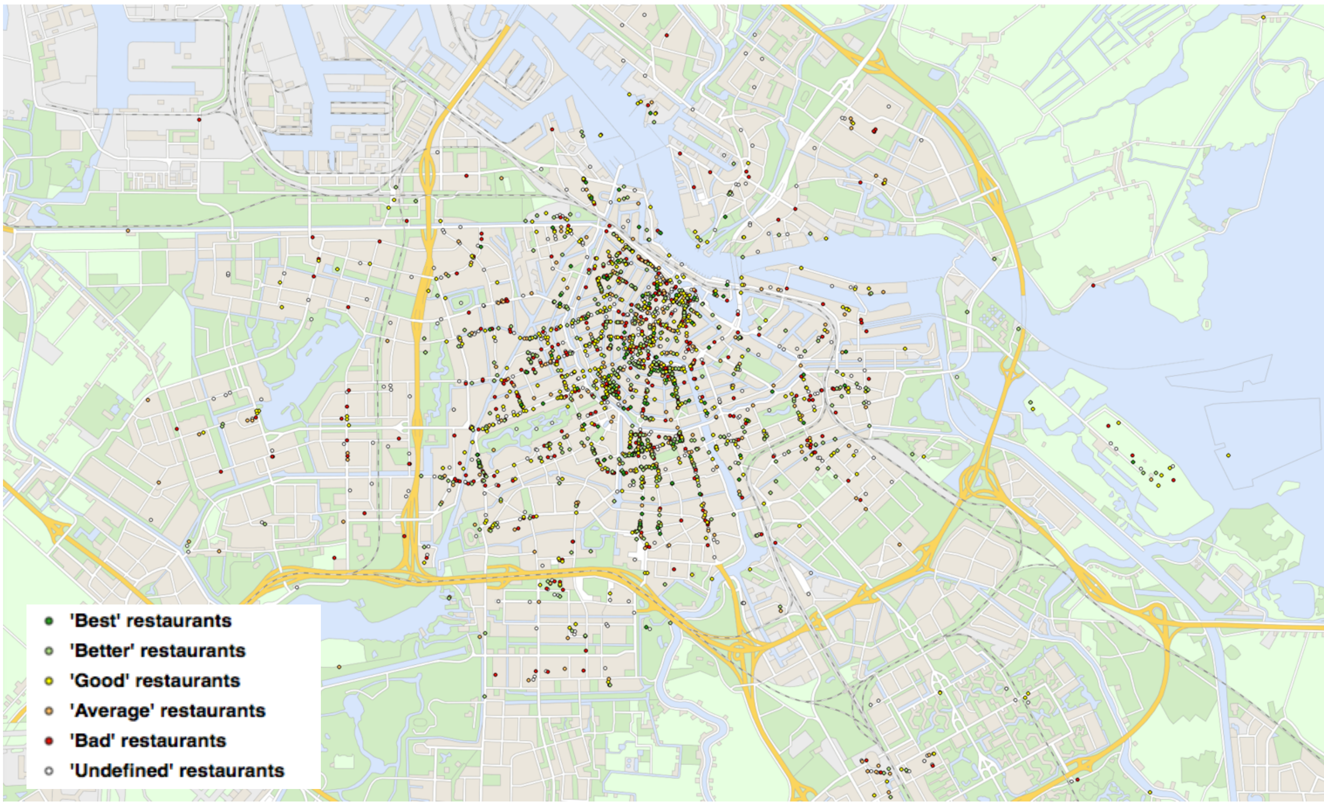
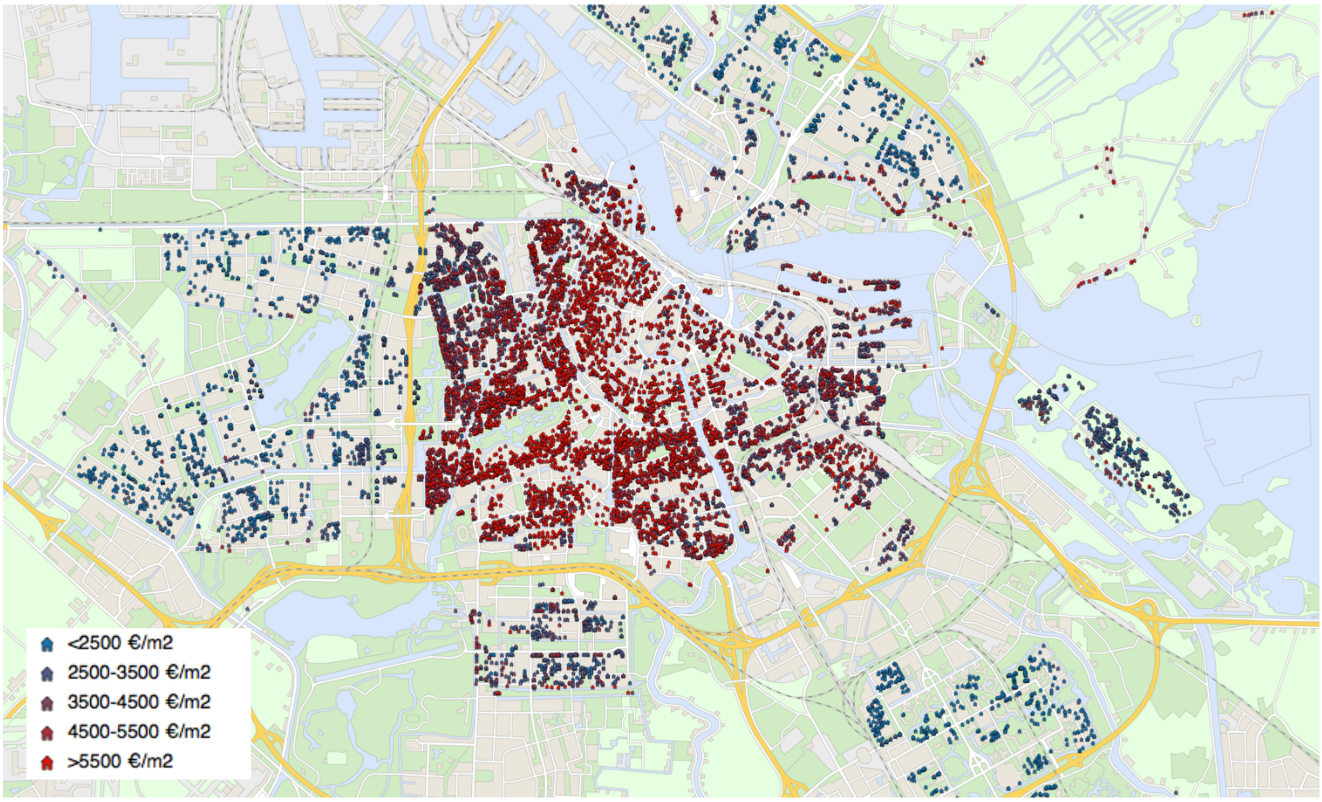


Figure 2. Geographic overview of the residential property price transactions in Amsterdam, by price



The transaction data of residential property contains information on house sales registered by the Netherlands' Cadastre, Land Registry and Mapping Agency (Kadaster) that are sold in Amsterdam between January 2013 and June 2016 (19.061 observations, mapped in figure 2). Apart from the sales price, date and duration, the dataset contains structural attributes collected by both the Kadaster and Funda, the largest housing advertisement website of the Netherlands. This includes property type, size and volume, year of construction, number of rooms, type of heating, presence of a garage, storage or monument status, size of outdoor area. Many of the transaction and structural attributes are transformed for analytical purpose. The technical appendix (A1) describes the data processing and transformation procedures in detail, for all three data sources. In addition, three property specific locational attributes are generated via GIS techniques to reflect their individual accessibility. That is, the Euclidean distance to the city centre, nearest heavy railway station and nearest highway ramp. In order to account for outliers a 99% winsorization is applied to the dependent variable square meter price.[4] [5] Table 2 presents all property specific variables, ordered per attributes class.

Table 2. Property specific attributes

Attribute class	Variable	Description
Transactional	House price m2	Winsorized square meter sales price
	Time	Year and quarter of sale
	Sales duration	"Quick (sales within a month)" / "Normal (sales between a month and a year)" / "Slow (sales over a year)"
Structural	Property type	"Detached" / "Semi-detached" / "Terraced" / "Apartment"
	Cohort	Decade built (<1900, ≥ 1900 and <1910, … , ≥2010 and <2020)
	High ceiling	High ceiling property dummy (≥2.80 m)
	Rooms	Number of rooms
	Heating	Good heating dummy (at least central, under floor, block or district heating)
	Garage	Garage dummy
	Storage	Storage dummy
	Monument	Monumental status dummy
	Outside	"No outdoor space" / "Small outdoor space (≤6m2)" / "Large outdoor space (>6m2)"
Locational	Distance centre	Distance to the centre (Dam square) in meters
	Distance station	Distance to the nearest train station (NS) in meters
	Distance highway ramp	Distance to the nearest highway ramp (A10) in meters

[4] Winsorization is a statistical technique often employed in housing studies (e.g. Campbell, Giglio & Pathak, 2011) where extreme values are limited to the $(1\text{-}x)/2^{th}$ and the $x+(1\text{-}x)/2^{th}$ percentile. In this case all observations below the 0,5th percentile and above the 99,5th percentile are set to these percentile values. This winsorization exercise is done after 19 of typographical error suspected observations were deleted.

[5] A log transformation of the dependent variable has been considered but not found to be an improvement of the degree of normality of its distribution.

The properties six-digit postal codes are then used to match them with the neighbourhood characteristics data of the Department for Research, Information and Statistics of the municipality of Amsterdam (OIS).[6] The census tracts divide Amsterdam in 95 distinct residential neighbourhoods[7] (listed in appendix 3). For all four critical urban amenity classes identified in the literature section – that is; accessibility, public services, the physical setting and consumer amenities – representative neighbourhood characteristics are available. On the basis of the discussed intraurban house price differentials literature a selection of relevant neighbourhood characteristics is composed. These statistics, indices and report marks include information regarding densities, social and racial compositions, quality of public offerings, land uses, (subjective) externalities, and establishment counts among others. Together with an added socio-demographic category the urban amenity classes, neighbourhood characteristic variables and their originating source are presented in table 3.

Table 3. Neighbourhood characteristics

Urban amenity classes	Variable	Description	Source
Socio-demographic	Population density	Population density per km2	OIS
	Non-western population	Percentage non-western population	OIS
	Ownership distribution	Percentage of owner occupied housing stock	OIS
	Income	Average net household income	CBS
Accessibility	Public transport	Public transportation report mark	WiA
	Centre	Neighbourhood within city centre dummy	Self created
	Ring	Neighbourhood within ring road dummy	Self created
Public services	Violent crime	High personal impact crime index	OOV
	Unsafety	Unsafety feeling index	OOV
	Primary schools quality	Primary education quality report mark	WiA
Physical setting	Beautiful surrounding	Appearance surrounding report mark	WiA
	Beautiful properties	Appearance properties report mark	WiA
	Beautiful green space	Appearance green spaces report mark	WiA
	Water surface	Percentage water land use	DRO
	Green space surface	Percentage green space land use	DRO
	Daily density	Sojourners density index (inhabitants, workers, visitors, passerby)	OIS
	Hospitality nuisance	Nuisance of hotel, restaurant and cafe like establishments, report mark	WiA
Services and consumer goods	Daily goods	Number of daily goods stores per 1000 inhabitants	ARRA
	Non-daily goods	Number of non-daily goods stores per 1000 inhabitants	ARRA
	Health care	Number of health care establishments per 1000 inhabitants	ARRA
	Culture	Number of cultural facilities per 1000 inhabitants	ARRA
	Restaurants	Number of restaurants per 1000 inhabitants	ARRA
	Cafés	Number of cafés per 1000 inhabitants	ARRA

Notes: sources include OIS, Central Bureau of Statistics of the Netherlands (CBS), departments "Wonen in Amsterdam" (WiA), "Openbare Orde en Veiligheid" (OOV), "Dienst Ruimtelijke Ordening" (DRO), and the business registry of Amsterdam (ARRA). All are publicly provided by the OIS.

[6] This is done based on a postcode-neighbourhood configuration scheme. Additionally, the same operation was performed via QGIS (see appendix 2) to check the consistency of the configuration scheme and the shape file neighbourhood boarders. The consistency was 99,9%[6], where the exceptions were caused by boarder cases.
[7] And 4 non-residential neighbourhoods where no residential property transactions occurred (B10, F11, M50 and T92)

3.2 Restaurant measures

To analyse the effect of restaurants, as local consumer amenities that foster encounters, on residential housing prices the raw restaurant data is transformed into multiple restaurant measures regarding their quantity, their quality and their diversity of cuisines. Here, restaurants can be thought of as being part of the neighbourhood identity and the neighbourhood consumer amenities supply, in which case the suitable restaurant measures are aggregated per neighbourhood.[8] Alternatively, the restaurants can be evaluated from a continuous space perspective, where it is not the set neighbourhood boundaries that are important but rather the nearby area around the house that determines the truly local consumer amenities offer. In this latter case the corresponding restaurant measures are aggregated per buffer radius around each property transaction.[9] This results in neighbourhood specific restaurant characteristics and property specific restaurant characteristics, respectively. Both methods of aggregation are considered in this research in order to evaluate the level of correspondence of the outcomes and in such to address the modifiable areal unit problem (MAUP).

It should be acknowledged that there is a considerable – and unavoidable – degree of arbitrariness in setting the buffer radius. Therefore, multiple radii will be considered in this study that are set in accordance with the following transparent reasoning: firstly, the average neighbourhood size in Amsterdam is about 135 hectares[10] and this corresponds to a round buffer area with a radius of 655 meters.[11] Secondly, on average the human walking pace is 5km/hour (Knoblauch, Pietricha & Nitzenburg, 1996; Carey, 2005) and the majority of the people's willingness to walk for restaurant trips is around 10 minutes (Iacono, Krizek & El-Geneidy, 2008), which equals a walking distance of approximately 833 meters. Note that considering a city grid this would result in a lower radius caused by the non-continues street pattern. Arnott and Rowse (2009) suggest an approximation of travel distance of $\sqrt{2}$ times the radius (corresponding to a rectangular grid), which would imply a radius of 589 meters. Following this reasoning the radius used in the main analysis is set at 650 meters, whereas buffer radii of 500 and 800 meters (150-meter interval around the base radius) are employed

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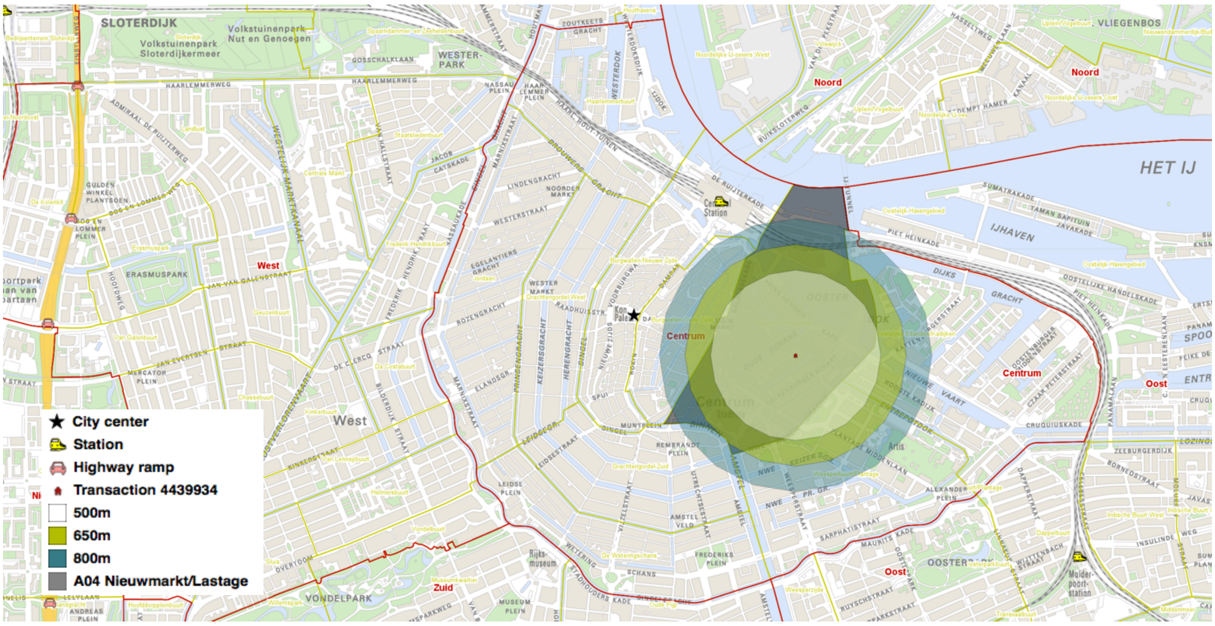
[8] Each restaurant is assigned their corresponding neighbourhood in QGIS. Since no postcodes are available for the restaurants it is not possible to assign them based on the postcode-neighbourhood configuration scheme that was used for the property transactions. However, we know from the property transactions case that the assignment via QGIS is 99,9% accurate.

[9] This is operationalized via a python script executed in QGIS. See appendix 2.

[10] The average is based on urban residential neighbourhoods, thereby excluding merely industrial, business and nature areas (B10, F11, M34, M50, N73 and T92).

[11] Buffer area equals pi times radius squared: $A = \pi \times r^2$.

Figure 3. Spatial data aggregation methods (neighbourhood and continuous space per buffer area)



for the sensitivity analysis. Figure 3 visualizes these buffer radii for an example property transaction.

Irrespective of the spatial data aggregation method m – with choice set {'nbhd', '650m', '500m', '800m'} – the same restaurant measures are determined based on the differing restaurant samples S_l displayed in table 1. First, this includes the restaurant quantity measure N_{mli}, which is a simple count variable of restaurant establishments. The quantity measure indicates the total number of restaurants of sample l that fall within the neighbourhood or buffer area boundaries m of property i.[12] A dummy $d_{m;k,i}$ indicates whether – for the given area boundaries m –restaurant k matches location with property i. Successful matches receive $d_{m;k,i} = 1$, while unsuccessful matches are recorded as zeros.

$$N_{mli} = \sum_{k=1}^{K} d_{m;k,i} \qquad (1)$$

Next, the restaurant quality measure is considered. A possible quality indicator is the average grade AG_{mli} of local restaurants. Similar to the quantity measure, all restaurants of sample l are evaluated on a locational match with property i's catchment area m. In addition, the dummy $d_{m;k,i}$ is multiplied by the grade g_k that restaurant k received on iens.nl. The resulting

[12] In case m = 'nbhd', the quantity measure needs adjustment for the neighbourhoods' size. It is therefore converted into a 'per 1000 inhabitants' statistic for comparison with the other consumer amenity count variables which have also been recorded in this format.

grade total GT_{mli} is thereafter averaged over the total number of contributing restaurants N_{mli}. Note that if there is no match – and thus $d_{m;k,i} = 0$ – the grade g_k does not add to the grade total GT_{mli}. For areas without any graded restaurants no average grade can be determined and a missing value is recorded.

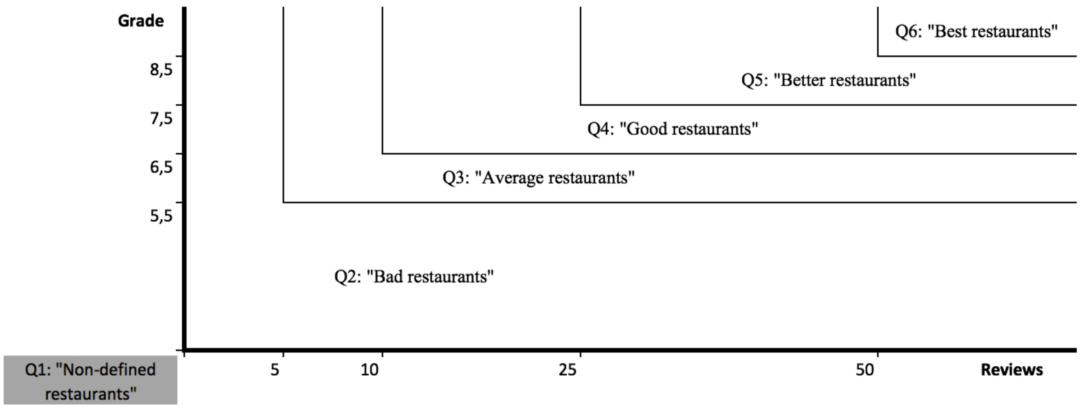
$$AG_{mli} = \frac{GT_{mli}}{N_{mli}} \tag{2}$$

$$\text{where,} \qquad GT_{mli} = \sum_{k=1}^{K} (d_{m;k,i} \times g_k) \tag{3}$$

Alternatively, the quality amenity measure can be presented by the distribution of restaurants over differing quality classes. Such quality classes are indirectly already existent within the restaurant subsamples created. However, where the restaurant subsamples only have lower limits, quality classes are two side bounded. That is, a particular restaurant k can be part of multiple subsample groups (as long as it received a grade) but is only part of one quality class. By adding the inclusive lower boundary of S_l as exclusive upper boundary to S_{l-1}, the six restaurant samples are transformed into six corresponding quality classes $Q_{l'}$. Figure 4 visualizes the quality classes in a graph.[13] The restaurant quality measure in this case counts the number of restaurant establishments per quality class and is termed $NQ_{ml'i}$ (4).

$$NQ_{ml'i} = \begin{cases} N_{mli} - N_{ml+1i} & \text{if } l = 1 \ {}^{t}/_{m} \ 5 \\ N_{mli}, & \text{if } l = 6 \end{cases} \tag{4}$$

Figure 4. Quality classes ($Q_{l'}$)



[13] As was stated in paragraph 3.1, a criterion is also applied to the number of reviews in order to account for their credibility. The higher the average grade is, the more reviews are deemed necessary for being credible.

The third and last restaurant amenity measure is that of the diversity of cuisines of local restaurants. This measure is operationalized by the use of a Herfindahl-Hirschman Index (HHI), a statistical measure of concentration that covers both the richness and evenness of a classification under consideration (Rhoades, 1993; Heip, Herman & Soetaert, 1998). For the construction of our HHI, the on iens.nl reported cuisines are generalized into a manageable number of cuisine categories ($NC^{old} = 79 \rightarrow NC^{new} = 15$, see appendix 1) of which their restaurant shares p_c serve as input for the HHI diversity measure (5). Before the cuisine category restaurant shares p_c can be calculated (6) the number of restaurants per cuisine category N_c needs to be determined (7) similarly to how it is done for the total restaurant counter (1), where c refers to the cuisine categories. Once normalized and inverted (8), the HHI^* ranges from 0 to 1, where 0 indicates a very homogenous restaurant offer and 1 reflects a very diverse restaurant offer in terms of cuisines. The $_{mli}$ subscripts are added to distinguish between the combination of aggregation- and buffer radii method m, restaurant subsample l and property i for which the $HHI^{(*)}$, p_c and N_c are calculated.

$$HHI_{mli} = \sum_{c=1}^{NC^{new}} {p_{cmli}}^2 \tag{5}$$

$$where, \quad p_{cmli} = \frac{N_{cmli}}{N_{mli}} \quad and, \quad N_{cmli} = \sum_{k=1}^{K} d_{cm;k,i} \qquad (6), (7)$$

$$HHI^*{}_{mli} = 1 - \frac{HHI_{mli} - \left(\frac{1}{NC^{new}}\right)}{1 - \left(\frac{1}{NC^{new}}\right)} \tag{8}$$

4. Methodology and empirical strategy

4.1 Housing price models

The majority of housing price studies originates from Rosen's (1974) theory of implicit markets and the resulting hedonic house price specification. His theoretical insight that houses are a differentiated product consisting of a bundle of attributes which are sold as a non-separable package, led to the conclusion that the prices of such attributes can be implicitly determined by analysing observed housing transactions. This translates into the hedonic house price function which estimates the implicit prices (marginal effects) of housing attributes (vector H) based on their package value, the house price (P). Together with a random error term (ε), the following vector notation applies:

$$P(H) = f(H) + \varepsilon \tag{9}$$

Traditionally, a functional distinction is made between structural and locational housing attributes. Structural attributes concern physical characteristics of the residential property and the corresponding land parcel, whereas locational attributes include characteristics associated with the geographic location of the property. This latter attribute class is of particular importance to the current study and can be further divided into absolute and relative locational attributes (Follain & Jimenez, 1985; Can, 1992; Orford, 2002). Absolute locational attributes are unique to each property and are related to the concepts of accessibility, adjacency and proximity. Therefore, such externalities are not restricted to neighbourhood boundaries. Relative locational attributes on the other hand, exactly refer to those externalities that are shared by all properties within the neighbourhood boundaries and include neighbourhood characteristics. The corresponding *traditional hedonic specification* (Can, 1992) can be defined as follow:

$$P_i = \alpha + \sum \beta_q STR_{qi} + \sum \gamma_r ALOC_{ri} + \sum \delta_s RLOC_{si} + \varepsilon_i \tag{10}$$

where subscripts *i, q, r and s* respectively refer to each property, and the multiple structural (STR), absolute locational ($ALOC$) and relative locational attributes ($RLOC$) included in the regression. The Greek symbols are the parameters to be estimated, of which α is the intercept, β_q, γ_r, and δ_s indicate the implicit prices of the housing attributes, and ε is the random error term.

The traditional hedonic model is estimated using Ordinary Least Squares (OLS) regression, which under specific multiple linear regression (MLR) assumptions produces unbiased estimates, and – under the Gauss-Markov assumptions – equals the Best (most efficient) Linear Unbiased Estimator (BLUE) (Woolridge, 2013). However, this methodology disregards the spatial perspective of residential property markets. Two effects that are specifically associated with modelling spatial data and that require a methodological evaluation are spatial heterogeneity and spatial dependence (Can, 1992; Orford, 2000).

The first spatial effect of heterogeneity is related to theoretical misspecification and can be caused by several factors, such as omitted (interaction) effects, an incorrect functional form or measurement errors. It implies that implicit prices of attributes may vary by sub-markets as defined by areal units such as census geographies (Orford, 2000). Treated as nuisance, this spatial heterogeneity violates the homoscedasticity assumption underlying the Gauss-Markov theorem. Hence, the OLS estimator will still be unbiased, but with invalid produced standard errors and thereby unreliable significance tests. This spatial effect at least requires a heteroscedasticity-robust fix or preferably the explicit modelling of the spatial heterogeneity in order to obtain reliable and more efficient estimated standard errors (Anselin, 1990; Can, 1992).

The second spatial effect of dependence is related to the underlying process-related dynamics, which in this research context refer to the dynamics of the housing price determination process. It reflects situations where values observed in one areal unit depend on the values of neighbouring observations in near-by areas. Spatial dependence can both be present in the error term and in the (in)dependent variables, which are termed spatial error dependence and spatial lag dependence respectively (Fischer & Wang, 2011). In terms of the house price determination process, one such dynamic that causes spatial error dependence are relative locational attributes which are shared by multiple properties and thereby invariant within spatial groupings. This common exposure gives rise to correlated or non-independent errors. If neglected, spatial error dependence – just as spatial heterogeneity – will result in incorrect estimated standard errors and thus incorrect statistical interference. To account for the underlying correlation structure between the error terms, observations need to be clustered in their spatial groupings or a methodology should be employed that explicitly models the grouping structure (Orford, 2000; Steele, 2008).

The statistical difficulties arising from spatial heterogeneity and spatial error dependence can most easily be overcome by adding both the robust and cluster option to the traditional hedonic OLS regression. However, in the current research context, with specific interest in neighbourhood effects, a simple robust and cluster proof OLS function will not be sufficient as it excludes the possibility to analyse such spatial grouping effects of neighbourhoods. A methodology that is capable of handling spatial grouping effects – and if desired also other spatial effects[14] – is multilevel analysis (Orford, 2000). Applied to housing price research this methodology is also termed *hierarchic hedonic modelling*. Multilevel

[14] That is, spatial heterogeneity can be explicitly modelled via the inclusion of random slope parameters that create parameter drift. And spatial lag dependence can also be explicitly modelled by including many higher levels up until the street or even the housing block (Orford, 2000). This is further discussed in section 6.

analysis is a form of regression analysis that explicitly models the nested hierarchical structure of (spatial) grouped data and efficiently combines the within and between variance dimensions. In that sense, multilevel analysis is a random effects model which however employs a different estimation technique, namely that of an iterative process by maximum likelihood[15].[16]

This study employs a two-level hierarchical random intercept model that analyses houses within neighbourhoods. Conceptually, the houses are considered the first level of analysis whereas the neighbourhoods in which they perfectly nest are regarded as the higher, second level. These two levels of analysis correspond to the compositional effect of the housing stock and contextual effects of place, respectively (Orford, 2002). A random intercept is obtained for every neighbourhood that reflects its attractiveness in terms of the grand mean property price plus a price premium that the market is willing to pay to reside in that particular neighbourhood as compared to a city-wide average location, ceteris paribus. This premium can be decomposed in and assigned to specific compositional or contextual effects by adding the relevant explanatory variables. From a technical perspective, the error term is split into two components corresponding to the two levels of analysis, namely an random neighbourhood effect μ_j – that together with the base intercept constitute the random intercept α_j (12) – and an individual random error term ε_{ij}.

Working along the lines of the traditional hedonic specification, the multilevel expansion requires the assignment of every term to be either property- or neighbourhood specific, implying a *ij* ('each property in its neighbourhood *j*') or *j* ('each neighbourhood') subscript, respectively. This is operationalized in the equation below.

$$P_{ij} = \alpha_j + \sum \beta_q STR_{qij} + \sum \gamma_r ALOC_{rij} + \sum \delta_s RLOC_{sj} + \varepsilon_{ij} \qquad (11)$$

$$where, \qquad \alpha_j = \alpha + \mu_j \qquad (12)$$

Function (11) is a micro-model based on individual data and represents the within-place equation. The multilevel model is obtained by letting the originally fixed intercept vary over the higher level of sub-markets. This results in the macro-model (12) that is based on

[15] Versus feasible Generalized Least Squares (fGLS)

[16] In addition, of course the data structure differs too, where RE uses panel data multilevel analysis uses (spatially) grouped data.

aggregated data and reflects the between-place model. Combined, these models form the *terminal multilevel hedonic model* (Orford, 2000):

$$P_{ij} = \alpha + \sum \beta_q STR_{qij} + \sum \gamma_r ALOC_{rij} + \sum \delta_s RLOC_{sj} + \mu_j + \varepsilon_{ij} \qquad (13)$$

Hereof, the first part from alpha up until the relative locational attributes is the fixed part and the two error terms constitute the random part of the model. This model forms the basis of this study.

4.2 Empirical strategy

In order to assess the hypothesized relations between restaurants and residential property prices at the neighbourhood level, a three-staged empirical strategy is employed that corresponds to the methodological capabilities of multilevel analysis as described above. This includes an exploratory evaluation of neighbourhood attractiveness, an in-depth analysis on the basis of the restaurant measures, and a sensitivity analysis to assess the robustness of the obtained results.

A null model is estimated as starting point of the exploratory evaluation. Of the fixed terms, this model only includes the base intercept and thereby returns the grand mean of the citywide housing prices per squared meter. The model is also informative about the initial absolute and relative magnitudes of the variances of the random error terms at both levels. An additional analysis on the level 2 variance provides the possibility to estimate the random neighbourhood effects for all neighbourhoods, which reflect the previously discussed neighbourhood premiums. Together with the base intercept the neighbourhood effects form the random intercepts that – in this simplest model – correspond to the neighbourhood averaged housing prices per squared meter (Jones & Bullen, 1994; Orford, 2002).

$$grand\ mean\ model\ (\mathrm{m}_0):$$

$$P_{ij} = \alpha + \mu_j + \varepsilon_{ij} \qquad (14)$$

Further expansions of the null model can thereafter be used to decompose the neighbourhood effects and to assign these price premiums to specific attributes. This is operationalized in a staggered manner. First, the compositional effects are added. Here a nuance is made regarding the level 1 attribute classes that are considered compositional. Within the current literature no distinction is made between the property specific attribute classes. However, given the definition of compositional effects as those differences in prices caused by spatial variation in the housing stock – as opposed to those differences a place makes and deemed contextual effects – it seems illogical to refer to absolute locational attributes as compositional. This attribute class will therefore be classified as semi level 1 variables and treated as contextual effects, figure 5 visualizes this conceptual framework. An attribute class that is included in the compositional model – and that has not been discussed in the methodological section yet – are the transactional characteristics that have been identified in the data section and that are particularly informative considering the multiannual timespan over which the cross sectional transaction data is gathered (i.e. market and timing effects). Based on the compositional model's variances, new random neighbourhood effects can be established that correspond more to the 'pure' neighbourhood premiums that are of interest to this study. Both locational attribute classes are thereafter added to analyse the factors that make up an attractive neighbourhood and this forms the contextual model.

$$\textit{compositional model } (\mathrm{m}_1):$$

$$P_{ij} = \alpha + \sum \lambda_v TRA_{vij} + \sum \beta_q STR_{qij} + \mu_j + \varepsilon_{ij} \qquad (15)$$

$$\textit{contextual model } (\mathrm{m}_2):$$

$$P_{ij} = \alpha + \sum \lambda_v TRA_{vij} + \sum \beta_q STR_{qij} + \sum \gamma_r ALOC_{rij} + \sum \delta_s RLOC_{sj} + \mu_j + \varepsilon_{ij} \quad (16)$$

Here, subscript v refers to the transactional attributes (TRA) and λ_v indicates their marginal effects on residential property prices.

After this first exploratory evaluation of neighbourhood attractiveness – that includes simple establishment counts of multiple consumer amenities – an in-depth analysis of the hypothesized relations can be performed based on the created restaurant measures discussed in paragraph 3.2. This will shed light on multiple aspects of local consumer amenities beyond jus their presence, including their quality and their diversity. In addition, the two methodological points raised in section 3 – the iens.nl restaurant data validity and the MAUP – can be assessed. Within the in-depth analysis the contextual model is expanded by the inclusion of the property specific, continuous space aggregated-, and neighbourhood specific and aggregated restaurant measures, both separately and simultaneous. Similar to the locational attributes classification, these are respectively referred to as absolute and relative restaurant measures[17] (see figure 5 for an overview). This completes the model.

$$complete\ model\ (\mathrm{m}_{3x}):$$
$$P_{ij} = \alpha + \sum \lambda_v TRA_{vij} + \sum \beta_q STR_{qij} + \sum \gamma_r ALOC_{rij} + \sum \delta_s RLOC_{sj}$$
$$+ \sum \varphi_{wx} ARES_{wxij} + \sum \pi_{zx} RRES_{zxj} + \mu_j + \varepsilon_{ij} \qquad (17)$$

Here, w and z refer to the multiple absolute- ($ARES$) and relative restaurant measures ($RRES$), and φ_w and π_z are their implicit prices. Moreover, the complete model is performed on the basis of two differing sets of restaurant measures x. This includes either the simple restaurant quantity measure (N_{mli}), average grade quality indicator (AG_{mli}) and normalized diversity measure ($HHI^*{}_{mli}$), or the combined quantity and quality measures ($NQ_{ml'i}$, for all l') and the same diversity measure. These sets are referred to as the *standard*- or *alternative* restaurant measures, and are termed model 3a (x=a) and 3b (x=b) respectively.

Figure 5. Conceptual framework

<table>
<tr><th>Measurement level</th><th>Attribute class</th><th>Level</th><th>Conceptual level</th><th>Included from model X onwards</th></tr>
<tr><td rowspan="2">Property</td><td>Transactional (TRA)</td><td rowspan="2">1</td><td rowspan="2">Compositional</td><td rowspan="2">1</td></tr>
<tr><td>Structural (STR)</td></tr>
<tr><td rowspan="2">(Continuous space, buffer aggregated)</td><td>Absolute locational (ALOC)</td><td rowspan="2">Semi 1</td><td rowspan="4">Contextual</td><td>2</td></tr>
<tr><td>Absolute restaurant measures (ARES)</td><td>3x</td></tr>
<tr><td>Neighbourhood</td><td>Relative locational (RLOC)</td><td rowspan="2">2</td><td>2</td></tr>
<tr><td>(Neighbourhood aggregated)</td><td>Relative restaurant measures (RRES)</td><td>3x</td></tr>
</table>

Ultimately, the established relations are subjected to a sensitivity analysis in order to assess their robustness. For the absolute restaurant measures this evidently requires the evaluation of multiple buffer radii, as described in paragraph 3.2. For the overall restaurant measures, both absolute and relative, an additional sensitivity check is performed on the basis of differing subsamples of the transaction dataset. First, the observations are restricted to properties within the ring road of Amsterdam. This reflects the natural division line between the urban core and the more suburban areas of the municipality, which is supported by their population densities of 15055 and 5980 per squared kilometre, respectively. In addition,

[17] These terms are used interchangeably in the rest of the paper. So keep in mind that property specific equals continuous space aggregated equals absolute, and neighbourhood specific equals neighbourhood aggregated equals relative.

home-seekers often clearly search for either a within the ring- or an outside the ring property, such that these can be seen as two different submarkets of the Amsterdam housing market. For the second transaction subsample selection the focus is shifted from the property's perspective towards that of the restaurants. Specifically, the selection is performed on the basis of their geographical distribution. In this respect, the city centre district stands out for accommodating over 40% of the restaurants, while just over 10% of the inhabitants reside here. Also, this district is known as the primary tourist area of the city and to a lesser extend reflects the 'regular' residential property market of town. Therefore, the last robustness exercise excludes transactions that occurred in the city centre district.

5. Results and robustness

5.1 Exploratory evaluation neighbourhood attractiveness

The iterative regression results for model zero through two are presented in table 4. Within the result tables the fixed and random terms are presented separately from each other in order to distinguish between their differing presented parameters, namely estimated model coefficients and variances of the estimated random residuals at the multiple levels, respectively.

The null model (m_0) is run on the basis of all observations and indicates an average house price in Amsterdam of 3611€ per squared meter, over the past 3,5-year time period up until June 2016. The variation around this grand mean is decomposed in a between- and a within grouping component. Hereof, the variance between neighbourhoods is of a greater magnitude than that of the property level within the neighbourhoods. More specifically, the variance partitioning coefficient (VPC) is 0.5815, indicating that 58,2% of the variance is at the neighbourhood level and can be explained by neighbourhood effects. The likelihood ratio of the multilevel specification of the empty model versus its linear or single level specification is highly significant, indicating the presence of significant neighbourhood effects and thus the need for a clustered methodology. Although the neighbourhood effects and thereby random intercepts are not directly estimated, an additional prediction analysis may return their Best Linear Unbiased Predictions (BLUP) (presented as caterpillar, map and list in appendix 3). As stated in section 4.2, the random intercepts of the null model simply refer to the neighbourhood averages of squared meter house prices. However, these are precision weighted, which implies that estimated neighbourhood effects based on a small local sales sample are weighted or 'shrunk' towards the overall citywide average (Orford, 2000).[18] A wide dispersion can be observed from as low as 1745€ in Bijlmer Oost (T94), a neighbourhood in the South-East of Amsterdam, to almost 5756€ in Grachtengordel Zuid, in the city centre. And this spread is even larger than the citywide average itself. However, these neighbourhood effects are still comprised of both compositional and contextual effects, which need to be decomposed in order to evaluate the neighbourhood attractiveness of its place.

The compositional model (m_1) adds the transactional and structural attributes to allow an assessment of the magnitude of the contextual effects of place. The attributes have been added as such that the intercept reflects the average square meter price of a typical house in Amsterdam that is sold in the most recent quarter under consideration (Q2 2016). For a 1930's three room apartment[19] this is estimated to be 4180€ per squared meter.[20] It should be noted that although there are very relevant timing and cohort effects – namely an increasing housing price trend since the first quarter of 2014 and an u-shaped impact of the decade built centred around the 1960's – for the sake of clarity, multiple of these dummies are suppressed in the results table, but can be found fully displayed in the appendix (table A4.2.1). Most of the fixed terms estimates are as expected, with the exception being the insignificant effect of a small outside area as compared to none. Worthwhile mentioning is the negative effect of the number of rooms over the median of 3 which reflects diminishing marginal returns of size on housing prices or the cramped ambiance that more rooms in a same sized apartment creates. Additionally, the relatively high effect of the heating dummy might proxy the overall maintenance state of the property, in the absence of an explicit maintenance measure. Lastly, and as opposed to the expected higher level effect identified in section 2, it is found that a monumental status does not affect its property price. This may be caused by opposing effects of owning a monumental property in terms of monumental uniqueness, beauty and subsidies versus regulatory (building) restrictions.

[18] This might also cause the random variations to decrease with decreasing sample sizes because shrinkage will be applied to groups with less observations. It also implies that the estimated neighbourhood effects are just approximated values.
[19] Without outside area, garage or monumental status but with a high ceiling, storage box and proper heating system, and that is sold within a normal sales duration. This typical apartment definition is based on the descriptive statistics table (and thereof the modus value) of the property specific attributes (Table A4.1.1).
[20] In comparison with the estimated intercept of the null model this difference may be caused by the most recent time period that is set the default in the compositional model, by the definition of the typical property in Amsterdam as one with interpretable (integer) characteristics, instead of having average – non existing – characteristics, and by the differing sample.

Table 4. Exploratory analysis neighbourhood attractiveness: model 0 to 2

Level	Class (symbol)	Attribute	Grand mean [m0]		Compositional [m1]		Contextual [m2]	
Fixed effects								
	Intercept (α)	Constant	3611.45**	(111.35)	4180.27**	(111.69)	4460.48**	(36.86)
1	Transactional (λ)	Time†: Q4 2013			-1091.30**	(28.26)	-1093.91**	(28.19)
		Sales duration: Quick			64.59**	(16.30)	62.27**	(16.30)
		Sales duration: Slow			-143.18**	(12.97)	-141.92**	(12.95)
	Structural (β)	Type: Detached			1554.27**	(60.11)	1593.61**	(60.14)
		Type: Semi-detached			1085.53**	(59.05)	1085.35**	(59.14)
		Type: Terraced			420.97**	(22.83)	452.09**	(22.87)
		Cohort†: 1960's			-433.63**	(36.98)	-437.31**	(36.40)
		Outside: Small			2.40	(12.85)	5.56	(12.79)
		Outside: Large			78.49**	(12.89)	80.99**	(12.86)
		Rooms			-39.78**	(4.92)	-42.08**	(4.92)
		Dummy high ceiling			104.27**	(10.29)	102.04**	(10.26)
		Dummy garage			113.36**	(22.15)	117.91**	(22.27)
		Dummy storage			28.12*	(11.66)	37.25**	(11.64)
		Dummy monument			0.85	(24.34)	-7.46	(24.30)
		Dummy heating			299.34**	(26.83)	304.88**	(26.70)
semi 1	Absolute locational (γ)	Distance centre[c]					-0.2104**	(0.0134)
		Distance station[c]					0.0366*	(0.0173)
		Distance highway ramp[c]					0.1195**	(0.0156)
2	Relative locational (δ)	Ownership distribution[z]					-129.23**	(34.37)
		Income[z]					195.15**	(70.40)
		Public transport[z]					48.71*	(23.13)
		Within ring[c]					453.82**	(100.76)
		Violent crime[z]					-74.92*	(37.28)
		Unsafety[z]					-96.95*	(47.59)
		Beautiful surrounding[z]					285.22**	(105.95)
		Beautiful properties[z]					-189.59*	(87.16)
		Health care[z]					274.59**	(63.08)
		Restaurants[z]					380.60*	(163.03)
		Cafés[z]					-313.80*	(131.02)
Random effects								
Level	Error term (symbol)							
2	Neighbourhood (μ)		1164366**	(170507)	1096442**	(160757)	37819**	(6702)
1	Property (ε)		837826**	(8609)	350158**	(4103)	343479**	(4056)
Variance Partitioning Coefficient (VPC)				0.5815		0.7579		0.0992
Number of observation				19037		14665		14440
Number of groups				95		95		86
Log likelihood				-157081		-114692		-112640.39
LR test vs. linear model				15549.35**		12029.94**		865.09**
LR test vs. preceding model††				-.		6821.67**		527.16**

Notes: Standard errors are in parentheses. * Significant at the 5% level. ** Significant at the 1% level. † Not all category dummies are included in this presentation, full model in appendix 4. †† LR test vs. preceding model can only be performed if the observations stayed the same, so these test statistics are obtained from LR tests between the current model and their preceding model with the observations restricted to the current model sample. [c] Centred. [z] Standardized. In footnote 15 it can be found what the reference apartment is for the level 1 variables.

More interesting to this study are the changed variances and random effects that now do refer to the more 'pure' neighbourhood effects. The inclusion of the non-contextual attributes resulted in a decline of both level variances, however a particular large decline was observed at the property level. This implies that the initial neighbourhood effects mostly reflected contextual effects already and that only a small part of it was caused by the compositional nature of the neighbourhood's housing stock.[21] This is also to be seen from the corresponding figures (6 and A3.4) and table A3.3, where in comparison with the previous set (presented in the appendix) mostly only small changes occurred. This is especially the case for the upper end of the distribution where in the top 25 most expensive neighbourhoods only one neighbourhood experienced a price premium change of more than a standard deviation and only minor ranking changes occurred.[22] The most notable case overall is that of Waterland (N73), whose estimated neighbourhood effect decreased by 1184€ and that dropped from rank 28 of most expensive neighbourhood to rank 60 of most place attractive neighbourhood. This extremely large difference is probably caused by the compositional effect of property type, as Waterland is a large rural 'neighbourhood' in the north of Amsterdam with almost solely detached or semi-detached properties that both have a very high marginal price as compared to apartments. Now that the approximate price premiums per neighbourhood for their place attractiveness are known, the random neighbourhood effects can be unpacked and assigned to specific locational attributes.

The contextual model (m_2) adds both the absolute and relative locational attributes that allows the evaluation of factors that make up an attractive neighbourhood. For interpretation purpose, the property specific distances are centred around their mean and the neighbourhood characteristics have been standardized to z-scores.[23] The base intercept of 4460€ now reflects the average square meter price of a typical house located at an average overall location in Amsterdam. For a clear presentation, only the significant locational attributes are included in the results table (see table A4.2.2 for the full estimation results). The pure level 1 fixed effects are similar to the previous model, for the reason that the added attributes almost only explain the higher level variance.[24] In addition, the vast majority of this

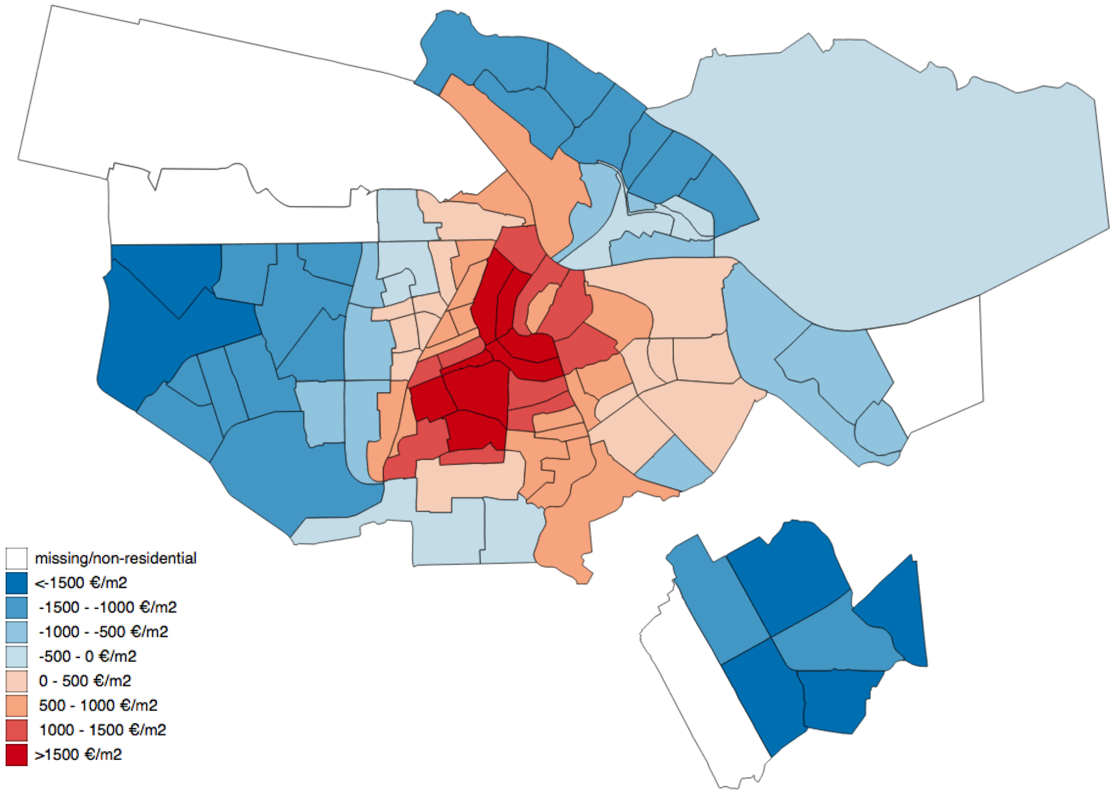
[21] Note that the most important compositional effect, namely that of size, is already filtered out by the dependent variable house prices that is adjusted for size to its square meter price.

[22] Namely the Oude Pijp (N71), which experienced a neighbourhood effect reduction of 190€ where the standard deviation of these differences equals 165€. It thereby lost three places on the ranking of most expensive neighbourhood (#12) to most place attractive neighbourhood (#15).

[23] Except for the neighbourhood specific dummies "Centre" and "Ring", which are centred around their mean, just as the distances.

[24] The fact that the semi level 1 attributes also mainly reduce the neighbourhood level variances indicates that these are correctly classified as contextual.

Figure 6. Topographic overview neighbourhood effects for the compositional model (m_1)



neighbourhood level variance is now explained. The estimated coefficients of the absolute locational attributes indicate that the distance to the city centre is of greatest magnitude (i.e. importance) and that this is the only distance variable with a price reducing effect. Distance to the nearest station and highway ramp on the other hand are positively related to house prices. This may be explained by the negative externalities of infrastructural land use in combination with the fact that the majority of the properties in Amsterdam have similar productive accessibility levels (Vermeulen et al., 2011).[25] With respect to the relative location characteristics, significant effects are found for attributes within all four critical urban amenity classes identified by Glaeser et al. (2001). These fixed effects are as expected, except for the the negative effect of beautiful evaluated properties within the neighbourhood and maybe some of the insignificant effects. With particular focus on the consumer amenities it is found that both health care establishments and restaurants increase neighbourhood attractiveness and house prices, whereas the (non) daily good stores and cultural facilities do not. Lastly, cafés seem to decrease residential property prices, even while there is controlled for their nuisance. However, for the nuisance levels no significant effect is found and it might be the case that house seekers a priori are not aware of real nuisance levels of an area but do

[25] Distances have also been added as squared or logarithmic effects, however this did not improve the model fit.

associate the presence of cafés with high nuisance, such that it takes over their expected negative effect. The significant consumer amenities are of a substantial effect too, as they present among the highest price effects per standard deviation change.

5.2 In-depth analysis restaurant measures

From the exploratory analysis it becomes apparent that local consumer amenities that foster encounters are of significant importance to neighbourhood attractiveness and residential property prices. However, this finding is based solely on simple establishment counts. The in-depth analysis considers the broader nature of such local consumer amenities based on the iens.nl restaurant measures that include quantity, quality and diversity measures. Table 5 present the empirical results concerning the relationship between the created restaurant measures and residential property prices. The pure level 1 fixed effects are very robust to the added restaurant measures and therefore excluded from the table for the sake of clarity.

First, the validity of the switch from officially recorded data by the business registry of Amsterdam (ARRA) to voluntary recorded data on iens.nl is shortly assessed. This is done by the replacement of the restaurant establishment count data of ARRA by its counterpart of iens.nl (the N_{mli} from section 3.2), and specifically the number of graded restaurants ($l = 2$) per neighbourhood ($m = 'nbhd'$).[26] The analysis provides strong support for the application, as the regression results based on the iens.nl restaurant counter (presented as m_2') mimic the significance and magnitude of the ARRA restaurant measure and the rest of the results of model 2, although some relative locational characteristics lost significance. The overall correspondence also makes sense from the perspective of the ARRA and iens.nl measures' pairwise correlation of 0.9627 (see the correlation matrix in appendix 4.3).

Next, the complete models (m_{3a} and m_{3b}) are evaluated. For intra aggregation-method comparison the restaurant measures are included as standardized values.[27] It is found that although both the absolute and relative restaurant measures mainly reduce the contextual variance of the neighbourhood level, their simultaneous inclusion does not conflict with their separate results, with the exception of two estimated coefficients. Therefore, only the simultaneous results are presented in this section, whereas the separate results of the absolute and relative restaurant measures can be found in appendix 4.2. The results obtained

[26] The graded restaurants sample (S2) is chosen as base sample over the full sample (S1) to overcome doubtful occurrences and, later on, the inability to determine average grades.

[27] Inter aggregation-method comparison of the magnitudes of estimated effects is not possible due to differing distributions and differing densities in which they measure; the neighbourhood aggregated, relative restaurant measures are about 'per 1000 inhabitants', whereas the continuous space aggregated, absolute restaurant measures are 'per xxx meter radius buffer area'.

Table 5. In-depth analysis restaurant measures

		Model	iens.nl validity		Complete (standard)		Complete (alternative)	
			[m2')		[m3a]		[m3b]	
Fixed effects								
Level	Class (symbol)	Attribute						
	Intercept (α)	Constant	4464.44**	(36.23)	4513.69**	37.17	4469.65**	(34.91)
semi 1	Absolute locational (γ)	Distance centre[c]	-0.2125**	(0.0132)	-0.1997**	(0.0154)	-0.1988**	(0.0137)
		Distance station[c]	0.0372*	(0.0171)	0.0437*	(0.0190)	0.0339*	(0.0170)
		Distance highway ramp[c]	0.1167**	(0.0155)	0.0962**	(0.0179)	0.1059**	(0.0161)
	Absolute restaurant measures (φ)†	Establishment count S2 (quantity)[z]			35.55*	(17.19)		
		Average grade (quality)[z]			-22.84**	(7.51)		
		Count Q1 (quality)[z]					-20.31	(32.01)
		Count Q2 (quality)[z]					32.91	(29.16)
		Count Q3 (quality)[z]					-86.42*	(37.87)
		Count Q4 (quality)[z]					-12.88	(30.27)
		Count Q5 (quality)[z]					165.39**	(30.23)
		Count Q6 (quality)[z]					-46.96*	(20.68)
		Normalized HHI (diversity)[z]			33.84**	(13.11)	37.98**	(10.86)
2	Relative locational (δ)	Ownership distribution[z]	-91.01**	(33.47)	-114.68**	(35.75)	-75.81*	(32.59)
		Income[z]	123.71	(64.10)	187.61**	(66.35)	92.54	(66.54)
		Public transport[z]	30.80	(22.53)	-10.54	(34.68)	27.32	(21.91)
		Within ring[c]	513.93**	(96.96)	558.85**	(102.52)	539.08**	(93.77)
		Violent crime[z]	-66.59	(35.79)	-47.70	(37.99)	-54.62	(33.95)
		Unsafety[z]	-133.26**	(45.05)	-118.06*	(51.44)	-137.24**	(51.30)
		Beautiful surrounding[z]	180.18	(94.90)	167.15	(94.37)	132.50	(91.11)
		Beautiful properties[z]	-138.54	(79.76)	-123.52	(79.69)	-90.45	(77.66)
		Daily density[z]	78.18	(53.63)	70.38	(53.00)	124.52*	(62.72)
		Health care[z]	270.47**	(59.55)	224.58**	(63.15)	228.91**	(58.52)
		Restaurants[r]	-	-	-	-	-	-
		Cafés[z]	-339.45**	(95.19)	-364.25**	(95.20)	-365.96**	(112.70)
	Relative restaurant measures (π)†	Establishment count S2 (quantity)[z]	409.41**	(106.47)	405.62**	(106.93)		
		Average grade (quality)[z]			58.45*	(26.66)		
		Count Q1 (quality)[z]					-95.36	(125.86)
		Count Q2 (quality)[z]					157.27	(126.80)
		Count Q3 (quality)[z]					-44.62	(80.27)
		Count Q4 (quality)[z]					231.46**	(87.40)
		Count Q5 (quality)[z]					119.13	(72.70)
		Count Q6 (quality)[z]					0.20	(63.64)
		Normalized HHI (diversity)[z]			-37.63	(37.22)	-5.23	(27.87)
Random effects								
Level	Error term (symbol)							
2	Neighbourhood (μ)		34438**	(6100)	30619**	(6002)	26978**	(4991)
1	Property (ε)		343451**	(4055)	349956**	(4279)	342606**	(4046)
Variance Partitioning Coefficient (VPC)				0.0911		0.0805		0.0730
Number of observation				14,440		13,473		14,440
Number of groups				86		78		86
Log likelihood				-112636		-105213		-112609
LR test vs. linear model				827.16**		546.48**		527.24**
LR test vs. preceding model††				-		31.85**		62.70**

Notes: Standard errors are in parentheses. * Significant at the 5% level. ** Significant at the 1% level. † Results of separate absolute and relative restaurant measures in appendix 4.2. †† Preceding model here is m2, either with 14400 observations or 13473 observations. m2' and m2, and m3a and m3b can not be compared by the LR test for that they are not nested models but alternative models. [c] Centred. [z] Standardized. [r] Included for overview only. The number of observations for m3a are lower due to missing values for the average grade variable in case no graded restaurants were in the area.

on the basis of the standard set of restaurant measures (m_{3a}) suggest that overall – both from the neighbourhood and the continuous space perspective – the presence of restaurants benefits residential property prices, and this is in accordance with the exploratory analysis. The qualitative and diverse restaurant measures present less unanimous results, i.e. that differ over the absolute and relative measures (i.e. MAUP). From the neighbourhood aggregated perspective it seems that the average grade of the restaurant offer adds to housing prices, however this is not the case in the separate relative measures model (m_{3a}_rel in figure A4.2.5). On the other hand, a negative significant effect is presented of the average restaurant grade on residential property prices for the continuous space aggregated measures. For the Herfindahl-Hirschman diversity measure the findings are partly opposed, in the sense that there is again no significant effect is found for the relative neighbourhood case, whereas now a positive effect estimated for the continuous space measure.

Alternatively, the qualitative aspect of the local restaurant offer might be judged on the basis of the establishment counts per quality class, as is presented in m_{3b}. It provides the additional insight that there is a non-linear and non-monotonic effect of restaurant quality on residential property prices. This specification is thereby preferred over the standard complete model. Specifically, the results present a positive significant impact of the presence of restaurants of the 4^{th} quality class on house prices for the neighbourhood aggregated restaurant data. In addition, the separate relative measures model (m_{3b}_rel in figure A4.2.7) estimates a similar though bit smaller effect for the 5^{th} quality class. For the continuous space aggregated restaurant data a more parabolic relation is found (downwards opened) with negative effects for the 3^{rd} and 6^{th} quality classes and a positive effect for the 5^{th}. Lastly, this model presents similar estimates for the diversity measure of both aggregation methods in comparison with the standard complete model, i.e. no effect for the relative measure and a positive impact on the absolute level.

To summarize the estimated fixed effects, for the relative restaurant measures the presence of restaurants seem to benefit residential property price and specifically so for the medium to upper segment (Q4 and Q5), whereas there is no evidence for any effect of the diversity of the local restaurant offer. For the absolute restaurant measures the overall presence of restaurants seem to benefit residential property prices too. However, with a more parabolic relation in the higher end of the quality spectrum (from Q3 to Q6), where the ends of the parabola even negatively influence prices. In addition, restaurant diversity does seem to positively impact house prices in this case. Considering the random effects, the addition of the restaurant measures again mainly reduced the variance at the neighbourhood level by almost a third, at most (m2→m3b). The variance partitioning coefficient further indicates that of the leftover variance just 7 to 8% still represents unexplained neighbourhood effects. This implies that the majority of the factors that determine neighbourhood attractiveness are now accounted for, as can also be seen from the predicted neighbourhood effects on the basis of the alternative complete model (presented in triple in appendix 3). Where the 'pure' neighbourhood effects (identified on the basis of m_1) varied from minus 1930€ to plus 2150€ per squared meter, the unexplained effects (leftover at m_{3b}) vary by just 350€ for both signs, of which the majority does not significantly differ from zero. Lastly, the likelihood ratio test statistics versus the proceeding, contextual, model suggests that the inclusion of the richer restaurant measures over the simple establishment count variable significantly improves the multilevel hedonic model.

5.3 Sensitivity analysis

The obtained results of the preferred, alternative complete model (m_{3b}) of the in-depth analysis are evaluated on robustness by varying the buffer radius and the sample of observations. For this purpose, only the restaurant measures attribute classes are shown here, whereas the full coefficient comparisons are included in the appendix (A4.2). Table 6 present the outcome of both sensitivity checks, of which the patterns of the price effect per quality class are also visualized in figure 7 trough 10.

The left parameter columns in the table presents the first sensitivity analysis, where the buffer radius of 650 meter is replaced by both 500 (m_{3b}_500) and 800 meter (m_{3b}_800). First, the estimated coefficients of the relative restaurant measures are consulted. As the assumption in the previous paragraph was that the simultaneous inclusion of the absolute and relative restaurant measures would not influence one another, the varying buffer radii underlying the absolute restaurant measures should not influence the estimated coefficients of the relative restaurant measures. This indeed seems to be the case, with the addition of the significant positive effect of the 5th quality class for the 800m buffer radius model (m_{3b}_800) that was also observed in the separate relative measures model (m_{3b}_rel in the appendix). With respect to the absolute restaurant measures, a less robust pattern is observed, where the differing buffer radii models present an amplifying effect of the buffer radii size on the relation between quality and property price impact (as is clearly visible from figure 8). That is, for the 500-meter radius a relatively small price impact is presented with a negative effect for Q2 and a positive effect for Q5, whereas for the 850-meter radius a larger impact is estimated with an upwards opened parabolic form around the medium quality segment with positive impacts of Q2 and Q5 and a negative impact of Q3. The only robust effect for the absolute measures thus seems to be the positive impact of Q5, as well as that of the diversity measure.

The parameter columns on the right of the table present the second sensitivity analysis, where the observations are either limited to properties within the ring road (m_{3b}_ring) or to properties outside the city centre district m_{3b}_ncen). For the within the ring submarket the remark must be made that the estimated effects of multiple relative location attributes – and in particular that of the consumer amenities – on residential property prices

Table 6. Sensitivity analyses alternative restaurant measures with differing buffer radii and transaction samples

		Base model	Complete (alternative)				
		Sensitivity check	Buffer radius		Reference	Transaction sample	
		Sub model	500m [m3b_500]	800m [m3b_800]	650m/All [m3b]†	Within ring [m3b_ring]	Outside centre [m3b_ncen]
Fixed effects							
Level	Class (symbol)	Attribute					
	Intercept (α)	Constant	4468.54**	4463.74**	4469.65**	4883.85**	4493.05**
semi 1	Absolute restaurant measures (φ)	Count Q1 (quality)^z	-5.51	6.67	-20.31	-7.39	-75.01
		Count Q2 (quality)^z	-48.13*	149.70**	32.91	47.82	-15.83
		Count Q3 (quality)^z	-35.22	-210.75**	-86.42*	-100.23*	-104.78*
		Count Q4 (quality)^z	19.67	-14.39	-12.88	3.26	11.46
		Count Q5 (quality)^z	76.76**	148.69**	165.39**	131.94**	210.97**
		Count Q6 (quality)^z	0.26	-16.51	-46.96*	-47.18*	-105.95**
		Normalized HHI (diversity)^z	53.63**	23.90*	37.98**	98.73**	34.05**
2	Relative restaurant measures (π)	Count Q1 (quality)^z	-86.20	-116.80	-95.36	165.94	-108.57
		Count Q2 (quality)^z	197.21	81.59	157.27	-116.56	201.47
		Count Q3 (quality)^z	-43.60	-20.78	-44.62	-154.49	-169.86
		Count Q4 (quality)^z	210.93*	240.08**	231.46**	87.63	417.63**
		Count Q5 (quality)^z	136.97	145.72*	119.13	202.09**	445.01**
		Count Q6 (quality)^z	-17.56	-17.74	0.20	-42.97	-139.81
		Normalized HHI (diversity)^z	-6.85	-1.47	-5.23	91.64	-11.53
Random effects							
Level	Error term (symbol)						
2	Neighbourhood (μ)		26520**	27705**	26978**	13467.24**	35402**
1	Property (ε)		342739**	342485**	342606**	369407.6**	299548**
Variance Partitioning Coefficient (VPC)			0.0718	0.0748	0.0730	0.0352	0.1057
Number of observation			14,440	14,440	14,440	10,174	12,760
Number of groups			86	86	86	50	76
Log likelihood			-112611	-112608	-112609	-79700	-98664
LR test vs. linear model			542.35**	513.82**	527.24**	174.03**	538.44**
LR test vs. preceding model††			58.44**	65.76**	62.70**	63.77**	82.93**

Note: Standard errors not presented * Significant at the 5% level. ** Significant at the 1% level. † Included for comparison purpose. †† Preceding model here is m2, with equal observations. ^{z} Standardized.

Figure 7. Pattern for relative measures and varying buffer radii

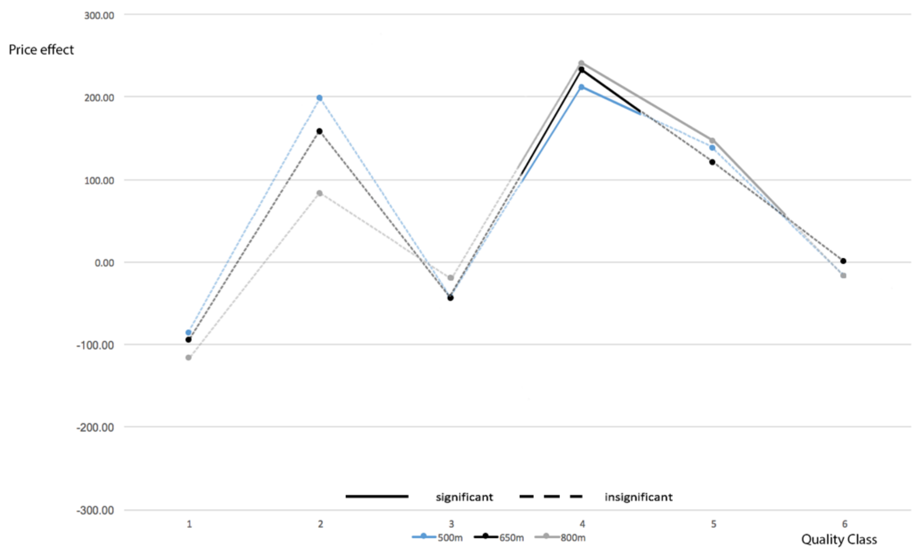


Figure 8. Pattern for absolute measures and varying buffer radii

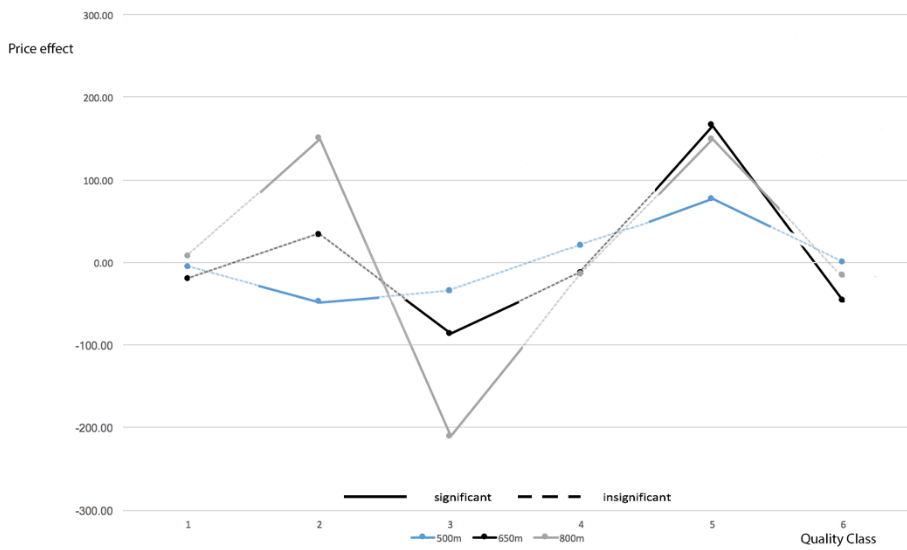


Figure 9. Pattern for relative measures and varying transaction samples

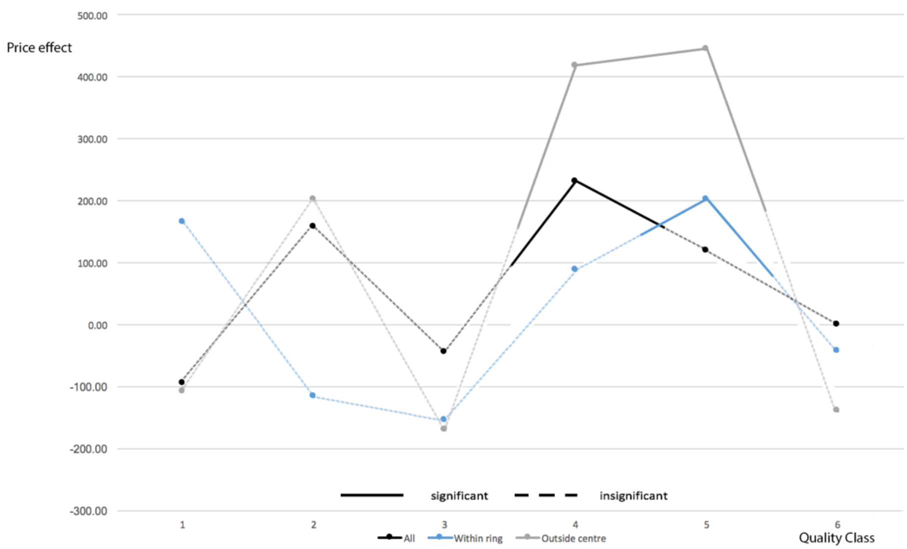
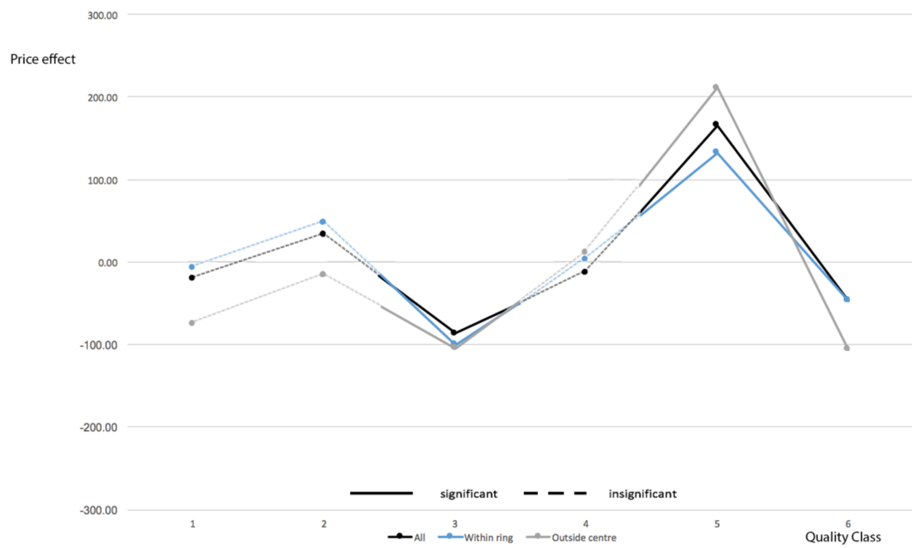


Figure 10. Pattern for absolute measures and varying transaction samples



change, although in an understandable fashion (see the full coefficient list in figure A4.2.9).[28] With respect to the relative restaurant measures predominantly robust estimates are found. Again, there seems to be a positive effect of medium to upper segment restaurants on residential housing prices. However, within the ring this only holds for the 5th quality class, whereas for the outside the centre sample the effect is present for both the 4th and 5th quality class. In addition, the magnitudes of the latter sample approximately doubled, indicating the higher relevance of qualitative restaurants if the most restaurant dense district is excluded (i.e. marginal diminishing returns). The relative diversity measure's null estimate is robust to the transaction sample selection. Lastly, the absolute restaurant measures robustness over differing samples is considered. This particular sensitivity analysis presents very robust estimates for the downwards opened parabolic effect of restaurant quality on house. The only notable difference is the magnitude of the diversity measure that almost tripled for the within the ring transaction sample, and this suggests that more importance is attached to the diversity of cuisines of local restaurants in more restaurant dense areas as compared to sparser ones (i.e. the subordinate importance of diversity with respect to restaurant presence).

The sensitivity analyses reveal an overall reasonable robustness of the estimated price effects of the alternative restaurant measures, however with some variance between the different restaurant aggregation methods and sensitivity checks. Specifically, the neighbourhood aggregated, relative restaurant measures are completely robust to the differing buffer radii of the absolute measures (as they should be) and fairly robust to the multiple transaction subsamples. On the other hand, the continuous space aggregated, absolute restaurant measures are somewhat robust to the differing buffer radii and completely robust to the subsamples of transactions.

6. Synthesis

6.1 Key findings

The exploratory evaluation of neighbourhood attractiveness identified the presence of significant and substantial neighbourhood effects within the residential property market of

[28] The nuisance of hotel, restaurant and café like establishments now decreases prices. Furthermore, daily good stores are perceived beneficial whereas the proximity of non-daily good stores is not. The positive effect of health-oriented establishments disappeared and cultural establishments surprisingly decrease property prices, where this latter may be a form of reversed causality where cultural minded establishments require low prices to subsist.

Amsterdam. Moreover, it is found that the majority of the city's housing price variance can actually be attributed to differences at the neighbourhood level, instead of differences at the property level. Specifically, it is attributable to the contextual composition of its place, as opposed to the neighbourhoods' compositional makeup of the housing stock. A first indicative analysis of the locational factors inherent to place supported the relevance of all Glaeser et al. (2001)'s critical urban amenity classes at the intraurban housing market level. In addition, it provided preliminary evidence for the hypothesized relation between restaurant presence and residential property prices. The negative estimated effect of cafés does show that this is not universal to all consumer amenities that foster encounters, particularly not for those that can be associated with high levels of nuisance or other potential negative externalities.

Hereafter, the GIS created restaurant measures of quantity, quality and diversity have been deployed for an in-depth analysis of the relation between restaurants and residential property prices. Next to the proven validity of the iens.nl based restaurant measures, it is found that the overall presence of restaurants – both from the neighbourhood and the continuous space perspective – benefits residential property prices and this confirms the preliminary evidence obtained from the exploratory analysis. Together, the exploratory and in-depth analyses provide credible support for the first hypothesis which linked the quantitative aspect of local restaurants, i.e. their presence, positively to residential property prices and neighbourhood attractiveness.

The in-depth analysis furthermore established a non-linear and non-monotonic effect of restaurant quality on residential property prices. As such, the quality class counters proved to be the preferred quality indicators, over the average restaurants grade. In addition, it is found that the price effects of qualitatively distinct restaurants and restaurant diversity differ by aggregation method, suggesting the presence of MAUP. These relations have been subjected to a sensitivity analysis that included varying buffer radii and multiple transaction subsamples for an evaluation of their robustness.

The in-depth and sensitivity analysis provided sufficient support for the second hypothesis. This hypothesis states that residential property prices and neighbourhood attractiveness are positively influenced by the quality level of local restaurants. It is found that only restaurants of the medium to upper segment of the quality spectrum – the 'good' and 'better' restaurants – have a consistent positive price effect for residential properties. From the neighbourhood aggregation perspective this effect is largest for properties outside the city centre district with the highest restaurant densities, indicating marginal diminishing returns of the restaurants' price effect. The continuous space aggregated measures further hint at, but are not in complete accord about, a negative price driving effect of restaurants classified as ‘average’ and ‘best’.

With respect to the third and last hypothesis no unanimous answer can be provided, although the estimated price effects of a diverse restaurant offer in terms of cuisines are robust to the sensitivity analysis. This disagreement is caused by the difference between the presented price effects for the neighbourhood- and continuous space aggregated diversity measures. Specifically, for the first there is no impact found, whereas for the latter there is a positive price effect found. As such, it can be concluded that if there would be any effect at all it would be a positive one. Also, the effect is largest for the transaction sample within the ring which indicates the subordinate importance of diversity to restaurant presence. The discrepancies between the two methods of aggregation are discussed in the next paragraph in the light of the modifiable areal unit problem (MAUP).

6.2 Discussion, limitations and future research

6.2.1 Iens.nl’s snapshot overview and causality

As was stated in paragraph 3.1, because of lacking information regarding the year of establishment, the simplifying assumption has been made that the restaurant offer of Amsterdam was approximately stable over the past three and a half years. However, according to registrations numbers of the Chamber of Commerce (over 2015) more than four new restaurants opened per week, versus just two closings. In addition, the numbers indicate that there were 20% more restaurants last year than five years before (Versprille, 2015). The overall growth over the period considered might have caused a downward bias of the estimated quantity effect, but this does not jeopardize the established positive results. If this growth has been equally distributed over the existing geographical restaurant distribution in terms of quantities, qualities and diversities the snapshot provided by iens.nl mid 2016 may still be a good representation from the individual neighbourhoods’ perspective. However, the validity remains questionable when considering that restaurants often arise in regenerating neighbourhoods (Bell & Binnie, 2005; Flint, 2014). Hence, this might cause biases to the estimated neighbourhood effects. This emphasises another previously raised note made in paragraph 5.1 that the estimated neighbourhood effects are just approximated values. Potential solutions are to acquire detailed business information data or, as Kuang (2015) did, to estimate the year of establishment on the basis of the first review that was written.

The notion of restaurants’ initial location decision also raises the question of reversed causality. Because is it really the restaurants (and their quality) that drive residential property prices, or is it the other way around and are (qualitative) restaurants attracted to areas with higher property prices? Gerritsen and Marlet (2011) raise this similar concern on an interurban level of analysis and argue that for man-made living-amenities – versus endogenous physical amenities – the causality is harder to ascertain. Moreover, they contend that consumer amenities may be attracted to sought-after "living" cities, exemplified by high house prices. However, once within such a consumer city, with a high overall client potential, it could be argued that restaurants are less urged to establish in the most expensive neighbourhoods as they may also succeed in more upcoming areas where rents are still lower and the cost-related business risk can be reduced. This is supported by an American survey held under residents of six dynamic US cities in which it is found that the most mentioned reason to venture out of one's neighbourhood and to visit new parts of town is to try a new restaurant (46% of the respondents) (Sasaki, 2014).

Clark (2003, p. 107) places the 'restaurants-follow-affluent-individuals' reasoning among the "traditional economic determinism" and instead argues that amenities like restaurants can shift individuals' and firms' location decisions. In his reversed reasoning he accuses the application of the traditional view to urban amenities of being a form of "overextended methodological individualism (p.108)". For the reason that individuals, and especially talented and younger persons who change jobs frequently, move in and out cities all the time whilst the development of urban amenities like opera and lakefronts change more slowly and thus are the causality drivers. The same case could be made for the sustained development of an attractive neighbourhood with a rich variety of services and consumer goods, such as restaurants, among others.

Basically, it is a 'which came first, the chicken or the egg?' debate. To this extent, the current cross sectional study only identified a correlation and is not informative about the direction of causality. To handle this concerns, future research should focus on prospectively tracking the development of the (qualitative) restaurant stock, residential property prices, and neighbourhood effects, or focus on the creation of such a time variant dataset retrospectively by gathering information on year of establishment (see previous suggestions at the end of the first subparagraph). In terms of the multilevel hedonic pricing methodology, the with time varying locational attributes could be incorporated as an intermediate level (i.e. quarters or years) between the residential properties and the neighbourhoods, or other variants[29] or methods could be employed. Note that the causality concern does not apply to the (yet inconclusive) effects of the diversity of cuisines aspect.

6.2.2 The modifiable areal unit problem (MAUP)

The partly inconsistent outcomes of the two methods of spatial data aggregation and the multiple buffer radii that are used to determine the iens.nl restaurant measures indicate the presence of the modifiable areal unit problem. That is, the empirical results are dependent upon the chosen, modifiable areal boundaries over which spatial data is collected or aggregated (Openshaw, 1983; Fotheringham & Wong, 1991). Within this research context, the MAUP could be interpreted in terms of the underlying dynamics of the housing price determination process. It can be argued that from a neighbourhood aggregated perspective the restaurant measures are more related to the neighbourhood image. Something which potential house buyers often evaluate at an early stage in their searching process while establishing desired or preferred areas to reside. On the other hand, from the continuous space (buffer) aggregated perspective the restaurant measures may reflect more truly the local supply. House seekers may only evaluate the truly local amenities at a later stadium in their searching process, after multiple properties are identified for further research or a viewing.

Within this line of reasoning the obtained results concerning the diversity of cuisines suggest the lack of importance of a restaurant diverse neighbourhood image for residential property prices and neighbourhood premiums, whereas restaurant diversity does seem to matter (i.e. contribute to housing prices) from a direct area evaluation perspective. At first glance this sounds counterintuitive, in the sense that the reverse would be more conceivable. Therefore, this interpretation requires a further analysis of the underlying consumer behaviour and decision processes, and an evaluation of the 'correct' neighbourhood level and continuous space buffer area at which the neighbourhood image is perceived and transferred and the direct area evaluation occurs. This can be assessed in future research.

6.2.3 Restaurant measures

With respect to the created restaurant amenity measures multiple points of discussion arise. First, considering the quantity measure, and particularly that of the continuous space perspective, no distance decay effect is incorporated. The majority of locational evaluating

[29] Such as a less appealing but still potentially useful two-level variant with a neighbourhood×time period grouping structure.

studies do include this feature (Li & Brown, 1980; Bhat et al., 2000, Kuang, 2015) and the simplified count measure employed in this research can therefore be seen as a limitation. Kuang's (2015) related study is among those studies that did incorporate the decreasing in distance effects, however her study employs a buffer radius of one mile (1610 meters). Therefore, the inclusion of distance decay effects is more urgent in comparison with the relatively small areas of consideration in this study. Nevertheless, ideally the quantity measure of this study would have taken into account the distance decay of restaurant impact on residential property prices. This also applies to both quality measures, as they originate directly from the quantity measure.

Second, regarding the quality measures, and specifically the quality class counters, the rapid increasing criteria on the number of reviews might be questionable. As was stated in section 3 (in the notes of table 1 and in footnote 13) this was done for (increasing) credibility concerns in combination with setting round criteria numbers as to approximate the conditioned number of restaurants in the subsamples. However, in such the side effect arises that besides measuring credible quality levels the quality class counters also measure popularity (the more clients, the more potential reviews) and the history of existence (the longer existence, the more potential reviews). This might also explain the somewhat rigid estimated price effects of the differing quality classes (see figures 7 to 10). Future research could improve on this by setting just one cut-off point for credibility in terms of number of reviews. In addition, future research could deepen the knowledge about the restaurant capitalization effects on residential property prices by analysing whether the effects differ for newer (and therefore maybe trendier) or more popular restaurants.

Also, the concern may be raised that restaurants on iens.nl, which is a TripAdvisor company, get differently reviewed by local users (who are the main actors on the housing market) and tourist users, and that this potentially harms the quality measure. However, an inspection of the reviews reveal that iens.nl is predominantly used by the Dutch, reducing this concern. Moreover, one might wonder whether the review grades given by customers on iens.nl reflect a pure quality measure, or a price-quality satisfaction indicator. Kuang (2015) argues that customers have higher expectations for upscale restaurants and therefore are less lenient in their reviews, such that the grades concern price-quality satisfaction. Also, she retrieved information regarding expenditure levels from Yelp and shows that the rating and expenditure level measures convey different information. This research lacks information on expenditures levels and therefore can not directly assess this issue for the iens.nl's case. However, indirectly, the result of this study that there is no effect of the 'best' reviewed restaurants on residential property prices might convey that the iens.nl grade is partly driven by pure quality. As exceptional quality is priced into restaurants' menu prices (Berry & Waldfogel, 2010) these restaurants are less attractive for the mass. In addition – under the assumption that the 'best' restaurants are also the most expensive – it can be argued that these distinct restaurants are more truly urban amenities instead of local ones since they have conceivably larger catchment areas.

For the diversity measure, the notion must be made that the Herfindahl-Hirschmann Index may partly be driven by neighbourhood size. A larger area has higher chances of having more restaurants and thereby has a higher chance of having a richer restaurant offer (which constitutes one part of the HHI). This is another limitation of the study and requires the careful interpretation of the allocated effects. In this sense, more validity can be assigned to the continuous space aggregated diversity measure and its estimated positive effect, as the buffer areas are of equal sizes. Lastly, and although no unanimous effect is presented for restaurant diversity, it might still be the case that diversity within the total class of consumer amenities matters. Future research could consider the development of an amenities diversity measure which is suitable for the interurban comparison of multiple consumer amenities over areas of differing sizes and densities.

6.2.4 Multilevel capabilities and spatial effects

One of the main advantages of multilevel modelling, besides the ability to analyse contextual effects and its statistical correct interference, is the ability to randomize the intercepts and slopes (Luke, 2004). This study utilized the capability of a random intercept, but neglected further potential improvements by the inclusion of randomized slopes. Within the current research context, spatial heterogeneity of the restaurants effects (i.e. effects varying over sub-markets) seems plausible. This is confirmed by the results suggesting decreasing marginal effects of (qualitative) restaurants and the subordinate effect of cuisine diversity to restaurant presence (i.e. higher restaurant effects in restaurant scarce areas and higher cuisine diversity effects in restaurant dense areas). As was stated in paragraph 4.1 and footnote 14, random slopes can be used to explicitly model spatial heterogeneity. As such, more of the higher level variance can potentially be explained and this increases the efficiency of the estimates. Practically, this could be exploited by including random effects for the restaurant count variables and diversity measure, with restaurant density as explanatory variable of their variation.

Lastly, paragraph 4.1 shortly touched upon the existence of spatial dependence of the independent variable. Applied to the residential property market it can be observed that next to the evaluation of structural and locational attributes, realtors also base their valuation on the price history of residential properties in the immediate surroundings (Millington, 1990). This dynamic causes spatial dependence of housing prices nearby each other (i.e. spatial lag). This is mainly circumvented in this study as the spatial groupings effects were deemed most relevant for the relation between restaurants and residential property prices. However, multilevel modelling provides room for further improvement in this regard by explicitly modelling the lag dependence. As apposed to the more 'technical fixes' of the inclusion of a spatial weight matrix of surrounding properties, multilevel analysis can explicitly model the drivers of spatial lag dependence by including many higher levels up until the street or even housing block (Orford, 2000). Especially considering the harmful effects of spatial lag (i.e. violation of the zero conditional mean MLR assumption and thus biased and inconsistent estimates), this might be something future research wants to undertake.

7. Conclusion

This paper has been concerned with the relation between local amenities and residential property prices at the neighbourhood level. Specifically, it studied the role of restaurants as local consumer amenities that foster encounters. This relation is deemed relevant in the light of two specific developments. The first is the observed trend within intraurban house price differentials studies that evolves from production related input amenities towards the more consumer related amenities. The second development regards the increasing importance of face to face contact and encounter in modern society dominated by information and communication technologies. The corresponding central research question was defined as follows: what is the effect of restaurants, as local consumer amenities that foster encounters, on neighbourhood attractiveness as reflected by its residential property prices?

Consumer generated content of the restaurant review website iens.nl has been processed by GIS techniques to generate rich neighbourhood and continuous space aggregated restaurant measures concerning their quantity, quality and diversity. For a correct conceptual and statistical treatment of the spatial grouping effects of neighbourhoods a multilevel hedonic pricing methodology is employed and a three-staged empirical strategy is performed. The results of the exploratory, in-depth and sensitivity analyses indicate the presence of substantial neighbourhood effects in Amsterdam and the importance of the restaurant measures for residential property prices. Specifically, and to answer the central research question, strong empirical evidence is provided for a positive effect of local restaurants of above average quality (except for the highest) on neighbourhood attractiveness, as reflected by higher residential property prices. Moreover, the sensitivity analysis suggests marginal diminishing returns for the restaurants' price effect and the subordinate importance of diversity of cuisines to restaurant presence, if there is to be any effect at all for diversity. The exploratory evaluation indicates that the positive effect of restaurants is not directly generalizable to all consumer amenities that foster encounters, depending on potential negative externalities that are associated with them. Unfortunately, the suggested causality can not be guaranteed due to the cross sectional nature of the analysis.

Besides the insights around the central research question this study also makes some data and methodological contributions. Most importantly, it showed the relevance and power of amenity measures created on the basis of consumer generated content on review websites. The relevance is endorsed by the proven validity of the iens.nl restaurant measures in comparison with the officially recorded data of the business registry and the power is illustrated by the rich created restaurant measures over simple establishment counts provided by this same party. In addition, the study showed that the spatial data aggregation method matters, in the sense that the neighbourhood aggregated and continuous space (buffer) aggregated restaurants measures lead to partly inconsistent results. This indicates the presence of MAUP for consumer amenities such as restaurants.

The findings imply that the consumer related amenities identified as urban success drivers are also important at the intra-urban level of analysis, such as that of the neighbourhood or local surrounding. In addition, it implies that from a neighbourhood development or regeneration perspective it is not sufficient to just promote the establishment of consumer amenities such as restaurants, but that attention should also be paid to the anticipated quality level of restaurants. Potentially, cuisine diversity should be considered too. Placed in a broader perspective, these implications might as well hold for a wide range of local amenities, such as sport facilities, cultural offerings or parks. Similar techniques, i.e. the combination of GIS, consumer generated content and multilevel modelling, could be used to evaluate such matters. As last note, this case study of Amsterdam exemplified the situation of a pure 'consumer city', it would be highly interesting to analyse how the results would develop if this research is replicated for a city considered more 'producer' orientated.

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Appendix 1 - Technical appendix

In this technical appendix the data processing steps and transformation actions of the restaurant, residential property and neighbourhood data are communicated.

Restaurant data – iens.nl

The restaurant data is scraped fromwww.iens.nl. To do so, unique values are filtered out of the page source underlying the search results "Amsterdam". Because the page source only shows 20 restaurants per page the retrieval process of the unfiltered page script has been automated with the use of Matlab script. Thereafter this raw data is filtered by means of a find a replace exercise where common symbols have been replaced by 'blanks'. After some formatting this reduces to the restaurant data, including restaurant name, coordinates, grade, number of reviews and cuisine. A unique restaurant ID number was manually added. Furthermore, STATA is used to categorize the 79 on iens.nl existent cuisines in Amsterdam (NC^{old}) into a manageable number of cuisine categories for the creation of the diversity measure (NC^{new}). In order to minimize the arbitrary nature of this task and for transparency purposes the following categorization rules are set and followed:

1. iens.nl cuisine categories that cover more than 50 restaurants form the basis for the new cuisine categorization, the two French categories that fulfil this criterion are combined into one ($NC^{old} = 15 \rightarrow NC^{new} = 14$).
2. iens.nl cuisine categories that include less than 10 restaurants are combined into the newly created cuisine category 'Other' ($NC^{old} = 39 \rightarrow NC^{new} = 1$).
3. All other iens.nl cuisine categories (that cover between 10 and 50 restaurants) are manually assigned to one of the newly created cuisine categories ($NC^{old} = 25$). The manual process relies on geographical regions as defined by the UNSD (United Nations Statistical Division)[30], concept relatedness and the rest category 'Other'.
4. Where necessary the new cuisine categories are renamed.

This process results in 15 newly generated cuisine categories ($NC^{old} = 79 \rightarrow NC^{new} = 15$) that are included in table A1.1 (p.t.o.)

[30] UNSD composition of regions 2013: http://unstats.un.org/unsd/methods/m49/m49regin.htm

Table A1.1 Cuisine categories

Cuisine category (# restaurants)	*(continued)*	*(continued)*
Alternative (107)	Japanese (89)	Other (166) *continued*
Biological (63)	Japanese (72)	Peruvian (3)
Vegetarian (27)	Sushi (17)	Raw food (3)
Regional (17)	Mediterranean (228)	Caribbean (2)
American/Meat (190)	Mediterranean (77)	Catalan (2)
BBQ/Grill (90)	Turkish (44)	Halal (2)
Argentinian (48)	Spanish (32)	Kosher (2)
American (34)	Fish (22)	Malaysian (2)
Mexican (18)	Greek (19)	Pakistani (2)
Chinese (95)	Moroccan (18)	Scandinavian (2)
Chinese (83)	Tapas/mezze (16)	South-African (2)
Chinese-Indian (12)	Other (166)	Tex-Mex (2)
Dutch (252)	Fusion (23)	Afghan (1)
Dutch (220)	Dessert (14)	African (1)
Pancakes (19)	Ethiopian (11)	Austrian (1)
Belgian (13)	Lebanese (8)	Bulgarian (1)
French (243)	Portuguese (7)	Cantonese (1)
French (122)	Arabic (6)	Colombian (1)
French-International (70)	Brazilian (6)	Dim sum (1)
French-Mediterranean (31)	Eclectic (6)	Georgian (1)
French-Classical (10)	English (6)	Hungarian (1)
French-Modern (10)	Korean (6)	Israeli (1)
Indian (53)	Wok (6)	Kurdish (1)
Indonesian (78)	Australian (5)	Romanian (1)
International (578)	Irish (5)	Swiss (1)
International (542)	Nepalese (5)	South-East Asia (84)
World cuisine (36)	German (4)	Thai (70)
Italian (306)	Persian (4)	Vietnamese (14)
Italian (283)	Tibetan (4)	Surinam (52)
Pizzeria (23)	Egyptian (3)	Unknown (204)

Thereafter the restaurant data is processed by two means; aggregated per neighbourhood and aggregated per buffer area around each property transaction. This results in neighbourhood specific restaurant characteristics (relative measures) and property specific restaurant characteristics (absolute measures), respectively. With respect to the first method, QGIS is used to assign each restaurant to their corresponding neighbourhood (see QGIS appendix A2) where after STATA is employed to convert the data into neighbourhood aggregated statistics. With respect to the second method of aggregation, the QGIS Python console plugin is employed to code and perform the creation of the locational characteristics (see QGIS appendix) which are then added to the transaction dataset.

Residential property data – Kadaster and Funda

Two separate datasets were received from Ortec Finance B.V. that included transaction data and structural characteristics provided by the Kadaster and Funda. The property data of both sources are combined based on their unique transaction ID by means of the VLOOKUP formula in Excel. The Funda sheet contained 27 double transaction ID's. Based on inspection of the 'bronid' (page source ID) and plausibility of the recorded data, for every pair one transaction ID was manually classified as the "False" observation.[31] The false observations received an "F" behind their transaction ID, such that VLOOKUP refers to the correct observation (the one without the F-extension). Moreover, not for every transaction a Funda webpage existed (bronid=-1) and the following empty cells of these observations have been recoded to -1 (missing). For two transactions with missing coordinates these were manually added based on their address.[32]

Both sources included data regarding the building year of the property and the floor space. For the Kadaster this data is based on the BAG (municipal administration of addresses and buildings) and for Funda this is recorded by the real estate agency that created the Funda advertisement page of the property. BAG data is officially recorded but has the potential risk of being outdated, whereas Funda data is recently recorded but potentially more subjective. Both data sources have been combined to reduce missing values an optimize reliability. For the building year of the property the Kadaster data is followed because this is a constant value over time and therefore less prone to errors caused by outdated data. Unknown (building year=1005) or missing values (building year='blank') are recoded by their Funda counterpart. Floor space, on the other hand, is more volatile over time which makes the BAG data less reliable. In addition, Funda requires real estate agents to follow the nen2580 measurement system for floor space and this reduces the potential subjectivity. Therefore, for the floor space Funda data is employed and only replaced by their Kadaster equivalent for missing values (floor space=0).

In order to be useful for the analysis some of the raw property information is transformed into derived variables. With regard to the transaction data the price per square meter – that serves as dependent variable – is generated on the basis of the sales price and the combined floor space variable described above. The transaction date is used to determine

[31] If the bronid was missing this observation was classified as the false one within the pair (n=3). For the other pairs the plausibility of the recorded data was assessed based on a comparison of the last asking price on Funda with the eventual sales price according to the Kadaster or a comparison of the period online and sales period.
[32] By means of the following address to coordinates converter: http://www.gps-coordinaten.nl/gps-coordinaten-converteren.

the year, quarter and month of sale. And the sales duration is categorized into "quick"/0 for sales within a month, "normal"/1 for sales between a month and a year, and "slow"/2 for sales that took over a year. Regarding the structural characteristics all properties are assigned to a cohort based on the year built. These cohorts refer to the decade built from 1900 onwards and includes a rest category for properties built before 1900. Volume is transformed into a dummy to distinguish between high and low ceiling houses, where the threshold is set at the median of 2.80 meters. For a meaningful intercept the number of rooms are centred around the median of 3. And in addition, the categorical variable "heating" (101 categories) is recoded to a dummy. All heating methods that include at least central heating, under floor heating, block heating or district heating are classified as "good"/1, and heating by all others means are identified as "bad"/0. Missing values (heating=0/-1) are set at -1. The outdoor space is split into "no"/0, "small"/1 and "large"/2 categories, where small refers to balconies or small terraces up to 6 square meters and large refers units greater than 6 square meters such as larger terraces and gardens.

Lastly, the distances of each property to the city centre (Dam square), nearest railway station (NS train stations) and nearest highway ramp (highway access points A10) determined in QGIS (see A2) are added to the property dataset. The included accessibility locations are listed in table A1.2.

Table A1.2 Overview of accessibility locations

Sort location (# locations)	
City centre (1)	
Dam square	
NS stations (10)	
Amsterdam Amstel	Amsterdam Muiderpoort
Amsterdam Bijlmer ArenA	Amsterdam RAI
Amsterdam Centraal	Amsterdam Science Park
Amsterdam Holendrecht	Amsterdam Sloterdijk
Amsterdam Lelylaan	Amsterdam Zuid
A10 access points (18)	
S101 Hemhavens	S110 Rivierenbuurt
S102 Sloterdijk	S111 Overamstel
S103 Westerpark	S112 Centrum
S104 Bos en Lommer	S113 Watergraafsmeer
S105 Geuzeveld	S114 Zeeburg
S106 Osdorp	S115 Niewendam
S107 Slotervaart	S116 Noord
S108 Oud Zuid	S117 Kadoelen
S109 Buitenveldert	S118 Tuindorp Oostzaan

Neighbourhood data – OIS Amsterdam

The neighbourhood data is retrieved from https://data.amsterdam.nl, the public databank of the research, information and statistics department of the municipality of Amsterdam (OIS). The BBGA ('Basisbestand Gebieden Amsterdam', version 18-07-2016) contains fragmented information on 'city' (n=1), 'city district' (n=8), 'area22'/'area27' (n=22/27), 'rayon' (n=54), 'neighbourhood combination/district' (n=99) and 'neighbourhood' (n=470) level from 2005 onwards.[33] From these area classifications the 'neighbourhood combination/district' level is the lowest aggregation level for which most, and the essential, data is still available. Therefore, the 'neighbourhood combination/district' statistics are used to represent the neighbourhood characteristics of the residential property sales. Per variable the most recent published statistics are obtained. In most cases this regards 2015, however for some statistics there is a delay in collecting process and these are therefore from earlier years.[34]

The selected statistics have been filtered out the BBGA via excel and the neighbourhood aggregated restaurant characteristics are added from the collapsed restaurant dataset out of STATA. For inter neighbourhood and methodological comparison purposes the restaurant count variable is normalized trough division by the proportion of inhabitants relative to the neighbourhood average.[35] In addition this and the other consumer amenities count variables are transformed into a 'per 1000 inhabitants' statistic. Lastly, two dummy variables are created that indicate whether the neighbourhood is in the centre (1 if city district=centre, 0 otherwise) and within the ring road on the south bank of the river IJ (1 if the restriction is satisfied based on a visual inspection of the neighbourhood boarders, 0 otherwise).

Via a 'many to 1' merge operation in STATA the transaction data is extended with the corresponding neighbourhood characteristics and this finalizes the dataset.

[33] These designations within quotation marks are the direct translations, however the last two are better interpreted as neighbourhood and sub neighbourhood, respectively.
[34] acreages are from 2014 and income is from 2012.
[35] The average is based on urban residential neighbourhoods, thereby excluding solely industrial, business and nature areas (B10, F11, M34, M50, N73 and T92).

Appendix 2 - QGIS

For the geographical analysis the geographical information system QGIS (version 2.14, Essen) is used. In this appendix the performed steps and data management operations done in QGIS are presented.

Setup

- Topographic base map:

The topographic base map of Amsterdam is provided by the municipality of Amsterdam on the following link: https://www.amsterdam.nl/stelselpedia/producten-stelsel/webservices/. The topography (url: http://www.diva.amsterdam.nl/cgi-bin/topografie) and areas (url: http://www.diva.amsterdam.nl/cgi-bin/gebieden) are added to QGIS as WMS layers. For these layers the coordinate reference system (CRS) is set at EPSG:4326, WGS 84.

- Areas classification 2015:

In order to geographically code the restaurant and housing transaction data the shapefiles of the areas classification 2015 (including city districts, neighbourhood combinations and neighbourhoods) are obtained from the municipality of Amsterdam and added as layers to the QGIS project. To prevent the area shapefiles from overlapping with the base map the style is set at blank fill and only the outlines are coloured. The corresponding CRS is EPSG: 28992, Amersfoort / RD New.

Matching restaurants and properties to their corresponding neighbourhood

- Restaurant locations:

The locations of the restaurants are mapped in a new layer. This is done via importing the restaurant csv file as delimited text layer. The encoding is set at UTF-8, the semicolon is selected as delimiter and the checkbox 'first record has field names' is checked. The geometry definition is point coordinates and for the X an Y field the corresponding columns (latitude and longitude) are chosen from the drop down menu. The CRS equals that of the base map: EPSG:4326, WGS 84, which measures in degrees.

- Matching process:

The attribute table of the restaurants location layer can be extended with extra columns that regard the area the restaurant belongs to. To do so, the "join attributes by location" data management tool is used. The target vector layer is the restaurants layer and the join vector layer is the neighbourhood combination area classification layer. The attributes of the first located feature are taken and all records are kept (including non-matching target records).

- Property locations and corresponding neighbourhood:

The locations of the housing transactions are mapped in the same manner as those of the restaurants. Also the same procedure is followed to match them to their corresponding neighbourhood, however in this case the target vector layer is the transaction data layer.

Creation of property specific data

- Accessibility points and distance matrices:

To control for accessibility, three types of locations have been added as separate delimited text layers; the city centre (represented by the Dam square), all heavy rail stations (NS train stations) and the highway access points of the A10 (Amsterdam's ring road). They are all added with CRS EPSG:4326, WGS 84 and thereafter saved as EPSG: 28992, Amersfoort / RD New. This is done because this CRS measures in meters instead of degrees. The transaction dataset is also saved as EPSG: 28992, Amersfoort / RD New, such that the input and target layers have the same CRS. The "distance matrix" analysis tool is used to determine distances between the properties (input point layer) and the accessibility points (target point layers). The output matrix type is linear (N*k x 3) and only the nearest (k=1) target points are used. This results in three separate .csv exports that are added to the transaction dataset in Excel.

- Restaurant data aggregated per buffer area around the properties:

The Python Console plugin is used in order to run script[36] that counts restaurants within a set buffer area around each property and determines the average grade and diversity of these specific restaurants. There are two loops; the first loop regards the transactions whereas the second loop regards the restaurants. This means that for every transaction (loop 1), all restaurants (loop 2) are evaluated based on overlap with the transaction's buffer area. The results are presented in extra columns that are added to the attribute table of the transactions dataset. As the distance of the buffer is set in meters, the transaction and restaurant layers are saved as shapefiles with the corresponding CRS; EPSG: 28992, Amersfoort / RD New. The script is run 18 times; for the six restaurant subsamples ('all', 'graded', 'best 1500', 'best 1000', 'best 500' and 'best 100') and per sample thrice for the three different buffer distances (500m, 650m and 800m). Note that the neighbourhood aggregated statistics are created in STATA and that those are not unique per transaction.

[36] The python script used as a basis for this paper was written by my supervisor, Jeroen van Haaren. As a joint effort, we wrote a specific python script for this particular application.

Project visualization

- Buffers areas:

In order to visually inspect the buffer area sizes and to manually recalculate the Python script's output for control purposes, buffer areas are created in the project. This is done via the "buffer(s)" geoprocessing tool. The input vector layer is set at the (test) transactions dataset and the segments to approximate are kept at the default of 5[37]. The buffer distance field is filled with the different buffer radii in meters (500, 650 and 800) and the output shapefile is saved and added as layer to the canvas. Lastly, some style adjustments are made in the properties section (i.e. transparency percentage and colour).

- Neighbourhood effects:

For visualization purposes the spatially formatted shapefile including area boundaries is extended with the predicted random neighbourhood effects. To do so, the compiled file with neighbourhood effects is imported as a delimited text layer without geometry (attribute only table). For QGIS to process the variables in the right format an additional file in csvt. format is created that specifies the data type of each column. Next, this attribute table is matched to the shapefile of the neighbourhood combination by means of a "table join". The join layer is the attribute table and the join and target field are set at the unique and common neighbourhood combination identification codes ("gebiedcode15" and "VOLLCODE", respectively).

[37] The buffer area is not a true circle but a x-sided polygon. The 'segments to approximate' represent the number of sides per quarter of the buffer area. The default setup thus results in a 20 sided polygon.

Appendix 3 - Additional tables and figures

Table A3.1 – Neighbourhoods of Amsterdam

Neighborhood (code and name)
A Centrum
A00 Burgwallen Oude Zijde
A01 Burgwallen Nieuwe Zijde
A02 Grachtengordel West
A03 Grachtengordel Zuid
A04 Nieuwmarkt/Lastage
A05 Haarlemmerbuurt
A06 Jordaan
A07 De Weteringschans
A08 Weesperbuurt/Plantage
A09 Oostelijke Eilanden/Kadijken
B Westpoort
B10 Westelijk Havenhebied[x]
E West
E12 Houthavens
E13 Spaarndammer- en Zeeheldenbuurt
E14 Staatsliedenbuurt
E15 Centrale Markt
E16 Frederik Hendrikbuurt
E17 Da Costabuurt
E18 Kinkerbuurt
E19 Van Lennepbuurt
E20 Helmersbuurt
E21 Overtoomse Sluis
E22 Vondelbuurt
E36 Sloterdijk
E37 Landlust
E38 Erasmuspark
E39 De Kolenkit
E40 Geuzenbuurt
E41 Van Galenbuurt
E42 Hoofdweg e.o.
E43 Westindische Buurt
E75 Chassébuurt
F Nieuw-West
F11 Bedrijventerrein Sloterdijk[x]
F76 Slotermeer Noordoost
F77 Slotermeer Zuidwest
F78 Geuzenveld
F79 Eendracht
F80 Lutkemeer/Ookmeer
F81 Osdorp Oost
F82 Osdorp Midden
F83 De Punt
F84 Middelveldsche Akerpolder
F85 Slotervaart Noord
F86 Overtoomse Veld
F87 Westlandgracht
F88 Sloter-/Riekerpolder
F89 Slotervaart Zuid
K Zuid
K23 Zuidas
K24 Oude Pijp
K25 Nieuwe Pijp
(continued)
K26 Zuid Pijp
K44 Hoofddorppleinbuurt
K45 Schinkelbuurt
K46 Willemspark
K47 Museumkwartier
K48 Stadionbuurt
K49 Apollobuurt
K52 Scheldebuurt
K53 IJselbuurt
K54 Rijnbuurt
K59 Prinses Irenebuurt e.o.
K90 Buitenveldert West
K91 Buitenveldert Oost
M Oost
M27 Weesperzijde
M28 Oosterparkbuurt
M29 Dapperbuurt
M30 Transvaalbuurt
M31 Indische Buurt West
M32 Indische Buurt Oost
M33 Oostelijk Havengebied
M34 Zeeburgereiland/Nieuwe Diep
M35 IJburg West
M50 IJburg Oost[x]
M51 IJburg Zuid
M55 Frankendael
M56 Middenmeer
M57 Betondorp
M58 Omval/Overamstel
N Noord
N60 Volewijck
N61 IJplein/Vogelbuurt
N62 Tuindorp Nieuwendam
N63 Tuindorp Buiksloot
N64 Nieuwendammerdijk/Buiksloterdijk
N65 Tuindorp Oostzaan
N66 Oostzanerwerf
N67 Kadoelen
N68 Waterlandpleinbuurt
N69 Buikslotermeer
N70 Banne Buiksloot
N71 Noordelijke IJ-oevers Oost
N72 Noordelijke IJ-oevers West
N73 Waterland
N74 Elzenhagen
T Zuidoost
T92 Amstel III/Bullewijk[x]
T93 Bijlmer Centrum (D,F,H)
T94 Bijlmer Oost (E,G,K)
T95 Nellestein
T96 Holendrecht/Reigersbos
T97 Gein
T98 Driemond

Notes: In grey are the districts to which the subsequent neighbourhoods belong. [x] indicates non-residential neighbourhoods were no residential property transactions occurred.

Figure A3.1 Map of Amsterdam's neighbourhoods (source: OIS)

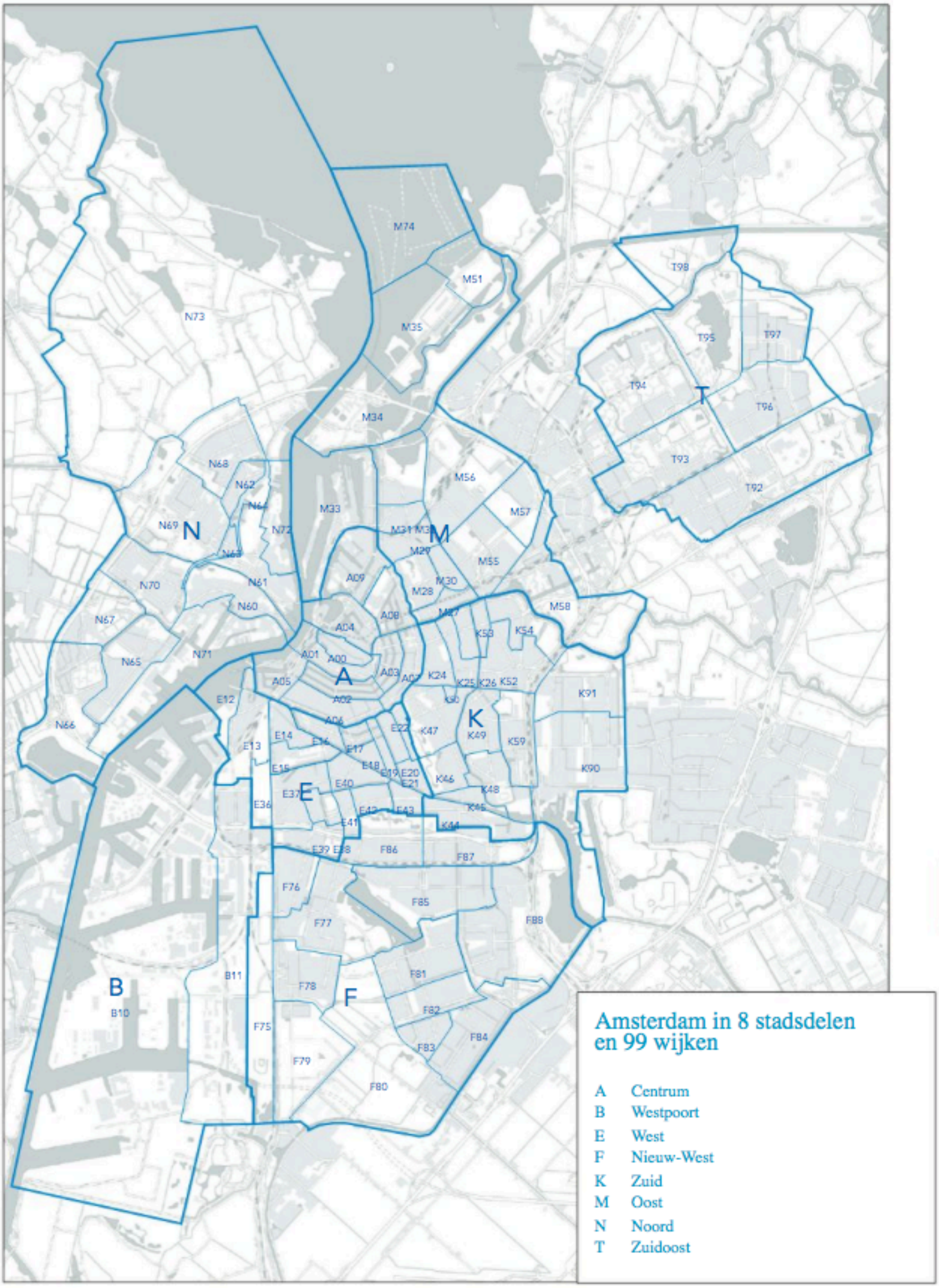

Figure A3.2 Caterpillar plot neighbourhood effects for the grand mean model (m0)

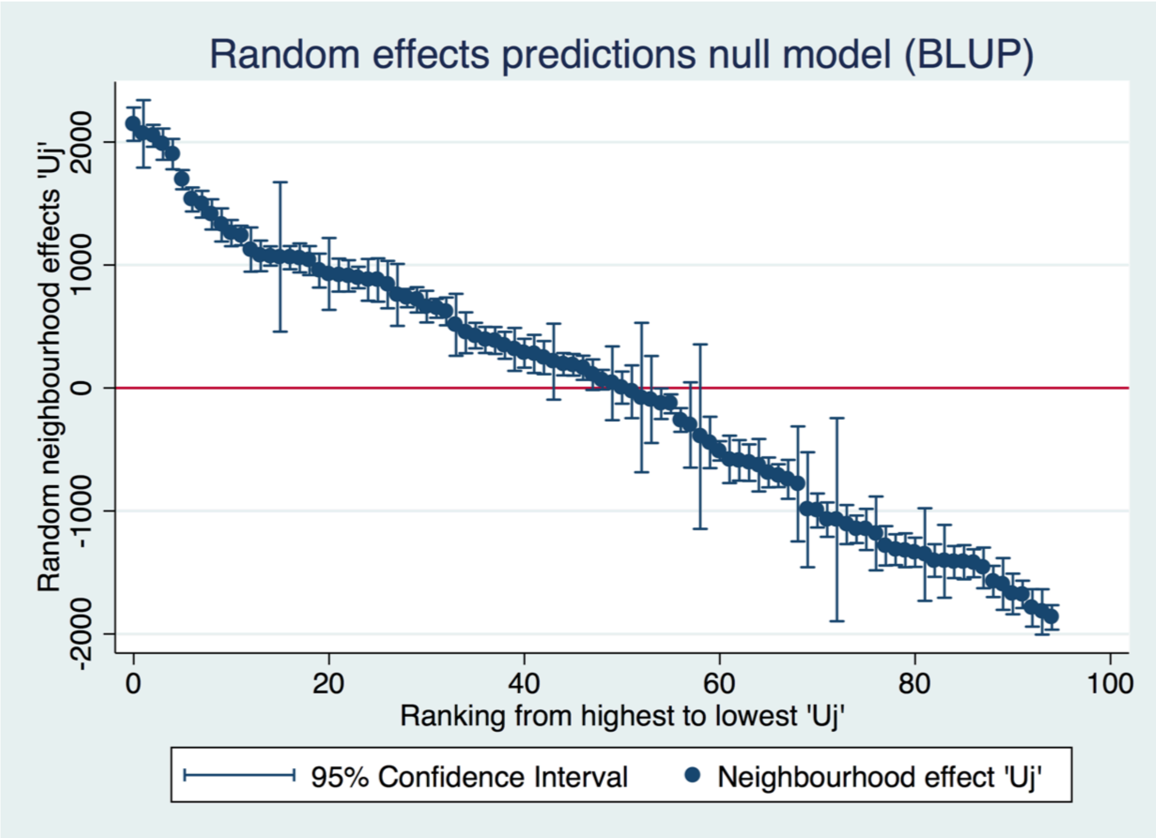

Figure A3.3 Topographic overview neighbourhood effects for the grand mean model (m0)

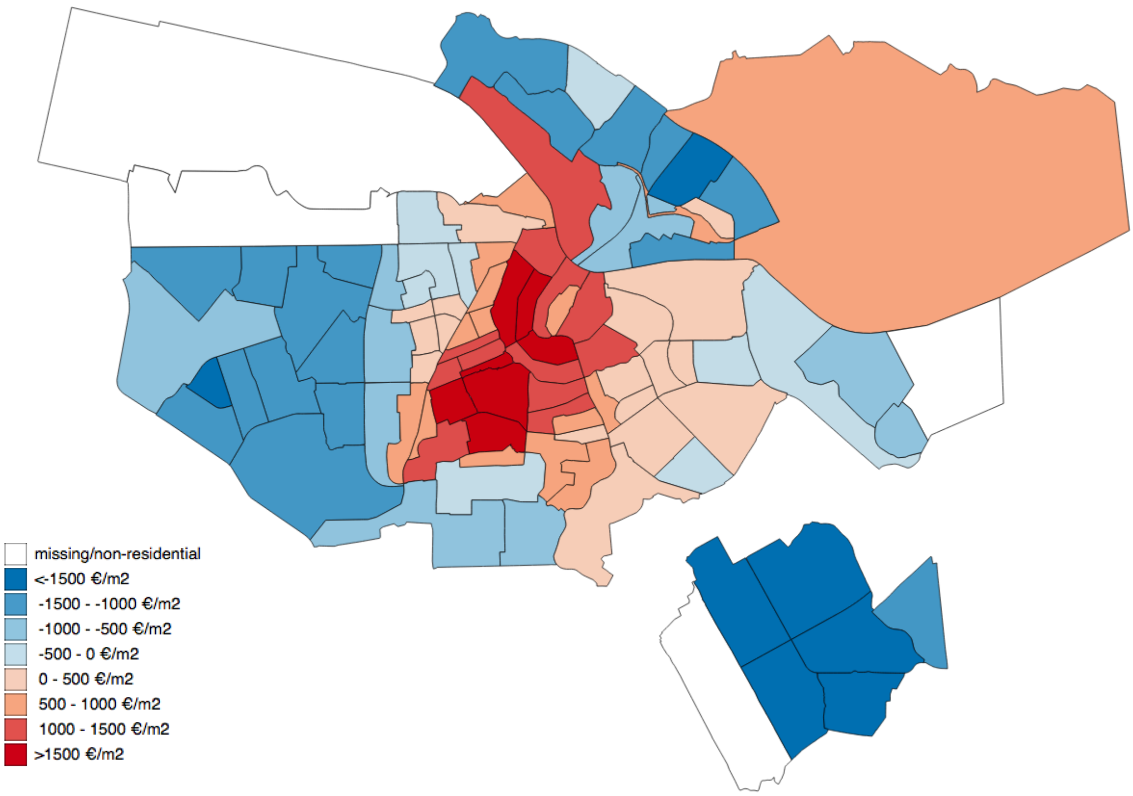

Table A3.2 Predicted random neighbourhood effects and random intercepts grand mean model (m0)

Rank	Neighbourhood	ID	Neighbourhood effect 'Uj'	(SE)	Random intercept 'aj'
1	Grachtengordel-Zuid	A03	2145.21	(69.05)	5756.66
2	Vondelbuurt	E22	2066.50	(140.04)	5677.95
3	Museumkwartier	K47	2050.65	(45.44)	5662.10
4	Grachtengordel-West	A02	1982.44	(64.77)	5593.89
5	Willemspark	K46	1901.90	(62.91)	5513.35
6	Jordaan	A06	1693.93	(39.81)	5305.38
7	Apollobuurt	K49	1532.82	(49.66)	5144.27
8	De Weteringschans	A07	1494.15	(55.33)	5105.60
9	Haarlemmerbuurt	A05	1411.61	(62.61)	5023.06
10	Weesperbuurt/Plantage	A08	1325.79	(68.66)	4937.24
11	Helmersbuurt	E20	1259.39	(54.34)	4870.84
12	Oude Pijp	K24	1239.91	(40.42)	4851.36
13	Burgwallen-Nieuwe Zijde	A01	1125.78	(91.66)	4737.23
14	Nieuwmarkt/Lastage	A04	1073.91	(63.51)	4685.36
15	Nieuwe Pijp	K25	1073.53	(40.15)	4684.98
16	Noordelijke IJ-oevers West	N71	1065.70	(309.98)	4677.15
17	Overtoomse Sluis	E21	1059.90	(48.06)	4671.35
18	Stadionbuurt	K48	1057.91	(60.13)	4669.36
19	Van Lennepbuurt	E19	1035.94	(60.13)	4647.39
20	Da Costabuurt	E17	954.46	(70.26)	4565.91
21	Houthavens	E12	927.43	(149.04)	4538.88
22	Schinkelbuurt	K45	917.95	(68.47)	4529.40
23	Weesperzijde	M27	911.80	(64.93)	4523.25
24	Scheldebuurt	K52	898.17	(44.41)	4509.62
25	Zuid Pijp	K26	879.29	(86.60)	4490.74
26	Prinses Irenebuurt e.o.	K59	878.14	(89.88)	4489.59
27	Burgwallen-Oude Zijde	A00	840.86	(98.29)	4452.31
28	Waterland	N73	756.80	(128.53)	4368.25
29	Hoofddorppleinbuurt	K44	730.92	(37.92)	4342.37
30	Frederik Hendrikbuurt	E16	716.71	(52.52)	4328.16
31	Kinkerbuurt	E18	661.68	(65.60)	4273.13
32	Staatsliedenbuurt	E14	647.93	(39.25)	4259.38
33	Rijnbuurt	K54	622.66	(57.69)	4234.11
34	Nieuwendammerdijk/Buiksloterdijk	N64	513.64	(128.53)	4125.09
35	IJselbuurt	K53	449.11	(84.72)	4060.56
36	Oostelijke Eilanden/Kadijken	A09	426.32	(52.87)	4037.77
37	Oosterparkbuurt	M28	390.83	(54.06)	4002.28
38	Westindische Buurt	E43	386.26	(55.73)	3997.71
39	Geuzenbuurt	E40	347.00	(55.84)	3958.45
40	Frankendael	M55	313.70	(89.02)	3925.15
41	Spaarndammer- en Zeeheldenbuurt	E13	282.85	(59.87)	3894.30
42	Chassébuurt	E75	277.04	(79.16)	3888.49
43	Dapperbuurt	M29	246.87	(68.66)	3858.32
44	Omval/Overamstel	M58	214.27	(157.63)	3825.72
45	Middenmeer	M56	193.31	(46.25)	3804.76
46	Indische Buurt West	M31	188.64	(44.79)	3800.09
47	Hoofdweg e.o.	E42	164.30	(50.03)	3775.75
48	Transvaalbuurt	M30	108.21	(63.36)	3719.66
	(continued)				
49	Oostelijk Havengebied	M33	67.59	(40.66	3679.04
50	Tuindorp Nieuwendam	N62	38.25	(153.15)	3649.70
51	Van Galenbuurt	E41	3.06	(66.63)	3614.51
52	Centrale Markt	E15	-30.59	(109.62)	3580.86
53	Zeeburgereiland/Nieuwe diep	M34	-77.71	(309.98)	3533.74
54	Zuidas	K23	-93.56	(180.49)	3517.89
55	Indische Buurt Oost	M32	-127.82	(63.51)	3483.63
56	Landlust	E37	-128.46	(39.25)	3482.99
57	Erasmuspark	E38	-260.09	(49.30)	3351.36
58	Sloterdijk	E36	-395.70	(382.73)	3215.75
58	Betondorp	M57	-300.74	(177.08)	3310.71
60	Kadoelen	N67	-442.93	(106.61)	3168.52
61	Buitenveldert-West	K90	-511.35	(40.11)	3100.10
62	De Kolenkit	E39	-580.57	(98.29)	3030.88
63	IJplein/Vogelbuurt	N61	-588.72	(84.01)	3022.73
64	Westlandgracht	F87	-607.09	(75.83)	3004.36
65	Volewijck	N60	-628.02	(108.84)	2983.43
66	Buitenveldert-Oost	K91	-686.70	(61.89)	2924.75
67	IJburg West	M35	-713.27	(47.35)	2898.18
68	IJburg Zuid	M51	-743.07	(80.68)	2868.38
69	Tuindorp Buiksloot	N63	-780.00	(238.58)	2831.45
70	Lutkemeer/Ookmeer	F80	-990.06	(238.58)	2621.39
71	Overtoomse Veld	F86	-996.22	(70.47)	2615.23
72	Tuindorp Oostzaan	N65	-1070.46	(71.32)	2540.99
73	Noordelijke IJ-oevers Oost	N72	-1070.82	(421.33)	2540.63
74	Slotervaart Zuid	F89	-1110.58	(80.99)	2500.87
75	Sloter/Riekerpolder	F88	-1148.96	(57.02)	2462.49
76	Slotervaart Noord	F85	-1150.43	(85.46)	2461.02
77	Elzenhagen	N74	-1182.57	(153.15)	2428.88
78	Slotermeer-Noordoost	F76	-1283.48	(81.63)	2327.97
79	Osdorp-Midden	F82	-1314.95	(63.82)	2296.50
80	Oostzanerwerf	N66	-1319.70	(70.26)	2291.75
81	Middelveldsche Akerpolder	F84	-1335.93	(60.52)	2275.52
82	Driemond	T98	-1354.47	(192.03)	2256.98
83	Slotermeer-Zuidwest	F77	-1402.96	(67.71)	2208.49
84	de Eendracht	F79	-1409.61	(151.05)	2201.84
85	Waterlandpleinbuurt	N68	-1415.43	(66.45)	2196.02
86	Banne Buiksloot	N70	-1416.74	(70.89)	2194.71
87	Osdorp-Oost	F81	-1425.04	(57.92)	2186.41
88	Geuzenveld	F78	-1462.82	(84.36)	2148.63
89	Buikslotermeer	N69	-1573.30	(64.77)	2038.15
90	De Punt	F83	-1593.83	(107.34)	2017.62
91	Gein	T97	-1674.86	(84.36)	1936.59
92	Bijlmer Centrum (D,F,H)	T93	-1678.34	(56.69)	1933.11
93	Holendrecht/Reigersbos	T96	-1788.36	(77.72)	1823.09
94	Nellestein	T95	-1820.92	(94.05)	1790.53
95	Bijlmer Oost (E,G,K)	T94	-1865.75	(50.87)	1745.70

Note: Standard errors are in parentheses.

Figure A3.4 Caterpillar plot neighbourhood effects for the compositional model (m1)

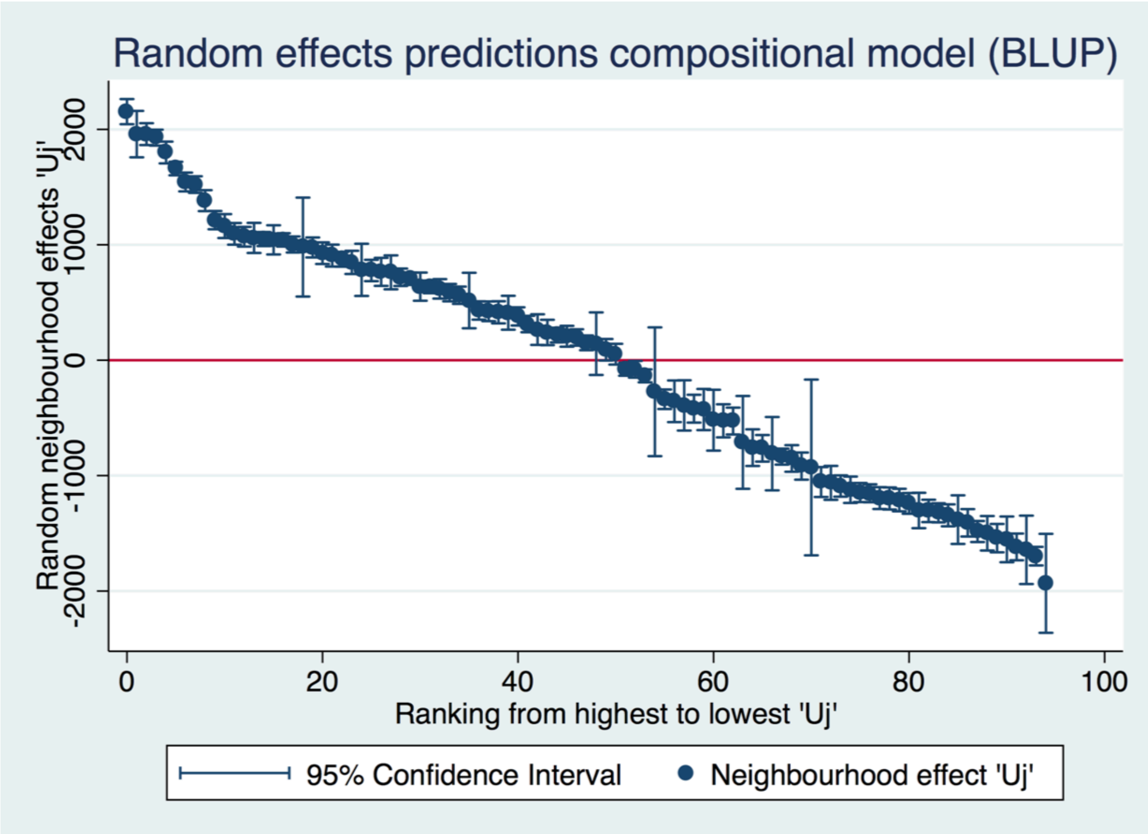

Figure A3.5 Topographic overview neighbourhood effects for the compositional model (m1)

(Duplicate from figure 6 in text)

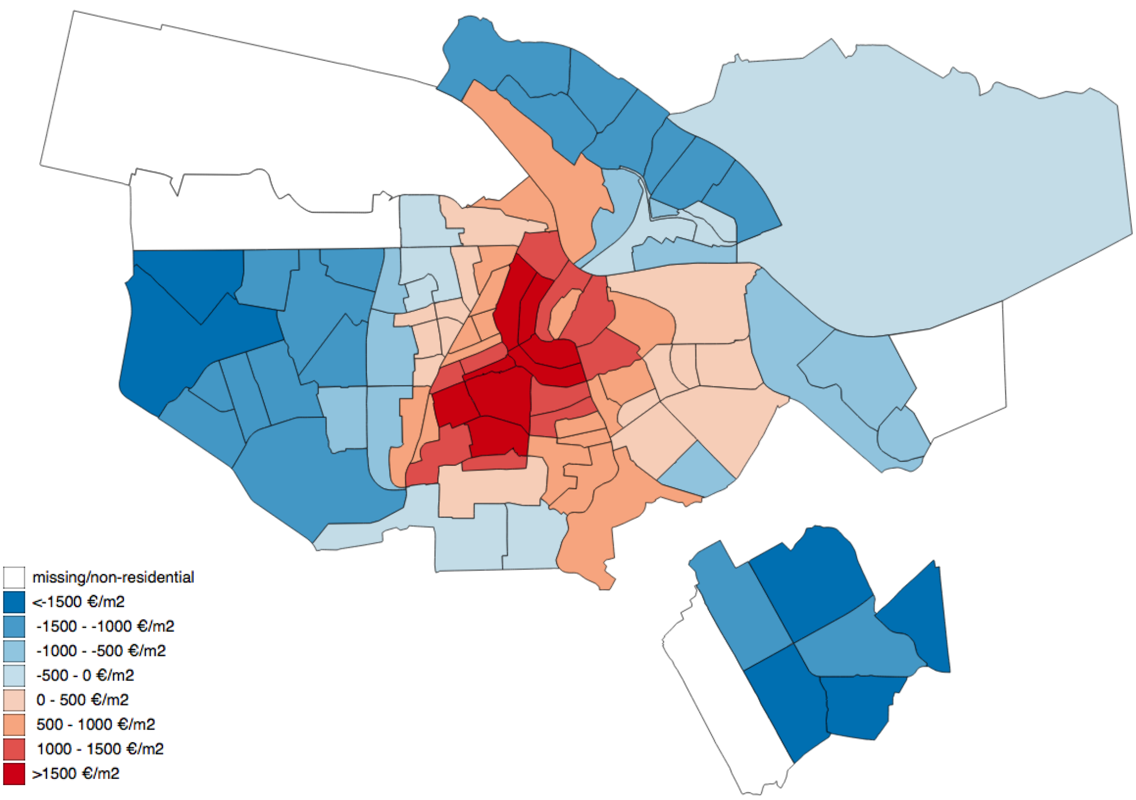

Table A3.3 Predicted random neighbourhood effects and random intercepts compositional model (m1)

ınk	Neighboudhood	ID	Neighbourhood effect 'Uj' (SE)		Random intercept 'aj'		*(continued)*				
1	Grachtengordel-Zuid	A03	2153.54	(55.59)	6333.81	49	Zuidas	K23	143.23	(138.25)	4323.
2	Vondelbuurt	E22	1958.81	(102.51)	6139.08	50	Van Galenbuurt	E41	90.39	(47.63)	4270.
3	Grachtengordel-West	A02	1958.67	(48.26)	6138.94	51	Indische Buurt Oost	M32	52.05	(45.88)	4232.
4	Museumkwartier	K47	1928.14	(35.16)	6108.41	52	Landlust	E37	-78.32	(28.56)	4101.
5	Willemspark	K46	1799.38	(48.10)	5979.65	53	Erasmuspark	E38	-78.57	(36.89)	4101.
6	Jordaan	A06	1660.33	(29.88)	5840.60	54	Buitenveldert-West	K90	-135.51	(28.66)	4044.
7	De Weteringschans	A07	1543.82	(41.50)	5724.09	55	Sloterdijk	E36	-273.48	(284.72)	3906.
8	Apollobuurt	K49	1521.53	(36.61)	5701.80	56	Buitenveldert-Oost	K91	-338.33	(43.12)	3841.
9	Haarlemmerbuurt	A05	1382.39	(46.30)	5562.66	57	Nieuwendammerdijk/Buiksloterdijk	N64	-356.24	(92.06)	3824.
10	Helmersbuurt	E20	1213.59	(40.42)	5393.86	58	Tuindorp Nieuwendam	N62	-391.67	(111.20)	3788.
11	Weesperbuurt/Plantage	A08	1162.02	(52.86)	5342.29	58	IJplein/Vogelbuurt	N61	-420.21	(61.59)	3760.
12	Nieuwmarkt/Lastage	A04	1094.81	(47.79)	5275.08	60	Waterland	N73	-427.51	(90.96)	3752.
13	Stadionbuurt	K48	1069.64	(43.59)	5249.91	61	Betondorp	M57	-519.95	(134.63)	3660.
14	Burgwallen-Nieuwe Zijde	A01	1059.35	(66.44)	5239.62	62	De Kolenkit	E39	-525.35	(73.22)	3654.
15	Oude Pijp	K24	1049.80	(31.04)	5230.07	63	Westlandgracht	F87	-527.21	(59.38)	3653.
16	Prinses Irenebuurt e.o.	K59	1042.64	(64.44)	5222.91	64	Zeeburgereiland/Nieuwe diep	M34	-712.16	(205.16)	3468.
17	Nieuwe Pijp	K25	1042.35	(29.50)	5222.62	65	Volewijck	N60	-757.73	(81.04)	3422.
18	Overtoomse Sluis	E21	1002.54	(35.34)	5182.81	66	Overtoomse Veld	F86	-763.50	(58.79)	3416.
19	Noordelijke IJ-oevers West	N71	979.98	(218.72)	5160.25	67	Tuindorp Buiksloot	N63	-809.91	(162.14)	3370.
20	Van Lennepbuurt	E19	976.55	(44.19)	5156.82	68	IJburg West	M35	-835.58	(35.41)	3344.
21	Weesperzijde	M27	927.29	(47.79)	5107.56	69	IJburg Zuid	M51	-851.34	(58.79)	3328.
22	Schinkelbuurt	K45	906.35	(48.43)	5086.62	70	Slotervaart Zuid	F89	-917.76	(59.98)	3262.
23	Scheldebuurt	K52	874.46	(32.71)	5054.73	71	Noordelijke IJ-oevers Oost	N72	-929.29	(388.55)	3250.
24	Da Costabuurt	E17	847.48	(51.25)	5027.75	72	Slotervaart Noord	F85	-1055.67	(66.03)	3124.
25	Houthavens	E12	782.66	(115.34)	4962.93	73	Kadoelen	N67	-1062.93	(74.96)	3117.
26	Kinkerbuurt	E18	777.32	(47.18)	4957.59	74	Waterlandpleinbuurt	N68	-1090.09	(47.18)	3090.
27	Zuid Pijp	K26	765.40	(61.92)	4945.67	75	Slotermeer-Noordoost	F76	-1122.51	(58.22)	3057.
28	Burgwallen-Oude Zijde	A00	761.19	(74.96)	4941.46	76	Osdorp-Oost	F81	-1146.59	(42.23)	3033.
29	Frederik Hendrikbuurt	E16	718.52	(38.57)	4898.79	77	Sloter/Riekerpolder	F88	-1153.01	(39.60)	3027.
30	Hoofddorppleinbuurt	K44	705.67	(27.37)	4885.94	78	Osdorp-Midden	F82	-1194.76	(48.26)	2985.
31	IJselbuurt	K53	637.23	(62.26)	4817.50	79	Banne Buiksloot	N70	-1198.00	(48.75)	2982.
32	Staatsliedenbuurt	E14	635.06	(28.04)	4815.33	80	Tuindorp Oostzaan	N65	-1211.70	(49.78)	2968.
33	Rijnbuurt	K54	618.15	(43.01)	4798.42	81	Buikslotermeer	N69	-1240.61	(45.88)	2939.
34	Oosterparkbuurt	M28	585.51	(38.41)	4765.78	82	De Punt	F83	-1302.24	(78.16)	2878.
35	Oostelijke Eilanden/Kadijken	A09	562.83	(38.17)	4743.10	83	Slotermeer-Zuidwest	F77	-1305.77	(49.43)	2874.
36	Omval/Overamstel	M58	517.05	(122.54)	4697.32	84	Middelveldsche Akerpolder	F84	-1322.35	(42.23)	2857.
37	Westindische Buurt	E43	430.76	(40.52)	4611.03	85	Oostzanerwerf	N66	-1344.03	(48.59)	2836.
38	Spaarndammer- en Zeeheldenbuurt	E13	423.60	(43.47)	4603.87	86	Elzenhagen	N74	-1381.41	(107.47)	2798.
39	Dapperbuurt	M29	414.96	(48.92)	4595.23	87	Geuzenveld	F78	-1408.81	(60.61)	2771.
40	Centrale Markt	E15	411.18	(74.96)	4591.45	88	Bijlmer Centrum (D,F,H)	T93	-1484.38	(46.45)	2695.
41	Geuzenbuurt	E40	379.58	(40.14)	4559.85	89	Nellestein	T95	-1499.39	(76.19)	2680.
42	Middenmeer	M56	313.25	(36.19)	4493.52	90	Gein	T97	-1541.64	(62.61)	2638.
43	Frankendael	M55	265.14	(67.74)	4445.41	91	de Eendracht	F79	-1552.29	(101.01)	2627.
44	Chassébuurt	E75	240.36	(56.08)	4420.63	92	Holendrecht/Reigersbos	T96	-1617.78	(59.08)	2562.
45	Indische Buurt West	M31	217.99	(32.27)	4398.26	93	Driemond	T98	-1643.19	(151.19)	2537.
46	Transvaalbuurt	M30	207.41	(46.02)	4387.68	94	Bijlmer Oost (E,G,K)	T94	-1697.77	(41.10)	2482.
47	Hoofdweg e.o.	E42	197.11	(36.19)	4377.38	95	Lutkemeer/Ookmeer	F80	-1933.15	(218.72)	2247.
48	Oostelijk Havengebied	M33	150.57	(32.71)	4330.84						

Note: Standard errors are in parentheses.

Figure A3.6 Caterpillar plot neighbourhood effects for the alternative complete model (m3b)

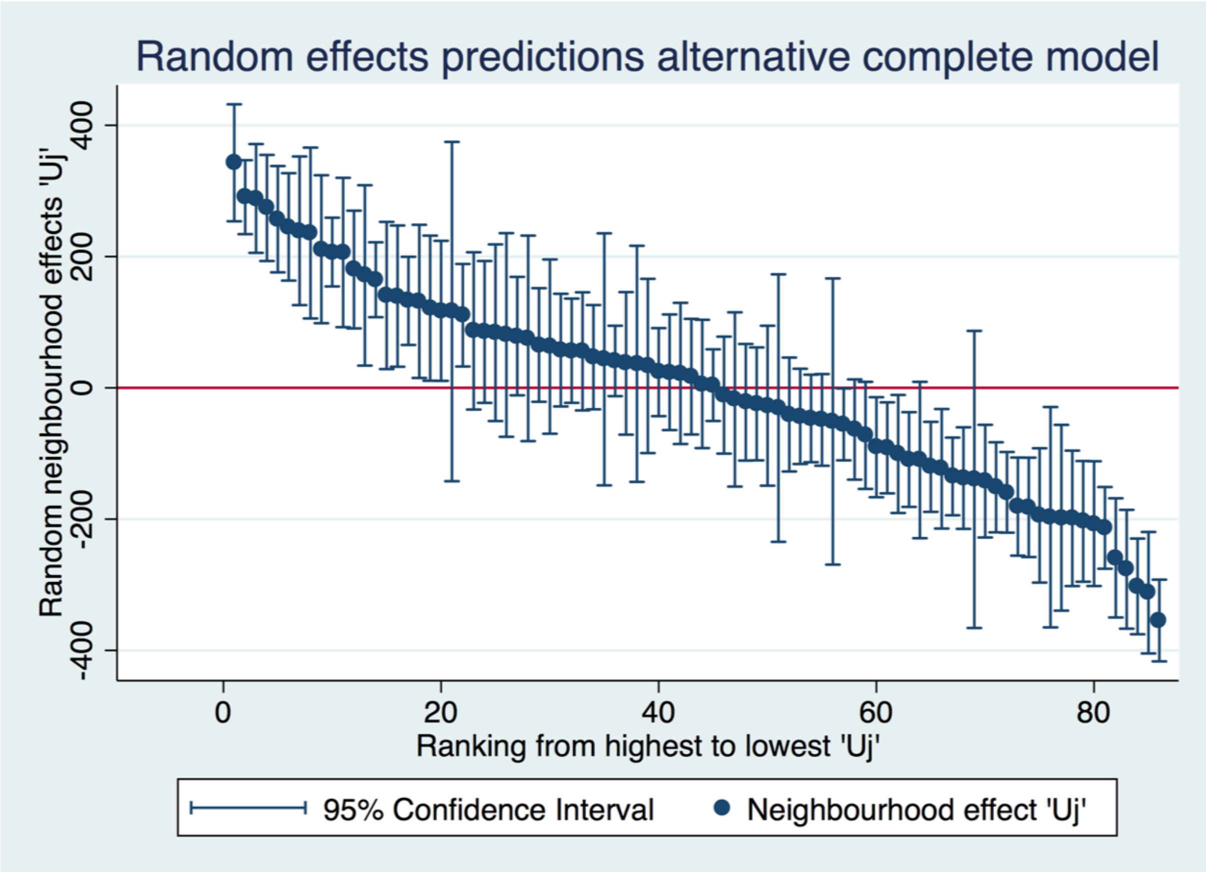

Figure A3.7 Topographic overview neighbourhood effects for the alternative complete model (m3b)

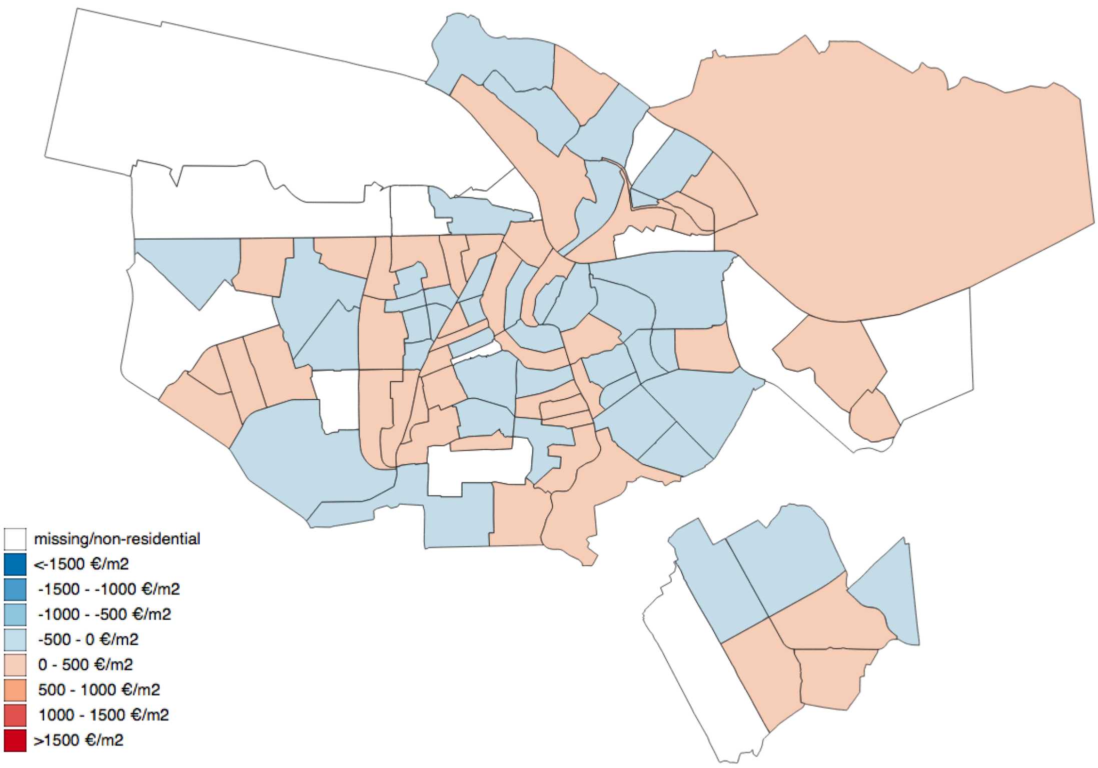

Table A3.4 Predicted random neighbourhood effects and random intercepts alternative complete model (m3b)

ık	Neighboudhood	Neighbourhood effect 'Uj'	(SE)	Random intercept 'aj'
1	M27 Weesperzijde	342.85	(45.47)	4812.50
2	K25 Nieuwe Pijp	290.44	(28.74)	4760.09
3	E19 Van Lennepbuurt	288.54	(42.28)	4758.20
4	K54 Rijnbuurt	274.01	(41.21)	4743.66
5	K91 Buitenveldert-Oost	256.92	(41.32)	4726.57
6	K48 Stadionbuurt	245.22	(41.73)	4714.87
7	K53 IJselbuurt	239.24	(57.76)	4708.89
8	E39 De Kolenkit	235.85	(66.40)	4705.50
9	K26 Zuid Pijp	211.16	(57.48)	4680.82
10	K44 Hoofddorppleinbuurt	206.83	(26.72)	4676.48
11	T97 Gein	206.17	(58.04)	4675.82
12	K46 Willemspark	180.21	(45.75)	4649.86
13	F83 De Punt	171.26	(70.11)	4640.91
14	A06 Jordaan	164.70	(29.10)	4634.35
15	N61 IJplein/Vogelbuurt	140.69	(57.20)	4610.34
16	M51 IJburg Zuid	139.75	(54.89)	4609.41
17	M35 IJburg West	132.49	(34.27)	4602.14
18	K59 Prinses Irenebuurt e.o.	131.70	(59.52)	4601.35
19	F78 Geuzenveld	121.34	(56.40)	4591.00
20	F76 Slotermeer-Noordoost	117.29	(54.42)	4586.94
21	N71 Noordelijke IJ-oevers West	116.17	(131.88)	4585.82
22	A07 De Weteringschans	110.58	(39.85)	4580.24
23	A01 Burgwallen-Nieuwe Zijde	86.72	(61.12)	4556.38
24	T96 Holendrecht/Reigersbos	85.16	(55.14)	4554.81
25	T95 Nellestein	83.94	(68.65)	4553.59
26	N73 Waterland	80.53	(79.14)	4550.18
27	K45 Schinkelbuurt	78.81	(46.03)	4548.46
28	N64 Nieuwendammerdijk/Buiksloterdijk	75.35	(79.88)	4545.00
29	A05 Haarlemmerbuurt	65.28	(44.16)	4534.93
30	N67 Kadoelen	62.83	(67.72)	4532.49
31	M32 Indische Buurt Oost	57.45	(43.79)	4527.10
32	F81 Osdorp-Oost	56.55	(40.52)	4526.20
33	F82 Osdorp-Midden	55.55	(45.89)	4525.20
34	F84 Middelveldsche Akerpolder	46.69	(40.52)	4516.34
35	M58 Omval/Overamstel	43.42	(97.96)	4513.08
36	E14 Staatsliedenbuurt	40.95	(27.36)	4510.60
37	F87 Westlandgracht	37.23	(55.38)	4506.88
38	N62 Tuindorp Nieuwendam	36.56	(91.75)	4506.22
39	E15 Centrale Markt	33.32	(67.72)	4502.97
40	E21 Overtoomse Sluis	23.92	(34.21)	4493.57
41	N68 Waterlandpleinbuurt	23.72	(44.93)	4493.38
42	F86 Overtoomse Veld	21.94	(54.89)	4491.59
43	E18 Kinkerbuurt	17.02	(44.93)	4486.67
	(continued)			
44	A08 Weesperbuurt/Plantage	5.91	(49.88)	4475.56
45	E37 Landlust	4.08	(27.85)	4473.74
46	A04 Nieuwmarkt/Lastage	-11.10	(45.47)	4458.55
47	A00 Burgwallen-Oude Zijde	-17.70	(67.72)	4451.96
48	E41 Van Galenbuurt	-22.01	(45.33)	4447.64
49	M30 Transvaalbuurt	-24.47	(43.91)	4445.18
50	M55 Frankendael	-27.25	(62.15)	4442.41
51	M57 Betondorp	-30.85	(103.96)	4438.80
52	T93 Bijlmer Centrum (D,F,H)	-40.68	(44.28)	4428.97
53	M28 Oosterparkbuurt	-43.49	(37.04)	4426.17
54	K47 Museumkwartier	-46.65	(34.04)	4423.00
55	E38 Erasmuspark	-48.88	(35.64)	4420.77
56	T98 Driemond	-51.32	(111.21)	4418.33
57	K90 Buitenveldert-West	-55.72	(27.95)	4413.93
58	E43 Westindische Buurt	-63.51	(38.96)	4406.14
58	E13 Spaarndammer- en Zeeheldenbuurt	-72.48	(41.63)	4397.17
60	E20 Helmersbuurt	-90.46	(38.88)	4379.20
61	K49 Apollobuurt	-91.44	(35.38)	4378.22
62	A02 Grachtengordel-West	-100.75	(45.89)	4368.90
63	A09 Oostelijke Eilanden/Kadijken	-109.24	(36.82)	4360.41
64	F85 Slotervaart Noord	-109.99	(60.79)	4359.66
65	E42 Hoofdweg e.o.	-120.39	(35.00)	4349.27
66	M29 Dapperbuurt	-123.32	(46.46)	4346.34
67	K24 Oude Pijp	-134.99	(30.20)	4334.67
68	T94 Bijlmer Oost (E,G,K)	-137.52	(39.49)	4332.13
69	N63 Tuindorp Buiksloot	-139.59	(115.46)	4330.06
70	N69 Buikslotermeer	-142.14	(43.79)	4327.51
71	M56 Middenmeer	-151.57	(35.00)	4318.08
72	M31 Indische Buurt West	-159.20	(31.35)	4310.45
73	F88 Sloter/Riekerpolder	-180.93	(38.13)	4288.72
74	E40 Geuzenbuurt	-182.08	(38.62)	4287.57
75	A03 Grachtengordel-Zuid	-194.41	(52.21)	4275.25
76	F79 de Eendracht	-197.08	(85.65)	4272.58
77	N60 Volewijck	-197.93	(72.21)	4271.72
78	E75 Chassébuurt	-198.84	(52.63)	4270.81
79	F77 Slotermeer-Zuidwest	-203.45	(46.91)	4266.20
80	E17 Da Costabuurt	-206.88	(48.49)	4262.77
81	K52 Scheldebuurt	-213.36	(31.76)	4256.29
82	N70 Banne Buiksloot	-259.06	(46.32)	4210.59
83	N66 Oostzanerwerf	-276.42	(46.17)	4193.23
84	E16 Frederik Hendrikbuurt	-302.52	(37.19)	4167.13
85	N65 Tuindorp Oostzaan	-312.12	(47.21)	4157.53
86	M33 Oostelijk Havengebied	-354.51	(31.76)	4115.14

Note: Standard errors are in parentheses. In addition to the non-residential neighbourhoods there are some neighbourhoods with missing neighbourhood characteristics and these are therefore dropped from the estimation. This includes F80, E12, E22, E36, F89, K23, M34, N72 and N74.

Appendix 4 - Raw STATA output

A4.1 Descriptive statistics

Table A4.1.1 Descriptive statistics transactional and structural attributes

Variable	Obs	Mean	Std. Dev.	Min	Max
JAAR_Q					
20132	19,037	.0321479	.1763975	0	1
20133	19,037	.0443872	.2059593	0	1
20134	19,037	.051111	.2202299	0	1
20141	19,037	.0493775	.2166607	0	1
20142	19,037	.0615118	.240273	0	1
20143	19,037	.078006	.2681881	0	1
20144	19,037	.1011714	.3015635	0	1
20151	19,037	.0649262	.2464021	0	1
20152	19,037	.078111	.2683533	0	1
20153	19,037	.1033251	.304391	0	1
20154	19,037	.1045858	.306027	0	1
20161	19,037	.0952356	.2935478	0	1
20162	19,037	.0978621	.2971359	0	1
sales_peri~t					
1	16,539	.6639458	.4723719	0	1
2	16,539	.2011609	.4008802	0	1
KAD_TYPE					
2	18,935	.0083443	.0909678	0	1
3	18,935	.1038817	.3051151	0	1
8	18,935	.8779509	.3273512	0	1
cohort					
1900	19,022	.1233309	.3288253	0	1
1910	19,022	.0738618	.2615528	0	1
1920	19,022	.1079277	.3102972	0	1
1930	19,022	.1269057	.332876	0	1
1940	19,022	.0202923	.141002	0	1
1950	19,022	.0410577	.198429	0	1
1960	19,022	.0687099	.2529668	0	1
1970	19,022	.0376932	.1904582	0	1
1980	19,022	.0731259	.2603498	0	1
1990	19,022	.0957838	.2943023	0	1
2000	19,022	.1096099	.3124111	0	1
2010	19,022	.0146147	.1200076	0	1
outside_cat					
1	16,537	.325573	.4686027	0	1
2	16,537	.3185584	.4659314	0	1
kamers_cen~d	16,443	.2922216	1.358384	-2	13
high_ceiling	16,593	.5023805	.5000094	0	1
DUMGAR	19,037	.0588328	.2353177	0	1
DUMBER	19,037	.4875243	.4998575	0	1
DUMMON	19,037	.0451227	.2075786	0	1
DUMVERW	14,954	.963488	.1875665	0	1

Table A4.1.2 Descriptive statistics absolute locational attributes

Variable	Obs	Mean	Std. Dev.	Min	Max
Distance_t~e	19,037	3497.519	2044.161	142.2335	11571.65
Distance_t~n	19,037	1687.11	889.4425	54.05584	8738.115
Distance_t~p	19,037	1885.898	999.7103	53.65004	6246.67

Table A4.1.3 Descriptive statistics relative locational attributes

Variable	Obs	Mean	Std. Dev.	Min	Max
Bevdicht	19,037	14477.74	7578.456	89	28445
BevNW_p	19,037	28.49594	17.06144	4	73.7
Wkoop_p	19,037	31.31685	10.5069	7.3	87.9
Ihhink_gem	18,850	33027.79	8622.807	23310	64621
ORomgeving~r	18,989	6.913987	.4443383	4.7	8.1
ORwoningen~r	18,981	6.968205	.6258028	5.4	8.8
ORgroenmoo~r	18,989	6.871252	.5295083	4.8	8.4
ORwater_p	19,037	13.44288	13.32028	1.4	66.7
ORgroen_p	19,037	13.25488	14.26557	0	93.7
ORverblijf_i	18,977	113.7414	94.15316	1	791
Lhorecaove~r	18,981	7.754512	.5641188	5	8.9
VKov_r	18,989	7.778519	.478286	2.2	8.9
Centrum	19,037	.1185061	.3232149	0	1
Ring	19,037	.701266	.457715	0	1
Vimpact_i	18,968	85.09295	27.22956	17	160
Vbeleving_i	18,968	93.96215	23.16302	59	168
OaanbodBAO_r	18,902	7.337562	.3480429	5.2	8.3
Bhv~tdg_1000	19,037	1.973802	2.079726	0	21.43367
Bhv~ndg_1000	19,037	8.086121	10.18835	.6242197	107.1684
Bhvest_gez~0	19,037	7.365765	3.876849	.5344735	28.16901
Bhvest_cul~0	19,037	15.44909	10.14739	1.557093	345.0704
Bhvest_re_~0	19,037	3.235029	5.045806	0	49.29578
Bhvest_ca_~0	19,037	1.420879	2.946911	0	27.4519

Table A4.1.4 Descriptive statistics absolute restaurant measures

Variable	Obs	Mean	Std. Dev.	Min	Max
nres650gra	19,037	50.41104	62.09525	0	334
mg650gra	17,992	7.836825	.268653	5.4	8.5
nres650_ng	19,037	19.70289	26.01284	0	178
nres650_n~55	19,037	11.71576	13.87766	0	90
nres650_5~65	19,037	10.68934	14.40864	0	74
nres650_6~75	19,037	13.67852	17.17264	0	94
nres650_7~85	19,037	11.87876	14.96316	0	81
nres650_85	19,037	2.448653	3.383885	0	19
hhin650gra	19,037	.790528	.2867707	0	.986085

Table A4.1.5 Descriptive statistics relative restaurant measures

Variable	Obs	Mean	Std. Dev.	Min	Max
nresBCg~1000	19,037	2.863984	4.482937	0	28.16901
mgBCgra	18,290	7.83136	.2859872	6.4	8.3
nresBC1000~g	19,037	1.145817	2.118934	0	19.52846
nresBC100~55	19,037	.6661953	1.082891	0	8.335318
nresBC100~65	19,037	.597836	.9932388	0	6.335053
nresBC100~75	19,037	.798225	1.286466	0	9.385265
nresBC100~85	19,037	.6629576	1.074463	0	14.08451
nresBC8~1000	19,037	.1387698	.2479992	0	1.484781
hhinBCgra	19,037	.7872534	.2473994	0	.9729234

A4.2 Estimation output

Table A4.2.1 Raw and full estimation results compositional model (m1)

Mixed-effects ML regression		Number of obs =	**14,665**
Group variable: **BC_number**		Number of groups =	**95**
		Obs per group:	
		min =	**2**
		avg =	**154.4**
		max =	**467**
		Wald chi2(**38**) =	**8701.39**
Log likelihood = **-114692.01**		Prob > chi2 =	**0.0000**

m2price_w	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
JAAR_Q						
20131	-1053.915	30.58114	-34.46	0.000	-1113.853	-993.9775
20132	-1095.075	32.35139	-33.85	0.000	-1158.483	-1031.667
20133	-1090.821	29.20723	-37.35	0.000	-1148.066	-1033.576
20134	-1091.3	28.25852	-38.62	0.000	-1146.686	-1035.915
20141	-984.0483	28.33279	-34.73	0.000	-1039.58	-928.5171
20142	-928.7509	27.06293	-34.32	0.000	-981.7933	-875.7085
20143	-852.7639	25.94372	-32.87	0.000	-903.6126	-801.9151
20144	-726.8743	23.45591	-30.99	0.000	-772.8471	-680.9016
20151	-658.886	25.94282	-25.40	0.000	-709.733	-608.039
20152	-562.6263	24.68168	-22.80	0.000	-611.0015	-514.2511
20153	-365.484	22.97572	-15.91	0.000	-410.5156	-320.4524
20154	-242.5775	23.0563	-10.52	0.000	-287.767	-197.388
20161	-105.3194	22.76259	-4.63	0.000	-149.9333	-60.70558
sales_period_cat						
0	64.58731	16.30018	3.96	0.000	32.63955	96.53507
2	-143.1819	12.97497	-11.04	0.000	-168.6124	-117.7514
KAD_TYPE						
1	1554.272	60.11079	25.86	0.000	1436.457	1672.087
2	1085.531	59.05156	18.38	0.000	969.7918	1201.27
3	420.9741	22.83292	18.44	0.000	376.2224	465.7258
cohort						
1100	104.3932	30.85198	3.38	0.001	43.92443	164.862
1900	38.0065	27.94263	1.36	0.174	-16.76004	92.77304
1910	70.57761	30.15551	2.34	0.019	11.47389	129.6813
1920	-.4071821	23.32968	-0.02	0.986	-46.13252	45.31815
1940	-109.8588	40.98963	-2.68	0.007	-190.197	-29.5206
1950	-220.8469	36.18504	-6.10	0.000	-291.7683	-149.9255
1960	-433.6268	36.97782	-11.73	0.000	-506.102	-361.1516
1970	-372.6965	39.87178	-9.35	0.000	-450.8438	-294.5492
1980	-262.4838	31.40779	-8.36	0.000	-324.0419	-200.9257
1990	-248.5436	30.54775	-8.14	0.000	-308.4161	-188.6711
2000	-159.4801	29.88751	-5.34	0.000	-218.0586	-100.9017
2010	166.029	49.65655	3.34	0.001	68.70396	263.3541
outside_cat						
1	2.401401	12.85136	0.19	0.852	-22.78681	27.58961
2	78.48564	12.88703	6.09	0.000	53.22753	103.7438
kamers_centered	-39.78115	4.919256	-8.09	0.000	-49.42271	-30.13958
high_ceiling_m1	104.27	10.28939	10.13	0.000	84.10315	124.4368
DUMGAR	113.3592	22.14671	5.12	0.000	69.95243	156.766
DUMBER_m1	28.12081	11.6618	2.41	0.016	5.264103	50.97751
DUMMON	.8512189	24.34142	0.03	0.972	-46.85709	48.55952
DUMVERW_m1	299.3409	26.83247	11.16	0.000	246.7502	351.9316
_cons	4180.265	111.6893	37.43	0.000	3961.358	4399.172

Random-effects Parameters	Estimate	Std. Err.	[95% Conf.	Interval]
BC_number: Identity				
var(_cons)	1096442	160756.8	822593.9	1461458
var(Residual)	350157.7	4102.591	342208.4	358291.7

LR test vs. linear model: chibar2(01) = **12029.94** Prob >= chibar2 = **0.0000**

Table A4.2.2 Raw and full estimation results contextual model (m2)

```
Mixed-effects ML regression                     Number of obs     =     14,440
Group variable: BC_number                       Number of groups  =         86

                                                Obs per group:
                                                              min =          7
                                                              avg =      167.9
                                                              max =        467

                                                Wald chi2(64)     =   11214.42
Log likelihood = -112640.39                     Prob > chi2       =     0.0000
```

m2price_w	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
JAAR_Q						
20131	-1061.591	30.51665	-34.79	0.000	-1121.402	-1001.779
20132	-1102.941	32.22839	-34.22	0.000	-1166.107	-1039.774
20133	-1102.827	29.21358	-37.75	0.000	-1160.085	-1045.57
20134	-1093.914	28.19211	-38.80	0.000	-1149.17	-1038.659
20141	-998.1754	28.31926	-35.25	0.000	-1053.68	-942.6706
20142	-941.7266	27.06632	-34.79	0.000	-994.7756	-888.6776
20143	-858.0967	25.93449	-33.09	0.000	-908.9273	-807.266
20144	-733.0716	23.39338	-31.34	0.000	-778.9218	-687.2214
20151	-666.9278	25.88511	-25.76	0.000	-717.6617	-616.194
20152	-563.5807	24.64352	-22.87	0.000	-611.8811	-515.2803
20153	-372.378	22.94216	-16.23	0.000	-417.3439	-327.4122
20154	-249.6022	23.0435	-10.83	0.000	-294.7666	-204.4378
20161	-107.6792	22.77238	-4.73	0.000	-152.3123	-63.0462
sales_period_cat						
0	62.26517	16.29532	3.82	0.000	30.32693	94.20342
2	-141.916	12.9531	-10.96	0.000	-167.3036	-116.5283
KAD_TYPE						
1	1593.607	60.13755	26.50	0.000	1475.74	1711.475
2	1085.349	59.13811	18.35	0.000	969.44	1201.257
3	452.0909	22.87393	19.76	0.000	407.2588	496.923
cohort						
1100	47.08684	30.63476	1.54	0.124	-12.95619	107.1299
1900	14.99068	27.43127	0.55	0.585	-38.77361	68.75498
1910	69.85314	29.56148	2.36	0.018	11.9137	127.7926
1920	-6.290255	22.98699	-0.27	0.784	-51.34392	38.76341
1940	-72.73709	40.73934	-1.79	0.074	-152.5847	7.110553
1950	-215.8253	36.16141	-5.97	0.000	-286.7003	-144.9502
1960	-437.3113	36.4039	-12.01	0.000	-508.6616	-365.961
1970	-384.764	39.10726	-9.84	0.000	-461.4128	-308.1152
1980	-300.926	31.08765	-9.68	0.000	-361.8566	-239.9953
1990	-278.145	30.02303	-9.26	0.000	-336.9891	-219.301
2000	-158.2425	29.58448	-5.35	0.000	-216.227	-100.258
2010	202.0539	50.75208	3.98	0.000	102.5817	301.5262
outside_cat						
1	5.558808	12.78763	0.43	0.664	-19.50448	30.6221
2	80.98609	12.86385	6.30	0.000	55.77341	106.1988
kamers_centered	-42.07698	4.9246	-8.54	0.000	-51.72902	-32.42494
high_ceiling_m1	102.0433	10.26492	9.94	0.000	81.92444	122.1622
DUMGAR	117.9076	22.26927	5.29	0.000	74.26059	161.5545
DUMBER_m1	37.24536	11.6395	3.20	0.001	14.43236	60.05835
DUMMON	-7.462859	24.29797	-0.31	0.759	-55.08601	40.16029
DUMVERW_m1	304.8768	26.70316	11.42	0.000	252.5396	357.214
Distance_to_centre_c	-.210352	.0133607	-15.74	0.000	-.2365384	-.1841655
Distance_to_station_c	.0365871	.0172741	2.12	0.034	.0027304	.0704437
Distance_to_ramp_c	.1194631	.0156312	7.64	0.000	.0888264	.1500997
Bevdicht_z	93.52151	53.11433	1.76	0.078	-10.58067	197.6237
BevNW_p_z	-9.952547	53.17158	-0.19	0.852	-114.1669	94.26184
Wkoop_p_z	-129.2322	34.36666	-3.76	0.000	-196.5896	-61.87477
Ihhink_gem_z	195.1512	70.40102	2.77	0.006	57.16776	333.1347
VKov_r_z	48.71005	23.1277	2.11	0.035	3.380593	94.0395
Centrum_c	-21.49164	121.4568	-0.18	0.860	-259.5427	216.5594
Ring_c	453.8198	100.7607	4.50	0.000	256.3324	651.3071
Vimpact_i_z	-74.92447	37.28333	-2.01	0.044	-147.9985	-1.850483
Vbeleving_i_z	-96.94983	47.59034	-2.04	0.042	-190.2252	-3.674485
OaanbodBAO_r_z	-36.76654	24.34055	-1.51	0.131	-84.47313	10.94005
ORomgevingmooi_r_z	285.2211	105.9509	2.69	0.007	77.56122	492.881
ORwoningenmooi_r_z	-189.5882	87.16235	-2.18	0.030	-360.4233	-18.75314
ORgroenmooi_r_z	-88.53263	66.77917	-1.33	0.185	-219.4174	42.35213
ORwater_p_z	-51.08701	36.94414	-1.38	0.167	-123.4962	21.32218
ORgroen_p_z	65.87041	36.81305	1.79	0.074	-6.281843	138.0227
ORverblijf_i_z	28.29929	53.01588	0.53	0.593	-75.60992	132.2085
Lhorecaoverlast_r_z	-61.15032	45.31101	-1.35	0.177	-149.9583	27.65763
Bhvest_winkvestdg_1000_z	-19.66142	77.14523	-0.25	0.799	-170.8633	131.5405
Bhvest_winkvestndg_1000_z	-95.71108	82.5067	-1.16	0.246	-257.4212	65.99908
Bhvest_gezzorg_1000_z	274.5945	63.08235	4.35	0.000	150.9554	398.2336
Bhvest_cult_1000_z	-79.90766	63.77305	-1.25	0.210	-204.9005	45.08522
Bhvest_re_1000_z	380.5964	163.0333	2.33	0.020	61.05698	700.1359
Bhvest_ca_1000_z	-313.8001	131.0191	-2.40	0.017	-570.5929	-57.00737
_cons	4460.482	36.86292	121.00	0.000	4388.232	4532.732

Random-effects Parameters	Estimate	Std. Err.	[95% Conf.	Interval]
BC_number: Identity				
var(_cons)	37819	6702.227	26721.53	53525.25
var(Residual)	343479	4055.955	335620.8	351521.3

LR test vs. linear model: chibar2(01) = 865.09   Prob >= chibar2 = 0.0000

Table A4.2.3 Comparison results contextual and iens.nl validity model (m2', here m2tt)

Variable	m2	m2t	m2tt
m2price_w			
JAAR_Q			
20131	-1061.5906***	-1061.5915***	-1061.6019***
20132	-1102.9405***	-1103.1806***	-1103.216***
20133	-1102.8272***	-1102.7934***	-1102.796***
20134	-1093.9143***	-1093.6294***	-1093.6276***
20141	-998.17536***	-997.96769***	-997.96373***
20142	-941.7266***	-941.7423***	-941.74183***
20143	-858.09666***	-858.10881***	-858.07674***
20144	-733.07161***	-733.01025***	-733.03353***
20151	-666.92784***	-666.85485***	-666.85615***
20152	-563.58074***	-563.7029***	-563.6838***
20153	-372.37805***	-372.30585***	-372.28463***
20154	-249.60218***	-249.26154***	-249.24036***
20161	-107.67924***	-107.59213***	-107.59633***
sales_peri~t			
0	62.265171***	62.300594***	62.292355***
sales_peri~t			
2	-141.91596***	-142.01351***	-142.01245***
KAD_TYPE			
1	1593.6073***	1599.2849***	1599.0885***
2	1085.3485***	1085.9941***	1085.3644***
3	452.09089***	451.12238***	451.12364***
cohort			
1100	47.086836	44.329685	44.6728
1900	14.990684	14.036885	14.504875
1910	69.853137*	68.777036*	69.258236*
1920	-6.2902551	-6.1825691	-6.0807907
cohort			
1940	-72.737091	-73.204464	-72.786842
1950	-215.82526***	-216.42141***	-215.82791***
1960	-437.3113***	-437.80538***	-437.34566***
1970	-384.76402***	-386.25822***	-386.4626***
1980	-300.92596***	-302.25826***	-301.92208***
1990	-278.14504***	-278.79412***	-278.07516***
2000	-158.24252***	-158.62616***	-158.11483***
2010	202.05394***	199.51103***	199.78785***
outside_cat			
1	5.5588081	5.6571612	5.6292038
2	80.986087***	80.957872***	80.969607***
kamers_cen~d	-42.076983***	-41.965839***	-41.984067***
high_ceili~1	102.04331***	102.19416***	102.20391***
DUMGAR	117.90756***	117.42116***	117.46581***
DUMBER_m1	37.245357**	37.285541**	37.267025**
DUMMON	-7.462859	-7.0393852	-7.0031442
DUMVERW_m1	304.8768***	304.61608***	304.57683***
Distance~e_c	-.21035198***	-.21186026***	-.21246962***
Distance~n_c	.03658706*	.03652871*	.03722476*
Distance~p_c	.11946309***	.11713865***	.11665095***
Bevdicht_z	93.521505	39.443352	31.019799
BevNW_p_z	-9.9525474	16.116936	21.823609
Wkoop_p_z	-129.23218***	-95.956811**	-91.005886**
Ihhink_gem_z	195.15122**	138.45977*	123.71311
VKov_r_z	48.710046*	32.836151	30.801306
Centrum_c	-21.491642	-85.0919	-74.431136
Ring_c	453.81976***	505.7292***	513.92676***
Vimpact_i_z	-74.924473*	-65.273411	-66.589349
Vbeleving_~z	-96.949833*	-126.64038**	-133.26184**
OaanbodBAO~z	-36.766542	-24.240796	-21.551358
ORomgeving~z	285.2211**	202.94854	180.17801
ORwoningen~z	-189.58821*	-152.46256	-138.5401
ORgroenmoo~z	-88.532632	-53.546312	-40.499995
ORwater_p_z	-51.087015	-39.637133	-36.5924
ORgroen_p_z	65.870413	36.775135	29.645457
ORverblijf~z	28.299292	78.931072	78.182298
Lhorecaove~z	-61.150317	11.415084	13.107986
B~tdg_1000_z	-19.661415	64.331364	66.730862
B~ndg_1000_z	-95.711082	-117.83313	-93.965007
Bhvest_gez~z	274.59452***	264.61214***	270.47385***
Bhvest_cul~z	-79.90766	-89.805487	-93.307558
Bhvest_re_~z	380.59643*	94.23885	
Bhvest_ca_~z	-313.80014*	-383.05205**	-339.44967***
nresBCgra1~z		375.73113**	409.40972***
_cons	4460.4821***	4464.6568***	4464.4385***
lns1_1_1			
_cons	5.2702834***	5.2198691***	5.2234591***
lnsig_e			
_cons	6.3734407***	6.3734094***	6.3733991***

legend: * p<0.05; ** p<0.01; *** p<0.001

Table A4.2.4 Raw and full estimation results standard complete model (m3a)

Mixed-effects ML regression		Number of obs =	13,473
Group variable: **BC_number**		Number of groups =	78
		Obs per group:	
		min =	7
		avg =	172.7
		max =	467
		Wald chi2(**69**) =	11223.77
Log likelihood = **-105213.07**		Prob > chi2 =	0.0000

m2price_w	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
JAAR_Q						
20131	-1131.925	32.31883	-35.02	0.000	-1195.269	-1068.581
20132	-1176.896	33.82905	-34.79	0.000	-1243.199	-1110.592
20133	-1164.825	30.5973	-38.07	0.000	-1224.794	-1104.855
20134	-1148.124	29.55912	-38.84	0.000	-1206.059	-1090.189
20141	-1056.401	29.67938	-35.59	0.000	-1114.572	-998.2309
20142	-996.2071	28.37327	-35.11	0.000	-1051.818	-940.5966
20143	-903.3341	27.06212	-33.38	0.000	-956.3749	-850.2933
20144	-777.2354	24.51431	-31.71	0.000	-825.2826	-729.1882
20151	-706.1259	27.10929	-26.05	0.000	-759.2591	-652.9927
20152	-595.3281	25.84606	-23.03	0.000	-645.9854	-544.6707
20153	-396.8662	24.16941	-16.42	0.000	-444.2374	-349.495
20154	-264.839	24.28217	-10.91	0.000	-312.4312	-217.2468
20161	-114.6517	24.03324	-4.77	0.000	-161.7559	-67.54738
sales_period_cat						
0	58.31562	16.88701	3.45	0.001	25.21769	91.41354
2	-149.6159	13.75394	-10.88	0.000	-176.5731	-122.6587
KAD_TYPE						
1	1742.291	73.05767	23.85	0.000	1599.1	1885.481
2	1220.459	68.94379	17.70	0.000	1085.331	1355.586
3	507.2268	25.23412	20.10	0.000	457.7689	556.6848
cohort						
1100	30.21001	31.51053	0.96	0.338	-31.5495	91.96951
1900	3.073258	28.12233	0.11	0.913	-52.0455	58.19202
1910	58.64677	30.17249	1.94	0.052	-.490217	117.7838
1920	-14.90716	23.56209	-0.63	0.527	-61.088	31.27368
1940	-82.54686	41.50701	-1.99	0.047	-163.8991	-1.194616
1950	-242.3282	37.99803	-6.38	0.000	-316.803	-167.8535
1960	-436.8664	38.86978	-11.24	0.000	-513.0498	-360.683
1970	-389.915	42.69846	-9.13	0.000	-473.6025	-306.2276
1980	-347.3089	32.9999	-10.52	0.000	-411.9875	-282.6303
1990	-283.0003	31.71708	-8.92	0.000	-345.1646	-220.836
2000	-157.1424	30.89339	-5.09	0.000	-217.6923	-96.59245
2010	241.3518	54.0412	4.47	0.000	135.433	347.2706
outside_cat						
1	5.163626	13.30929	0.39	0.698	-20.92211	31.24936
2	86.21064	13.44845	6.41	0.000	59.85216	112.5691
kamers_centered	-42.20179	5.109439	-8.26	0.000	-52.21611	-32.18747
high_ceiling_m1	101.7006	10.72386	9.48	0.000	80.68218	122.7189
DUMGAR	99.85246	23.6834	4.22	0.000	53.43385	146.2711
DUMBER_m1	45.90328	11.96029	3.84	0.000	22.46154	69.34503
DUMMON	-16.43625	24.6434	-0.67	0.505	-64.73642	31.86393
DUMVERW_m1	310.6327	27.4476	11.32	0.000	256.8364	364.429
Distance_to_centre_c	-.1997071	.0153747	-12.99	0.000	-.229841	-.1695733
Distance_to_station_c	.0436698	.018982	2.30	0.021	.0064658	.0808738
Distance_to_ramp_c	.0961758	.0178859	5.38	0.000	.0611201	.1312315
Bevdicht_z	22.65047	50.94355	0.44	0.657	-77.19705	122.498
BevNW_p_z	36.31608	53.58642	0.68	0.498	-68.71137	141.3435
Wkoop_p_z	-114.6765	35.74963	-3.21	0.001	-184.7444	-44.60848
Ihhink_gem_z	187.6092	66.35105	2.83	0.005	57.56352	317.6549
VKov_r_z	-10.5394	34.6787	-0.30	0.761	-78.5084	57.42961
Centrum_c	-43.82241	113.2272	-0.39	0.699	-265.7437	178.0989
Ring_c	558.8477	102.5241	5.45	0.000	357.9041	759.7913
Vimpact_i_z	-47.69756	37.99083	-1.26	0.209	-122.1582	26.76311
Vbeleving_i_z	-118.0567	51.43544	-2.30	0.022	-218.8683	-17.24514
OaanbodBAO_r_z	-4.201322	29.99825	-0.14	0.889	-62.9968	54.59416
ORomgevingmooi_r_z	167.145	94.37218	1.77	0.077	-17.82105	352.1111
ORwoningenmooi_r_z	-123.5168	79.69162	-1.55	0.121	-279.7095	32.67589
ORgroenmooi_r_z	-35.24576	58.69002	-0.60	0.548	-150.2761	79.78455
ORwater_p_z	-51.17877	36.36224	-1.41	0.159	-122.4474	20.08991
ORgroen_p_z	46.67079	34.74509	1.34	0.179	-21.42833	114.7699
ORverblijf_i_z	70.38054	52.99503	1.33	0.184	-33.48781	174.2489
Lhorecaoverlast_r_z	15.08212	53.52138	0.28	0.778	-89.81785	119.9821
Bhvest_winkvestdg_1000_z	125.0789	79.23724	1.58	0.114	-30.22319	280.3811
Bhvest_winkvestndg_1000_z	-125.1986	65.1285	-1.92	0.055	-252.8481	2.450887
Bhvest_gezzorg_1000_z	224.5764	63.1512	3.56	0.000	100.8023	348.3505
Bhvest_cult_1000_z	-45.46358	61.84999	-0.74	0.462	-166.6873	75.76017
Bhvest_ca_1000_z	-364.2517	95.19508	-3.83	0.000	-550.8306	-177.6727
nres650gra_z	35.5472	17.19128	2.07	0.039	1.852909	69.24149
mg650gra_z	-22.84489	7.506499	-3.04	0.002	-37.55736	-8.132421
hhin650gra_z	33.83813	13.10707	2.58	0.010	8.148731	59.52752
nresBCgra1000_z	405.6204	106.9328	3.79	0.000	196.036	615.2049
mgBCgra_z	58.44822	26.66035	2.19	0.028	6.194896	110.7015
hhinBCgra_z	-37.63099	37.22262	-1.01	0.312	-110.586	35.32401
_cons	4513.688	37.17231	121.43	0.000	4440.832	4586.545

Random-effects Parameters	Estimate	Std. Err.	[95% Conf.	Interval]
BC_number: Identity				
var(_cons)	30618.51	6002.246	20850.68	44962.23
var(Residual)	349955.5	4278.842	341668.8	358443.2

LR test vs. linear model: chibar2(01) = **546.48** Prob >= chibar2 = **0.0000**

Table A4.2.5 Comparison results separate and simultaneous standard complete models (m3a's)

Variable	m2	m3a_abs	m3a_rel	m3a
m2price_w				
JAAR_Q				
20131	-1061.5906***	-1121.9588***	-1101.9172***	-1131.9249***
20132	-1102.9405***	-1166.7501***	-1138.3875***	-1176.8957***
20133	-1102.8272***	-1155.3375***	-1135.9912***	-1164.8248***
20134	-1093.9143***	-1142.6084***	-1123.9988***	-1148.1237***
20141	-998.17536***	-1045.7089***	-1033.4832***	-1056.4014***
20142	-941.7266***	-988.18872***	-970.49447***	-996.20715***
20143	-858.09666***	-896.73588***	-886.3027***	-903.3341***
20144	-733.07161***	-771.56103***	-758.83939***	-777.2354***
20151	-666.92784***	-703.6882***	-687.50684***	-706.12591***
20152	-563.58074***	-592.51108***	-582.86117***	-595.32807***
20153	-372.37805***	-395.30682***	-387.60407***	-396.86622***
20154	-249.60218***	-263.91623***	-259.89288***	-264.83899***
20161	-107.67924***	-115.17704***	-109.1532***	-114.65165***
sales_peri~t				
0	62.265171***	59.731358***	57.657735***	58.315616***
sales_peri~t				
2	-141.91596***	-148.07617***	-144.52633***	-149.61589***
KAD_TYPE				
1	1593.6073***	1705.9804***	1599.503***	1742.2906***
2	1085.3485***	1227.4947***	1121.7694***	1220.4586***
3	452.09089***	506.62777***	468.90485***	507.22683***
cohort				
1100	47.086836	27.484306	42.013876	30.210008
1900	14.990684	-.77683091	12.421181	3.0732577
1910	69.853137*	55.161259	66.899569*	58.646772
1920	-6.2902551	-16.295108	-10.572344	-14.907159
cohort				
1940	-72.737091	-82.320388*	-72.996653	-82.54686*
1950	-215.82526***	-241.36577***	-234.70935***	-242.32824***
1960	-437.3113***	-439.82924***	-437.56968***	-436.86638***
1970	-384.76402***	-393.29043***	-383.78621***	-389.91504***
1980	-300.92596***	-345.51937***	-311.52091***	-347.30889***
1990	-278.14504***	-290.96947***	-284.87147***	-283.00031***
2000	-158.24252***	-162.26029***	-149.88113***	-157.14238***
2010	202.05394***	241.72252***	207.40009***	241.35181***
outside_cat				
1	5.5588081	2.7521115	7.1269322	5.1636264
2	80.986087***	83.234079***	86.365231***	86.210644***
kamers_cen~d	-42.076983***	-42.87633***	-41.065005***	-42.201791***
high_ceili~1	102.04331***	102.06206***	100.56397***	101.70055***
DUMGAR	117.90756***	101.11738***	106.65395***	99.852459***
DUMBER_m1	37.245357**	44.294771***	41.646602***	45.903282***
DUMMON	-7.462859	-15.454042	-9.6937661	-16.436247
DUMVERW_m1	304.8768***	310.3194***	306.43459***	310.63266***
Distance~e_c	-.21035198***	-.19796916***	-.21809887***	-.19970712***
Distance~n_c	.03658706*	.03993484*	.05020964**	.04366982*
Distance~p_c	.11946309***	.0978232***	.11391559***	.09617577***
Bevdicht_z	93.521505	101.41677	21.596673	22.650471
BevNW_p_z	-9.9525474	-30.460145	25.674385	36.316083
Wkoop_p_z	-129.23218***	-160.9416***	-100.91942**	-114.67646**
Ihhink_gem_z	195.15122**	246.22138***	151.13041*	187.60919**
VKov_r_z	48.710046*	45.792339	31.031544	-10.539395
Centrum_c	-21.491642	24.86087	-51.461042	-43.822406
Ring_c	453.81976***	446.41394***	492.55286***	558.84767***
Vimpact_i_z	-74.924473*	-79.799235*	-71.508926	-47.697559
Vbeleving_~z	-96.949833*	-52.756648	-109.30978*	-118.05674*
OaanbodBAO~z	-36.766542	-30.484935	-40.849013	-4.2013217
ORomgeving~z	285.2211**	252.15908*	212.56276*	167.14501
ORwoningen~z	-189.58821*	-150.95927	-134.08018	-123.51682
ORgroenmoo~z	-88.532632	-63.16057	-54.800293	-35.245762
ORwater_p_z	-51.087015	-64.758694	-44.471834	-51.17877
ORgroen_p_z	65.870413	78.802687*	19.51791	46.670791
ORverblijf~z	28.299292	15.491267	64.444952	70.380538
Lhorecaove~z	-61.150317	-63.885901	-19.479785	15.08212
B~tdg_1000_z	-19.661415	27.785044	105.46914	125.07894
B~ndg_1000_z	-95.711082	-119.05298	-127.81507	-125.19862
Bhvest_gez~z	274.59452***	220.99165***	266.23827***	224.57641***
Bhvest_cul~z	-79.90766	-45.066036	-111.6945	-45.463576
Bhvest_re_~z	380.59643*	330.99783*		
Bhvest_ca_~z	-313.80014*	-300.11961*	-350.61253***	-364.25168***
nres650gra_z		39.497407*		35.547201*
mg650gra_z		-21.61632**		-22.84489**
hhin650gra_z		35.685195**		33.838125**
nresBCgra1~z			382.48141***	405.62043***
mgBCgra_z			39.759428	58.448218*
hhinBCgra_z			4.9818773	-37.63099
_cons	4460.4821***	4506.3597***	4487.2248***	4513.6883***
lns1_1_1				
_cons	5.2702834***	5.2431423***	5.2174035***	5.16468***
lnsig_e				
_cons	6.3734407***	6.3800806***	6.3814437***	6.3827807***

legend: * p<0.05; ** p<0.01; *** p<0.001

Table A4.2.6 Raw and full estimation results alternative complete model (m3b)

```
Mixed-effects ML regression                     Number of obs     =     14,440
Group variable: BC_number                       Number of groups  =         86

                                                Obs per group:
                                                              min =          7
                                                              avg =      167.9
                                                              max =        467

                                                Wald chi2(77)     =   12085.10
Log likelihood = -112609.04                     Prob > chi2       =     0.0000
```

m2price_w	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
JAAR_Q						
20131	-1061.6	30.48318	-34.83	0.000	-1121.346	-1001.854
20132	-1103.726	32.19546	-34.28	0.000	-1166.828	-1040.624
20133	-1102.051	29.17714	-37.77	0.000	-1159.237	-1044.865
20134	-1092.886	28.15817	-38.81	0.000	-1148.075	-1037.697
20141	-997.9361	28.28843	-35.28	0.000	-1053.38	-942.4918
20142	-941.8609	27.03234	-34.84	0.000	-994.8433	-888.8785
20143	-858.0697	25.90291	-33.13	0.000	-908.8385	-807.301
20144	-732.9267	23.36679	-31.37	0.000	-778.7248	-687.1287
20151	-668.1823	25.86056	-25.84	0.000	-718.8681	-617.4965
20152	-563.1072	24.6143	-22.88	0.000	-611.3504	-514.8641
20153	-372.1725	22.91781	-16.24	0.000	-417.0905	-327.2544
20154	-250.5271	23.01968	-10.88	0.000	-295.6448	-205.4093
20161	-108.5558	22.74488	-4.77	0.000	-153.1349	-63.97662
sales_period_cat						
0	62.94497	16.27473	3.87	0.000	31.04709	94.84285
2	-143.4179	12.93786	-11.09	0.000	-168.7757	-118.0602
KAD_TYPE						
1	1607.85	60.05611	26.77	0.000	1490.143	1725.558
2	1084.909	59.03482	18.38	0.000	969.2029	1200.615
3	455.5636	22.92169	19.87	0.000	410.6379	500.4893
cohort						
1100	46.36308	30.84912	1.50	0.133	-14.10008	106.8262
1900	8.77831	27.41849	0.32	0.749	-44.96095	62.51756
1910	59.9506	29.55458	2.03	0.043	2.024683	117.8765
1920	-21.38678	23.14942	-0.92	0.356	-66.75881	23.98526
1940	-75.68495	40.81306	-1.85	0.064	-155.6771	4.307184
1950	-217.3859	36.06108	-6.03	0.000	-288.0644	-146.7075
1960	-438.551	36.31081	-12.08	0.000	-509.7189	-367.3832
1970	-390.0267	38.9774	-10.01	0.000	-466.421	-313.6324
1980	-304.9184	31.13382	-9.79	0.000	-365.9396	-243.8972
1990	-275.9979	29.97833	-9.21	0.000	-334.7543	-217.2414
2000	-155.6277	29.57618	-5.26	0.000	-213.5959	-97.65941
2010	203.772	50.73159	4.02	0.000	104.3399	303.2041
outside_cat						
1	4.277023	12.77416	0.33	0.738	-20.75987	29.31391
2	80.61469	12.84857	6.27	0.000	55.43196	105.7974
kamers_centered	-42.20945	4.920266	-8.58	0.000	-51.85299	-32.5659
high_ceiling_m1	102.9591	10.2541	10.04	0.000	82.86138	123.0567
DUMGAR	116.9731	22.23875	5.26	0.000	73.38593	160.5602
DUMBER_m1	39.24594	11.63313	3.37	0.001	16.44543	62.04645
DUMMON	-7.829439	24.30187	-0.32	0.747	-55.46022	39.80135
DUMVERW_m1	303.9554	26.6783	11.39	0.000	251.6669	356.244
Distance_to_centre_c	-.1987644	.0137061	-14.50	0.000	-.2256279	-.1719009
Distance_to_station_c	.033892	.017027	1.99	0.047	.0005197	.0672644
Distance_to_ramp_c	.105942	.0161055	6.58	0.000	.0743757	.1375082
Bevdicht_z	3.616141	49.61948	0.07	0.942	-93.63626	100.8685
BevNW_p_z	.5449748	47.94118	0.01	0.991	-93.41801	94.50796
Wkoop_p_z	-75.81225	32.59497	-2.33	0.020	-139.6972	-11.92728
Ihhink_gem_z	92.53975	66.54218	1.39	0.164	-37.88053	222.96
VKov_r_z	27.31662	21.90899	1.25	0.212	-15.62421	70.25746
Centrum_c	-12.30807	110.9554	-0.11	0.912	-229.7768	205.1606
Ring_c	539.0775	93.76856	5.75	0.000	355.2945	722.8605
Vimpact_i_z	-54.61605	33.94612	-1.61	0.108	-121.1492	11.91712
Vbeleving_i_z	-137.242	51.30188	-2.68	0.007	-237.7918	-36.69217
OaanbodBAO_r_z	-16.46865	23.04249	-0.71	0.475	-61.63109	28.69379
ORomgevingmooi_r_z	132.4965	91.11157	1.45	0.146	-46.07886	311.0719
ORwoningenmooi_r_z	-90.44988	77.6596	-1.16	0.244	-242.6599	61.76013
ORgroenmooi_r_z	-36.7269	54.34577	-0.68	0.499	-143.2427	69.78885
ORwater_p_z	-31.36501	34.42838	-0.91	0.362	-98.8434	36.11338
ORgroen_p_z	38.71854	32.28065	1.20	0.230	-24.55037	101.9874
ORverblijf_i_z	124.5181	62.71704	1.99	0.047	1.594913	247.4412
Lhorecaoverlast_r_z	33.9217	46.54293	0.73	0.466	-57.30077	125.1442
Bhvest_winkvestdg_1000_z	94.61099	77.48822	1.22	0.222	-57.26313	246.4851
Bhvest_winkvestndg_1000_z	-61.28296	77.93811	-0.79	0.432	-214.0389	91.47294
Bhvest_gezzorg_1000_z	228.9094	58.51997	3.91	0.000	114.2123	343.6064
Bhvest_cult_1000_z	-114.1697	65.07525	-1.75	0.079	-241.7148	13.37547
Bhvest_ca_1000_z	-365.962	112.6991	-3.25	0.001	-586.8483	-145.0758
nres650_ng_z	-20.31392	32.00922	-0.63	0.526	-83.05083	42.42299
nres650_ng_55_z	32.91078	29.15545	1.13	0.259	-24.23285	90.05441
nres650_55_65_z	-86.42178	37.87047	-2.28	0.022	-160.6465	-12.19703
nres650_65_75_z	-12.88452	30.2718	-0.43	0.670	-72.21616	46.44713
nres650_75_85_z	165.3884	30.23028	5.47	0.000	106.1382	224.6387
nres650_85_z	-46.96055	20.67815	-2.27	0.023	-87.48897	-6.432126
hhin650gra_z	37.97535	10.85979	3.50	0.000	16.69056	59.26014
nresBC1000_ng_z	-95.35832	125.8631	-0.76	0.449	-342.0454	151.3288
nresBC1000_ng_55_z	157.2706	126.8038	1.24	0.215	-91.26024	405.8015
nresBC1000_55_65_z	-44.61718	80.26566	-0.56	0.578	-201.935	112.7006
nresBC1000_65_75_z	231.4606	87.39557	2.65	0.008	60.16846	402.7528
nresBC1000_75_85_z	119.1284	72.70149	1.64	0.101	-23.36395	261.6207
nresBC85_1000_z	.2018186	63.63698	0.00	0.997	-124.5244	124.928
hhinBCgra_z	-5.225515	27.86928	-0.19	0.851	-59.8483	49.39727
_cons	4469.653	34.90785	128.04	0.000	4401.235	4538.071

Random-effects Parameters	Estimate	Std. Err.	[95% Conf.	Interval]
BC_number: Identity				
var(_cons)	26977.88	4991.065	18772.86	38769.04
var(Residual)	342606.2	4046.014	334767.2	350628.7

LR test vs. linear model: chibar2(01) = 527.24   Prob >= chibar2 = 0.0000

Table A4.2.7 Comparison results separate and simultaneous alternative complete models (m3b's)

Variable	m2	m3b_abs	m3b_rel	m3b
m2price_w				
JAAR_Q				
20131	-1061.5906***	-1061.8052***	-1061.6028***	-1061.6001***
20132	-1102.9405***	-1103.3781***	-1103.1673***	-1103.7256***
20133	-1102.8272***	-1101.8695***	-1102.9267***	-1102.051***
20134	-1093.9143***	-1093.3419***	-1093.4593***	-1092.8863***
20141	-998.17536***	-998.30712***	-997.79488***	-997.93609***
20142	-941.7266***	-941.8761***	-941.72276***	-941.86088***
20143	-858.09666***	-858.52211***	-857.76146***	-858.06972***
20144	-733.07161***	-733.0436***	-732.92959***	-732.92673***
20151	-666.92784***	-668.21257***	-666.92337***	-668.18231***
20152	-563.58074***	-563.26637***	-563.39424***	-563.10724***
20153	-372.37805***	-372.42497***	-372.19711***	-372.17245***
20154	-249.60218***	-251.34817***	-249.05075***	-250.52705***
20161	-107.67924***	-108.75988***	-107.56295***	-108.55577***
sales_peri~t				
0	62.265171***	62.93541***	62.23007***	62.944967***
sales_peri~t				
2	-141.91596***	-143.36136***	-142.06606***	-143.41791***
KAD_TYPE				
1	1593.6073***	1601.7973***	1597.0373***	1607.8503***
2	1085.3485***	1085.262***	1083.404***	1084.9091***
3	452.09089***	456.68349***	450.17948***	455.56361***
cohort				
1100	47.086836	47.373366	46.122295	46.363084
1900	14.990684	6.6386297	16.65182	8.7783095
1910	69.853137*	57.648313	71.261029*	59.950596*
1920	-6.2902551	-23.129891	-5.505077	-21.38678
cohort				
1940	-72.737091	-76.015344	-72.464202	-75.684951
1950	-215.82526***	-219.34967***	-214.19849***	-217.38594***
1960	-437.3113***	-443.11157***	-432.86543***	-438.55104***
1970	-384.76402***	-390.22799***	-384.31547***	-390.02665***
1980	-300.92596***	-306.52885***	-300.00533***	-304.91838***
1990	-278.14504***	-279.48934***	-274.95842***	-275.99786***
2000	-158.24252***	-159.23463***	-155.3247***	-155.62767***
2010	202.05394***	204.28855***	202.2277***	203.772***
outside_cat				
1	5.5588081	4.1241395	5.5314813	4.2770234
2	80.986087***	80.639057***	80.928676***	80.614692***
kamers_cen~d	-42.076983***	-42.229359***	-41.970658***	-42.209449***
high_ceili~1	102.04331***	102.94907***	102.12645***	102.95905***
DUMGAR	117.90756***	117.39625***	117.68224***	116.97307***
DUMBER_m1	37.245357**	38.894538***	37.353824**	39.24594***
DUMMON	-7.462859	-8.066789	-7.5212714	-7.8294386
DUMVERW_m1	304.8768***	304.17689***	304.65393***	303.95544***
Distance~e_c	-.21035198***	-.19507078***	-.21236918***	-.19876437***
Distance~n_c	.03658706*	.03068642	.03719065*	.03389201*
Distance~p_c	.11946309***	.10681938***	.11911188***	.10594196***
Bevdicht_z	93.521505	85.286193	-4.2438818	3.6161406
BevNW_p_z	-9.9525474	-26.001024	10.817761	.54497482
Wkoop_p_z	-129.23218***	-124.67008***	-71.161938*	-75.812246*
Ihhink_gem_z	195.15122**	193.36503**	74.581876	92.539747
VKov_r_z	48.710046*	46.417759*	24.795792	27.316625
Centrum_c	-21.491642	3.9203427	-40.27659	-12.308068
Ring_c	453.81976***	432.69977***	554.27341***	539.07754***
Vimpact_i_z	-74.924473*	-72.864082*	-56.139605	-54.616047
Vbeleving_~z	-96.949833*	-74.472225	-147.96579**	-137.24201**
OaanbodBAO~z	-36.766542	-36.664168	-14.598963	-16.468648
ORomgeving~z	285.2211**	284.31885**	110.82229	132.49654
ORwoningen~z	-189.58821*	-174.00555*	-82.001719	-90.44988
ORgroenmoo~z	-88.532632	-90.201825	-31.708904	-36.726898
ORwater_p_z	-51.087015	-56.879611	-28.069968	-31.365011
ORgroen_p_z	65.870413	67.071602*	28.514392	38.718539
ORverblijf~z	28.299292	19.495564	141.90595*	124.51806*
Lhorecaove~z	-61.150317	-54.204012	41.732949	33.921697
B~tdg_1000_z	-19.661415	-3.182231	87.266252	94.610993
B~ndg_1000_z	-95.711082	-96.115532	-62.286206	-61.28296
Bhvest_gez~z	274.59452***	239.01223***	264.1669***	228.90938***
Bhvest_cul~z	-79.90766	-58.40072	-126.80101	-114.16967
Bhvest_re_~z	380.59643*	329.97864*		
Bhvest_ca_~z	-313.80014*	-281.52938*	-375.42866**	-365.96203**
nres650_ng_z		-35.668319		-20.313917
nres650~55_z		40.101666		32.910783
nres650_55~z		-84.049614*		-86.421784*
nres650_65~z		-8.5209215		-12.884517
nres650_75~z		167.47937***		165.38845***
nres650_85_z		-44.246513*		-46.960548*
hhin650gra_z		36.313364***		37.975347***
nresBC10~g_z			-101.29978	-95.358325
nresBC1~55_z			153.49839	157.27062
nresBC1~65_z			-49.883201	-44.617184
nresBC1~75_z			223.37279*	231.46063**
nresBC1~85_z			186.88606*	119.12835
nresBC85_1~z			-20.037335	.20181864
hhinBCgra_z			9.7122166	-5.2255147
_cons	4460.4821***	4468.0804***	4464.5355***	4469.6529***
lns1_1_1				
_cons	5.2702834***	5.1671837***	5.1813942***	5.1013862***
lnsig_e				
_cons	6.3734407***	6.3722578***	6.3734113***	6.3721685***

legend: * p<0.05; ** p<0.01; *** p<0.001

Table A4.2.8 Comparison results varying buffer radii (m3b_xxx)

Variable	m3b	m3b_rob_500	m3b_rob_800
m2price_w			
JAAR_Q			
20131	-1061.6001***	-1061.9245***	-1059.1617***
20132	-1103.7256***	-1105.0815***	-1105.5474***
20133	-1102.051***	-1104.8957***	-1101.7347***
20134	-1092.8863***	-1094.2624***	-1092.7286***
20141	-997.93609***	-1000.3499***	-997.53559***
20142	-941.86088***	-941.16825***	-941.03892***
20143	-858.06972***	-859.8291***	-857.82284***
20144	-732.92673***	-733.47557***	-731.75989***
20151	-668.18231***	-670.32553***	-664.72583***
20152	-563.10724***	-566.17795***	-564.72613***
20153	-372.17245***	-373.09531***	-370.787***
20154	-250.52705***	-251.70572***	-248.57968***
20161	-108.55577***	-109.2554***	-107.41566***
sales_peri~t			
0	62.944967***	62.086164***	60.929752***
sales_peri~t			
2	-143.41791***	-142.77084***	-141.9501***
KAD_TYPE			
1	1607.8503***	1607.0755***	1609.4946***
2	1084.9091***	1092.9402***	1089.6321***
3	455.56361***	459.63637***	453.11902***
cohort			
1100	46.363084	42.14885	49.401599
1900	8.7783095	14.386144	13.169381
1910	59.950596*	61.998478*	68.387954*
1920	-21.38678	-13.175543	-13.505613
cohort			
1940	-75.684951	-87.071468*	-70.675088
1950	-217.38594***	-221.84374***	-212.59583***
1960	-438.55104***	-433.32283***	-437.96214***
1970	-390.02665***	-391.58991***	-384.39589***
1980	-304.91838***	-298.40084***	-302.27169***
1990	-275.99786***	-276.15564***	-274.22436***
2000	-155.62767***	-154.61408***	-151.45345***
2010	203.772***	210.54923***	204.46016***
outside_cat			
1	4.2770234	5.582532	5.7784859
2	80.614692***	81.706639***	80.457445***
kamers_cen~d	-42.209449***	-42.287913***	-42.969351***
high_ceili~1	102.95905***	102.90426***	101.70326***
DUMGAR	116.97307***	121.24701***	114.72095***
DUMBER_m1	39.24594***	39.083615***	37.828886**
DUMMON	-7.8294386	-5.733206	-14.345429
DUMVERW_m1	303.95544***	304.52081***	302.52852***
Distance~e_c	-.19876437***	-.19613891***	-.19549768***
Distance~n_c	.03389201*	.03194578	.0303435
Distance~p_c	.10594196***	.10469157***	.10795368***
Bevdicht_z	3.6161406	7.1357532	.79498163
BevNW_p_z	.54497482	-4.6164244	-4.5359428
Wkoop_p_z	-75.812246*	-75.572632*	-75.327949*
Ihhink_gem_z	92.539747	86.572869	89.590757
VKov_r_z	27.316625	28.704962	28.270246
Centrum_c	-12.308068	-7.0641018	-40.160107
Ring_c	539.07754***	521.95617***	542.1326***
Vimpact_i_z	-54.616047	-54.408797	-58.035193
Vbeleving_~z	-137.24201**	-135.02038**	-134.80435**
OaanbodBAO~z	-16.468648	-16.855316	-17.84841
ORomgeving~z	132.49654	121.87523	131.8143
ORwoningen~z	-90.44988	-81.940126	-94.979663
ORgroenmoo~z	-36.726898	-37.005575	-39.771939
ORwater_p_z	-31.365011	-33.080455	-26.487041
ORgroen_p_z	38.718539	37.631221	38.766732
ORverblijf~z	124.51806*	125.51227*	119.67713
Lhorecaove~z	33.921697	28.573747	38.094202
B~tdg_1000_z	94.610993	83.180258	93.862906
B~ndg_1000_z	-61.28296	-67.125614	-27.973832
Bhvest_gez~z	228.90938***	242.15449***	228.27864***
Bhvest_cul~z	-114.16967	-113.98986	-111.36508
Bhvest_ca_~z	-365.96203**	-374.20127***	-353.77242**
nres650_ng_z	-20.313917		
nres650~55_z	32.910783		
nres650_55~z	-86.421784*		
nres650_65~z	-12.884517		
nres650_75~z	165.38845***		
nres650_85_z	-46.960548*		
hhin650gra_z	37.975347***		
nresBC10~g_z	-95.358325	-86.196372	-116.80246
nresBC1~55_z	157.27062	197.20504	81.585433
nresBC1~65_z	-44.617184	-43.604251	-20.777521
nresBC1~75_z	231.46063**	210.93093*	240.08428**
nresBC1~85_z	119.12835	136.96539	145.72445*
nresBC85_1~z	.20181864	-17.556507	-17.737419
hhinBCgra_z	-5.2255147	-6.8544464	-1.4747491
nres500_ng_z		-5.5081505	
nres500~55_z		-48.12509*	
nres500_55~z		-35.217855	
nres500_65~z		19.665118	
nres500_75~z		76.75943***	
nres500_85_z		.25556428	
hhin500gra_z		53.627847***	
nres800_ng_z			6.6671044
nres800~55_z			149.69613***
nres800_55~z			-210.74898***
nres800_65~z			-14.389262
nres800_75~z			148.68806***
nres800_85_z			-16.509826
hhin800gra_z			23.900832*
_cons	4469.6529***	4468.5385***	4463.742***
lns1_1_1			
_cons	5.1013862***	5.0928236***	5.1146776***
lnsig_e			
_cons	6.3721685***	6.3723623***	6.3719915***

legend: * p<0.05; ** p<0.01; *** p<0.001

Table A4.2.9 Comparison results varying transaction sample (m3b_xxxx)

Variable	m3b	m3b_ring	m3b_ncen
m2price_w			
JAAR_Q			
20131	-1061.6001***	-1375.9506***	-1014.6872***
20132	-1103.7256***	-1368.7654***	-1086.8526***
20133	-1102.051***	-1372.9742***	-1063.682***
20134	-1092.8863***	-1336.7896***	-1073.8016***
20141	-997.93609***	-1228.2228***	-994.32653***
20142	-941.86088***	-1167.1593***	-917.14015***
20143	-858.06972***	-1036.2604***	-848.00819***
20144	-732.92673***	-916.98671***	-716.31455***
20151	-668.18231***	-842.91736***	-638.7797***
20152	-563.10724***	-725.29748***	-557.89641***
20153	-372.17245***	-473.51555***	-364.18522***
20154	-250.52705***	-296.2286***	-247.9989***
20161	-108.55577***	-140.43261***	-118.29781***
sales_peri~t			
0	62.944967***	32.573739	48.522949**
sales_peri~t			
2	-143.41791***	-200.62853***	-131.65307***
KAD_TYPE			
1	1607.8503***	2979.1746***	1644.0083***
2	1084.9091***	2002.4213***	1112.6713***
3	455.56361***	799.67109***	440.02472***
cohort			
1100	46.363084	10.337676	126.52482***
1900	8.7783095	-3.8731456	83.578718**
1910	59.950596*	51.603464	103.1446***
1920	-21.38678	-23.549415	-11.56214
cohort			
1940	-75.684951	-45.515818	-55.033467
1950	-217.38594***	-255.8574***	-207.11262***
1960	-438.55104***	-451.25543***	-454.48675***
1970	-390.02665***	-426.78513***	-403.10949***
1980	-304.91838***	-432.10375***	-289.2821***
1990	-275.99786***	-298.24224***	-245.39302***
2000	-155.62767***	-172.35611***	-196.4585***
2010	203.772***	388.74848***	81.404417
outside_cat			
1	4.2770234	-11.396374	-22.925642
2	80.614692***	99.224161***	51.609692***
kamers_cen~d	-42.209449***	-42.035954***	-35.330973***
high_ceili~1	102.95905***	109.37684***	93.888039***
DUMGAR	116.97307***	132.24785***	104.11278***
DUMBER_m1	39.24594***	64.795551***	56.282621***
DUMMON	-7.8294386	-62.293417*	15.911595
DUMVERW_m1	303.95544***	315.63859***	313.09721***
Distance~e_c	-.19876437***	-.18195092***	-.23091836***
Distance~n_c	.03389201*	.09023462**	.08338823***
Distance~p_c	.10594196***	.13500169**	.11784568***
Bevdicht_z	3.6161406	122.49824*	-74.50747
BevNW_p_z	.54497482	-321.31772***	31.200376
Wkoop_p_z	-75.812246*	-94.953142*	-90.339763*
Ihhink_gem_z	92.539747	133.67763*	66.243294
VKov_r_z	27.316625	-55.663847	-8.9385322
Centrum_c	-12.308068	197.18043	(omitted)
Ring_c	539.07754***	(omitted)	544.20194***
Vimpact_i_z	-54.616047	68.499371	-32.230803
Vbeleving_~z	-137.24201**	77.278153	-152.91413*
OaanbodBAO~z	-16.468648	-39.078116	-7.8021714
ORomgeving~z	132.49654	4.805958	224.4293
ORwoningen~z	-90.44988	184.37883	-224.58662*
ORgroenmoo~z	-36.726898	40.106142	-42.64516
ORwater_p_z	-31.365011	-29.626336	-1.3409917
ORgroen_p_z	38.718539	77.589877	-26.356308
ORverblijf~z	124.51806*	55.994513	309.40635
Lhorecaove~z	33.921697	-233.61284***	118.14041*
B~tdg_1000_z	94.610993	173.46008*	9.8804979
B~ndg_1000_z	-61.28296	-167.53102*	-198.33551
Bhvest_gez~z	228.90938***	106.17535	296.89503***
Bhvest_cul~z	-114.16967	-399.37938***	-168.19958
Bhvest_ca_~z	-365.96203**	-361.17785**	-288.88744
nres650_ng_z	-20.313917	-7.3857909	-75.007474
nres650~55_z	32.910783	47.824346	-15.826366
nres650_55~z	-86.421784*	-100.23261*	-104.77921*
nres650_65~z	-12.884517	3.2611221	11.463486
nres650_75~z	165.38845***	131.94133***	210.97436***
nres650_85_z	-46.960548*	-47.183706*	-105.95308***
hhin650gra_z	37.975347***	98.731606***	34.047486**
nresBC10~g_z	-95.358325	165.93696	-108.5723
nresBC1~55_z	157.27062	-116.55843	201.46657
nresBC1~65_z	-44.617184	-154.48826	-169.85957
nresBC1~75_z	231.46063**	87.630592	417.63256**
nresBC1~85_z	119.12835	202.08585**	445.01261**
nresBC85_1~z	.20181864	-42.973646	-139.81346
hhinBCgra_z	-5.2255147	91.635142	-11.532815
_cons	4469.6529***	4883.8536***	4493.0528***
lns1_1_1			
_cons	5.1013862***	4.7540078***	5.2372616***
lnsig_e			
_cons	6.3721685***	6.409828***	6.3050156***

legend: * p<0.05; ** p<0.01; *** p<0.001

A4.3 Correlation matrices

Table A4.3.1 Pairwise correlation ARRA and iens.nl restaurant counter

	Bhvest..	nr~a1000
Bhvest_re_~z	**1.0000**	
nresBCg~1000	**0.9627**	**1.0000**