Supermarket turnover assessments: The impact of omnichannel retailing

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Abstract

The grocery retail market is undergoing major changes due to a rapidly increasing market share of online groceries (e-groceries). The aim of this paper is divided into two pillars. Firstly, to analyse the effects of e-groceries on turnovers of physical supermarkets. Secondly, to assess the effects of the most common counter-action to the increasing role of e-commerce, namely enhancing "customer experience". Both trends were quantitatively analysed with panel data. Results suggest that online sales relate positively to sales in physical supermarkets, which indicates that within Dutch omnichannel supermarket retailing, online sales are complementary to offline sales. Customer experience relates positively to supermarket turnovers in general, however, most impact is observed in rural areas. The evidence of further spatial implications remains limited for e-commerce. Regarding customer experience, the results suggest positive spatial relations. These spatial relations indicate that perceived customer experiences not solely depend on specific supermarkets, but also depend on the customer experience of neighbouring supermarkets.

Keywords: omnichannel retailing, turnover predictions, e-commerce, shopping experience

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I. Table of contents

1. Introduction

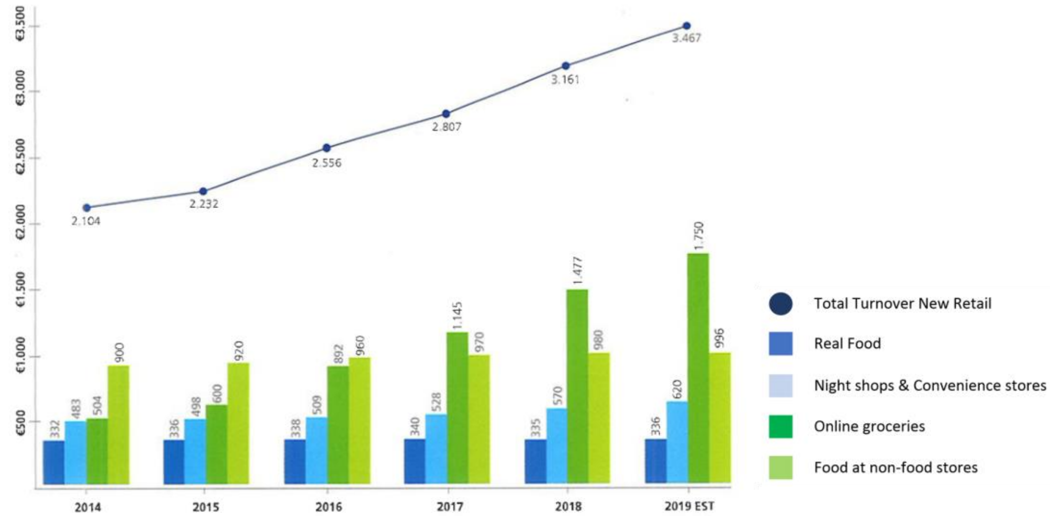
Supermarket retailing is subject to a large, highly competitive, diverse and quickly innovating market (Kumar, Anand & Song, 2017). For retailers, expanding by opening new locations is key for turnover- and market size growth (Roig-Tierno, Baiera-Puig & Mas-Verdu, 2013). Opening new retail locations, however, implies large financial risks due to high real estate costs and unknown return-on-investments. Therefore, predicting turnovers of new supermarket locations is crucial prior to the acquisition of real estate (Birkin, Clarke & Clarke, 2017). Yet turnover predictions are also subject to dynamic and quickly developing market conditions. This paper examines two developments that affect contemporary turnover assessments: *e-commerce* and *shopping experience*.

The first development is the impact of online sales on offline sales in supermarket retailing. The second development is the impact of customer experience on supermarket sales. The effects of both phenomena are analysed within urban and rural areas to test for spatial variations. This leads to the following main question:

To what extent do e-commerce and shopping experience affect supermarket turnovers and to what extent does the impact differ between urban and rural areas in the Netherlands?

Today, assessments of turnovers are predominantly based on demographic data, market size and store characteristics (Turhan, Akalin, & Zehir, 2013; Kumar et al., 2017). However, in omnichannel business operations, online- and offline business operations are extensively intertwined (Zhang, Ge, Gou, & Chen, 2018; Birkin, Clarke & Kirby-Hawkins, 2018). Within companies, for example, it leads to the cannibalisation of turnovers, which is the process of turnover losses in one operation due to the rise of new business operations (Weltevreden, 2007). This is the case of Albert Heijn supermarkets in the Netherlands. E-grocery shopping is increasingly common among Dutch customers and more online competition is coming up, as is illustrated in figure 1 (FSIN, 2018; Gorczynski & Kooijman, 2015). To illustrate this, seven out of ten people will buy their groceries online before 2025 (IGD, 2018). Assuming that online groceries are a substitute for offline groceries, it is expected that high use of online shopping in a supermarket's service area results in lower performances of those supermarkets (Shi, Vos, Yang & Witlox, 2019; Weltevreden, 2007).

Figure 1. The growth of online supermarket sales in the Netherlands (indicated in dark green) versus other food trends.



Source: FSIN, 2019 pp. 40.

Furthermore, it is argued that the effects of e-commerce on turnover performances vary between urban and rural areas (Birkin, Clarke & Kirby-Hawkins, 2018; Roig-Tierno, 2013). Birkin et al. (2018) suggest in their study on the UK e-commerce market that significant differences are found between urban and rural areas. Whereas Beckers et al. (2018) argue that geography does not matter for the Belgian market, and therefore urban areas and rural areas are relatively similar. The Dutch market has not yet been analysed in these regards. Thus, this paper's first pillar focuses on both the impact of e-commerce and aims at investigating the spatial differences.

As a result of omnichannel retailing, the role of supermarkets is changing in order to compete with and distinguish themselves from online markets (IGD, 2018; FSIN, 2019 pp. 49). This leads to the second pillar of this paper: *consumer shopping experience.* Supermarkets are differentiating themselves by investing in dynamic "customer experiences" (Healy, Beverland, Oppewal, & Sands, 2007; IGD, 2018), for example by providing live cooking corners and sushi bars. The customer experience is being adopted by an increasing number of supermarkets (IGD, 2018; FSIN, 2019), but its effects on turnover have not yet been analysed quantitatively (Verhoef, Lemon, Parasuraman, Roggeveen & Schlesinger, 2009). As it is crucial for omnichannel supermarket chains to maintain well-performing physical stores (Roig-Tierno et al., 2013), knowledge of the effects of "customer experience" is important in regard to turnover assessments.

This paper contributes to research in the fields of retailing and economic geography by offering a contemporary view on trends in supermarket retailing that presumably affect turnover estimates. The results are drawn upon quantitative analyses of panel data. Donald and Lang (2007) suggest studying panel data is optimal for assessing turnover developments. Using a dataset provided by Albert Heijn, an Ahold Delhaize company and market leader in the Netherlands, the results offer unique insights into the Dutch market. The results are of relevance for practitioners as well, in particular for Albert Heijn's location strategy department. New knowledge of e-commerce and consumer shopping experience enhances the accuracy of sales estimates. Moreover, research into cannibalisation effects between online and offline sales channels offer all markets that are affected by the upcoming of e-commerce insights into the effects. This could affect future supermarket locations in terms of location and size. Furthermore, insights into the turnover effects of experience offer retailers knowledge into the effects of investing in customer experiences. This could result in strategies enhancing the store experience differently across the Netherlands.

The structure of the paper is as follows. In the second section, existing studies on retail turnover predictions, e-commerce (pillar 1) and customer experience (pillar 2) are discussed and hypotheses are formulated. In the third section, the data are explored, the methodology is elaborated on and applied. The fourth section interprets the results according to the theoretical discussion of section two. The final section draws conclusions and managerial implications for retailers to effectively position new locations in a changing consumption environment.

2. Literature review

Within the area of retailing research and economic geography, predicting turnover performances have been of interest for nearly a hundred years (Turhan et al., 2013; Wood & Reynolds, 2012). This academic attention is primarily focused on predicting store turnovers based on location-specific information, which is essential knowledge prior to opening new stores (Turhan et al, 2013; Roig-Tierno et al., 2013). However, the turnover calculations are subject to dynamic and quickly developing markets (Kumar et al., 2017). Roig-Tierno et al. (2013) composed four general parameters that predict the retail turnover performances: demographics, competition, establishment and location. These parameters are verified by Kumar et al. (2017) and Turhan et al. (2013), who have drawn their conclusions on comprehensive literature reviews. Therefore, these parameters are applied as a framework in this paper for the grocery retail sector. Each parameter is shortly introduced below.

(1) *Demographics*

Hoch, Kim & Montgomery (1995) argue that the population structure is the most important parameter for explaining supermarket turnovers. Turhan et al. (2013) confirm this in their research into supermarket turnover predictions. This parameter provides information on population, its economic characteristics that lead to an assessment of purchasing habits. Demographics could, therefore, indicate the potential market size of new supermarkets (Ellickson & Grieco, 2013).

Indicators within this parameter are *population density, age, gender, education, average income* and *household size.*

(2) Competition

Competition, which forms the market structure, consists of two components: competition between firms and market saturation (Kumar et al., 2017). Competition between firms depends on the presence of similar products in the same service area, in this case, of supermarkets. Competition has increased among supermarkets across the Netherlands due to growth in operations (e.g. online), zoning regulations and most of all consolidation of supermarket chains (Turolla, 2016). As a result, larger supermarket chains compete for limited available growth markets. On top of that, differences between growing urban areas and declining rural areas are increasing (Beckers et al., 2018). Besides spatial differences, grocery retailing itself is heterogeneous. Even within supermarket chains, different formulas fulfil different roles in local markets.

The level of market saturation, the second component of the market structure, is considered to be the ratio of the demand for a product or service divided by the available supply (Dunne, Lusch & Carver, 2008). A high saturation level results in a low potential market share. Customers are, namely, habit persistent and new entrants have, consequently, competitive disadvantages (Kumar et al., 2017). Contrary to that, Arbia et al. (2015) suggest that large supermarkets are attracted by locations with smaller food stores. Therefore, the saturation level might not be the optimal predictor, because large supermarkets have competitive advantages due to their scale and price elasticity (Arbia et al., 2015). Regarding supermarket location planning, the following competition factors should be considered: *size of competitors, number of competitors* and *market saturation*.

(3) Establishment

The establishment refers to store characteristics. These characteristics are the size (square meters of sales floor), parking facilities, the number of departments and the number of checkouts (Roig-Tierno et al., 2013; Turhan et al., 2013). This parameter thus forms a property-specific indication of potential supermarket sales.

(4) Location

The ease of accessibility is the main indicator of a successful location (Turhan et al., 2013). The accessibility must be viewed from the perspective of the car, bicycle and walking accessibility (Roig-Tierno et al., 2013; Ellickson & Grieco, 2013). This does not refer to parking space, but more to infrastructural characteristics surrounding the potential supermarket location. Furthermore, the location parameter incorporates whether a supermarket is located in a rural or urban area.

The parameters provide a generalised and practical view of new supermarket locations and its potential. All parameters are intertwined, for example, the optimal supermarket size depends on the market size and competition (Kumar et al., 2017). Trends like online grocery shopping are not taken into account by general turnover predictions. Also, extensive additions to store experiences, as is occurring increasingly, is not taken into account. The parameters of Roig-Tierno et al. (2013) are thus a framework under which contemporary additions could be added. In the following section, an in-depth theoretical analysis is provided for both e-commerce and consumer shopping experience.

2.1 Development of e-commerce (pillar 1)

In today's grocery retail market, a new form of competition is upcoming: e-commerce. In the past years, the online market share has increased from 2% in 2017 to 4% in 2019 of the total grocery spending in the Netherlands (FSIN, 2019). In 2019 the online market share is expected to increase with another 31% (FSIN, 2019).

E-commerce is a technology on the global internet that enables the exchange of product, order, payment and shipping information in order to fulfil end-to-end Business-to-Consumer (B2C), Business-to-Business (B2B) and Consumer-to-Consumer (C2C) transactions (Visser & Lanzendorf, 2003; Ho, Kauffman & Liang, 2007). In the case of supermarkets, e-commerce consists of B2C online sales, home-delivery and pick-up points for online orders (Birkin et al., 2017). The e-commerce branch of grocery retailing is expected to grow significantly in the coming years (Gorczynski & Kooijman, 2015; FSIN, 2019).

2.1.1 The impact of e-commerce on turnovers

Within the retailing literature, the impact of e-commerce on supermarket turnover performances is yet uncharted (Gorczynski & Kooijman, 2015; Arbia, Cella, Espa & Giuliani, 2015). Nevertheless, the impact of omnichannel retailing has significant impacts on the proportions of turnovers between offline and online sales (Birkin et al., 2018). Firstly, the rise of e-commerce in the Dutch supermarket retailing is explained. Then, the expected impact will be elaborated upon.

The growth of e-commerce platforms in the supermarket sector can be explained by evolutionary economics, which considers the path-dependence nature of economic processes (Arthur, 1994). Path-dependence is an aspect of economic and social development that is subject to corporate routines, a variation of routines, selection of routines and imitation of routines (Nelson & Winter, 1982). Path-dependence offers insights into the upcoming of e-commerce, but could also confirm that e-commerce will play a role in the future. To illustrate the evolutionary economic perspective, Albert Heijn (AH) provides an example in this case. The grocer started offering home-deliveries by telephone-order in the early nineties ("James Telesuper"), which was a variation in the then-dominant supermarket routine (Gorczynski & Kooijman, 2015). The routine appeared not to be accepted by the market and failed to exist. The internet enhanced the potential of omnichannel retailing, which enhanced the previous routine. In 2001, the supermarket launched Albert.nl, a website offering the products as a non-e-commerce platform. This new routine in supermarket retailing received a positive market response (Gorczynski & Kooijman, 2015). This applies to Schumpeter (1942) who suggested that innovations within companies are the result of recombinations and integrations of the new (online) into the old (offline). The success led to an imitation of this routine by other grocers (Gorczynski & Kooijman, 2015). AH Online, the current online operation of the supermarket, has had many competitors who have developed different routines (e.g. PicNic, an exclusively online supermarket). By taking over Bol.com, the largest Dutch e-commerce platform in 2012, AH online expanded its e-commerce knowledge (Gorczynski & Kooijman, 2015). In 2014, as a result of the takeover, AH online started with home delivery services and in 2018 the turnover exceeded 400 million euros (Distrifood, 2017). As a result, AH online proved to be a major innovation consisting of incremental innovations, which led to imitations of competing supermarkets and the rise of full online supermarkets (e.g. PicNic). This process has changed the current market and applies to evolutionary economics (Nelson & Winter, 2002). Further alterations of the market are expected as a result of e-commerce (FSIN, 2019).

The assumption that e-commerce in supermarket retailing impacts offline turnovers is based on the type of products supermarkets sell (Shi, Vos, Yang & Witlox, 2019). Four effects of e-commerce are proposed: (1) substitution, (2) complementarity, (3) neutrality and (4) modification.

(1) In the first type of impact, substitution, it is believed that e-commerce replaces shopping trips to physical stores. Many empirical studies have found evidence of substitution effects in the United States (Weltevreden, 2007). Weltevreden & Rietbergen (2009b) confirm this in a Dutch study with regard to general retailing. This study suggests that 20% of customers are now less inclined to go to physical stores.

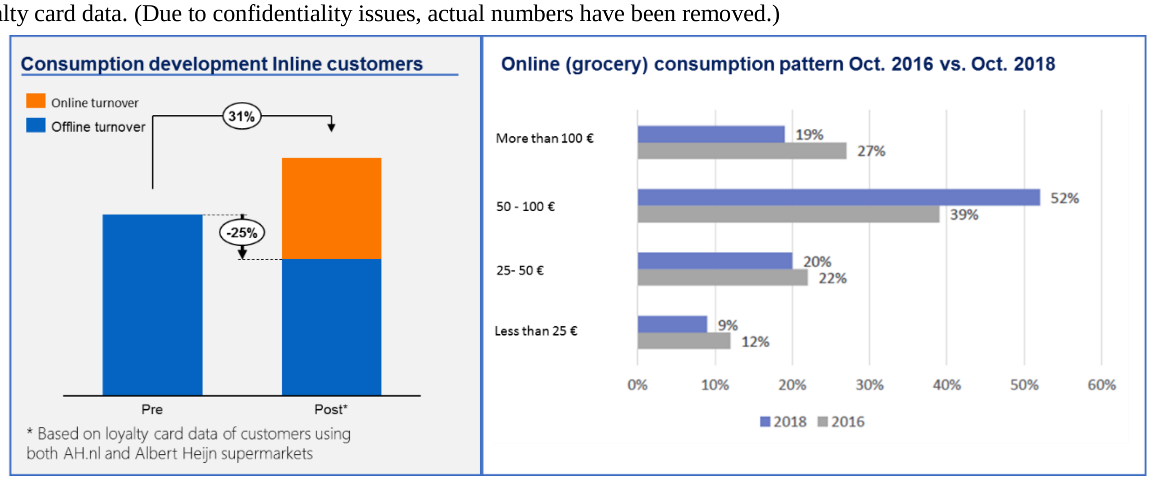
(2) Contrary to this study, Farag, Schwanen, Dijst & Faber (2007), suggest that e-commerce has a complementary effect to visits to physical stores. Consumers are, according to this study, more inclined to visit physical stores due to online encouragement of consumption (Shi et al., 2019).

(3) The third effect, neutrality, suggests that there is no effect on shopping trips at all (Shi et al., 2019). The neutrality assumes that certain products are bought online, and others are not. Therefore, both shopping channels could operate without interacting effects (Weltrevreden, 2007). However, the neutrality effect seems to become less likely due to the rapid expansion of e-commerce platforms in retailing.

(4) Lastly, the modification effect indicates that shopping behaviour changes. For instance, shoppers are more likely to buy products online if it saves time or money (Shi et al., 2019). The study suggests that long-distance shopping is replaced by e-commerce and short distance shopping is not. In other words, modification emphasises that consumer behaviour changes due to multichannel shopping (Weltevreden, 2007).

In supermarket retailing, online sales are assumed to be a substitute for shopping trips (Gorczynski & Kooijman, 2015). Weltevreden & Rietbergen (2009b) suggest that mainly city centres are facing losses due to e-commerce, but this study has concluded this prior to e-grocery shopping. Substitution does not necessarily mean that turnovers decrease, ss is the case with AH supermarkets (Weltevreden, 2007). The general consumption rises for customers who use both online and offline shopping, but offline consumption decreases with 25% (figure 2). Moreover, in the right side of figure 2 it is illustrated that general online consumption per customer rises (Weerd, 2018). The figure namely shows that sales lower than fifty euros have decreased whereas sales higher than 50 euros have increased. As a result, it is concluded that the variety of products that are sold has increased and thus explains the substitution effect illustrated in the left side of figure 2. To conclude, in assessing the parameter 'competition', as suggested by Roig-Tierno et al. (2013), online competition cannot be left unexplored. An additional potential indicator of competition could, therefore, be the market share of online grocery shopping, as Birkin et al. (2018) suggest.

Figure 2. The consumption pattern of customers who have become both offline and online customers (i.e. inline) based on loyalty card data. (Due to confidentiality issues, actual numbers have been removed.)



Source: Internal data (left), Weerd (2018) (right)

2.1.2 Spatial considerations of e-commerce

The impact of grocery e-commerce should, according to Beckers et al. (2018), be viewed with a spatial component. Continuing the attempt of Boschma & Weltevreden (2008) to clarify the location effects of e-commerce, two hypotheses on spatial differences in use of e-commerce are distinguished. Firstly, the hypothesis that people use online shopping for *efficiency*. The efficiency statement argues that e-commerce is used in areas where supermarkets are less accessible (Kumar et al., 2017). Thus, rural areas have higher demands for e-commerce. As opposed to this, the second hypothesis argues that e-commerce is used in areas in which innovation is more accepted (Beckers et al., 2018). This *Innovation-diffusion* hypothesis is thus suggesting that urban areas are more inclined to using online channels (Clarke, Thompson & Birkin, 2015). This is related to large groups of young people (25-44 years of age) living in urban areas, who demand more convenience and flexibility in their shopping (Birkin et al., 2018; FSIN, 2019). In different papers, both hypotheses have been accepted, which indicates that they are not mutually exclusive. In the UK, Birkin et al. (2017) argue that differences have been observed between urban and rural areas confirming the innovation-diffusion hypothesis. However, Becker et al. (2018) concluded that there are no significant differences between rural and urban areas in Belgium. Both hypotheses could thus be accepted in different countries. In the Netherlands, comparable studies have not been carried out in recent years, in spite of Boschma & Weltevreden's (2008) suggestion that more research into spatial variations is required. Within the grocery retail market, the spatial analysis on e-commerce provides new insight into the discussion of whether geography matters.

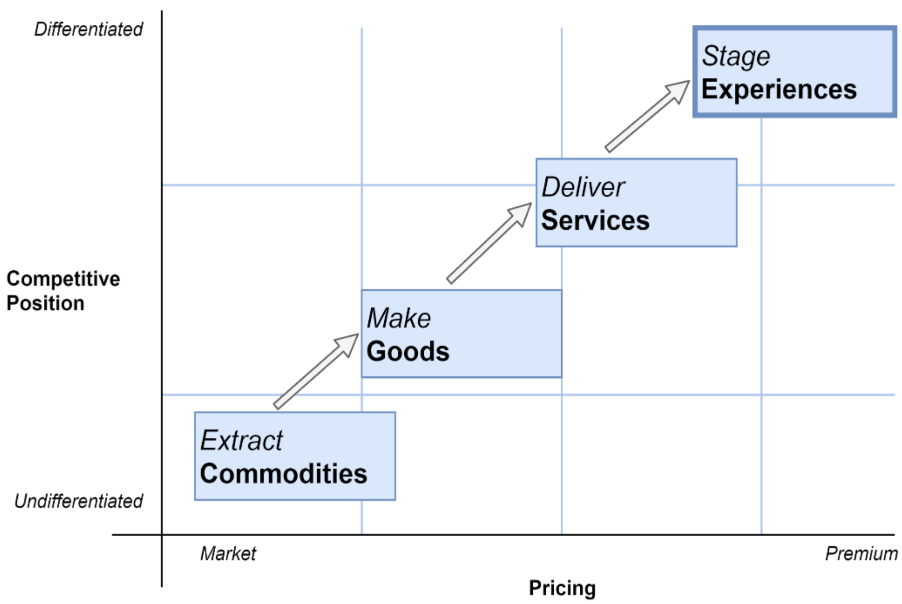
2.2 Development of Consumer Shopping Experiences (pillar 2)

As a counter-action to the shift towards online groceries, supermarkets are increasingly "moving from what is sold, to how it is sold" (Burt, 2010). This transition is referred to as adding more "consumer shopping experience", a holistic view of customer's cognitive, affective, emotional, social and physical reactions to a supermarket (Verhoef et al., 2009). Terblanche (2018) argues that investing in consumer shopping experiences contribute to repatronage intentions, which is defined as the intention to revisit. Strategies focused on customer experiences are, therefore, considered to be a way of bringing online and offline sales to an equilibrium in a competitive market (Grewal, Levy & Kumar, 2010; Turolla, 2016). Customer experiences are considered to add to a retailer's distinctiveness, which also contributes to its market position and sales (Tsai & Yang, 2013).

The customer experience within retailing has been studied for decades. Pine & Gilmore (1998) described the basis of the experience economy and illustrate the basis of the customer experience. In their paper, customer experience is divided into two dimensions: *customer participation* and *connection*.

Customer participation means that people are part of the experience, either actively or passively. A connection with a customer could be arranged by creating an environmental relationship, like certain smells or sounds. Both dimensions result in companies offering their products by "wrapping them in experiences" in order to sell better (Pine & Gilmore, 1998). In figure 3, an illustration is given of "the progression of economic value", which means that experiences add value to services. In this figure, basic commodities are less valuable than products that are sold with additional experiences. Pine & Gilmore (1998) illustrated early on the process in which the service economy would turn into an experience economy.

Figure 3. The progression of economic value.



Source: Pine & Gilmore (1998)

The experience economy has become a distinct economic offering, since it provides new sources of revenue (Pine & Gilmore, 2011). As a result of the experience economy, customers are paying for the time spent in a place. In the case of supermarkets, new sources of revenue could be opened up by offering more experiences like fresh sushi bars, juice bars and other interactive in-store activities.

Expending suggestions of Pine & Gilmore (1998), customer experience in retailing is divided into two streams: static and dynamic (Healy et al., 2007). Static experience, in the case of supermarkets, is the corporate design which is similar in all supermarket chains. The dynamic experience consists of more interactive contact between the supermarket and customer in, for example, live cooking (Healy et al., 2007). Verhoef et al. (2009) describe the customer experience as inherently subjective, which makes it complex to quantify. Packer and Ballantyne (2016) suggest that experience is an event outside of one's usual environment. All supermarkets offer static experiences and even dynamic experiences like a bakery or a butcher, however, according to the definition of consumer shopping experiences, a supermarket must offer something out of the usual environment. As a result, new shopping experiences adopted by a specific supermarket are to become “usual”. Consequently, customer experiences are limited by time and space (Packer & Ballantyne, 2016). As Boschma and Weltevreden (2008) suggest, companies that adopt e-commerce also change in their offline operations. Investments in customer experiences and convenience are thus the result of a changing business model. This trend is confirmed by the Dutch Food Research Company, who advocate that “the contemporary offline supermarket business model is under pressure due to the omnichannel retailing” (FSIN, 2019 pp. 49). Investments in customer experience are assumed to result in improved turnover performances. This assumption, however, is not empirically tested in regard to supermarkets and will therefore be tested further on.

2.2.1 Spatial considerations of customer experience

The definition of customer experience varies across space, as Packer & Ballantyne (2016) concluded. Therefore, it is interesting to analyse whether the impact of customer experience on turnovers varies across space. In other words, do customers in rural areas feel more attracted to additional experiences than urban customers or vice versa? There is, in fact, evidence that the impact of experiences is larger in urban areas than in rural areas (Arentze & Timmermans, 2001; Findlay & Sparks, 2008). As Verhoef et al. (2009) suggest, the customer experience is subjective. Consequently, customers in rural regions might perceive experiences differently than in urbanised regions (Arentze & Timmermans, 2001). In rural areas, there is a general decline in retailers and as a result less comparable retail experiences. Whereas, in urban areas more supermarkets are active. Therefore, a spatial association between experiences is expected.

To conclude section 2.2, consumer shopping experiences is a proposed addition to “establishment” as meant in Roig-Tierno et al. (2013) (table 1). The experience, as meant in this paper, is part of the perceived shopping experience inside supermarkets. Besides the customer experience as a proposed addition to existing parameters, the first pillar is also added to the parameters in table 1. E-commerce is potentially part of the competition parameter as Roig-Tierno et al. (2013) propose. E-commerce is expected to substitute offline sales and therefore form a competitive threat to offline sales. Table 1 provides an overview of the literature, parameters and the proposed additions.

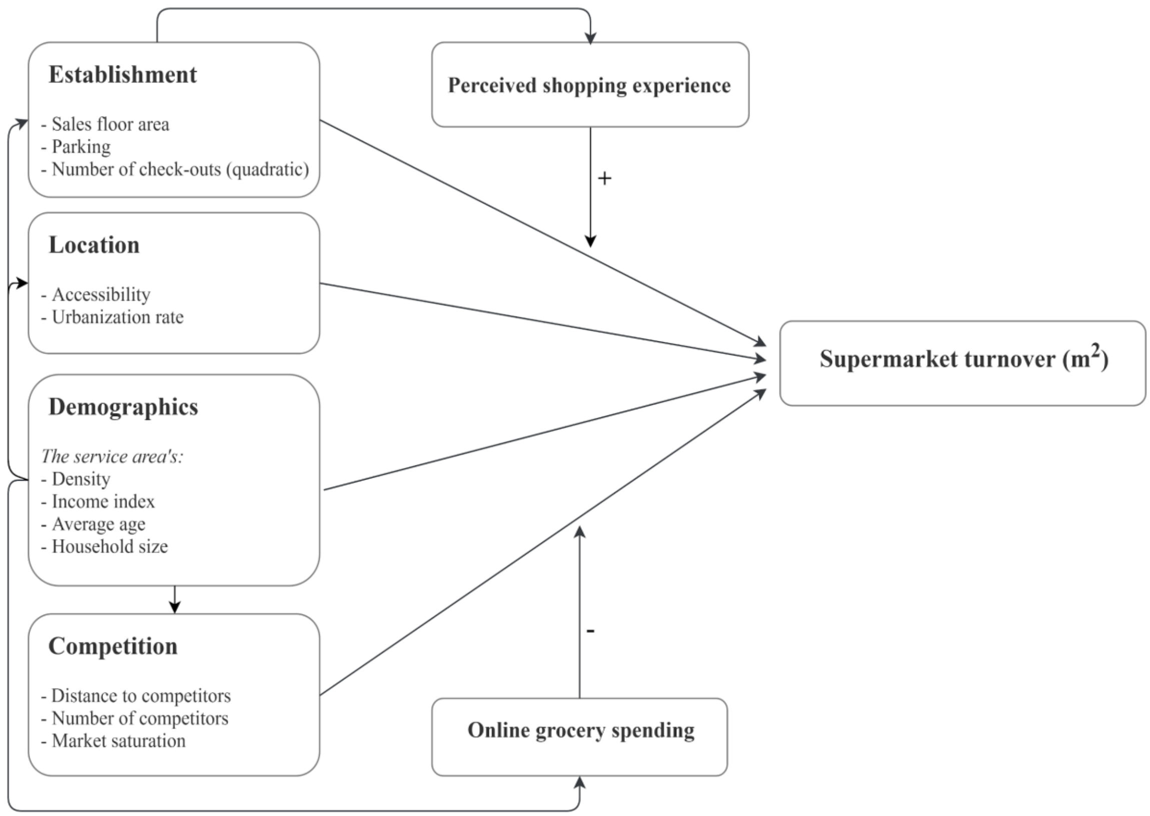
Table 1. Overview of parameters and their subcriteria, including the proposed additions to current parameters.

Parameter		**Subcriteria**	**Indicative research literature**
Demographic factors		Population density Income index Average age Household size	Turhan et al. (2013); Kumar et al. (2017) and Wood & Reynolds (2012)
Competition	 →	Level of saturation Distance to competition Number of competitors **Use of e-commerce (urban or rural)**	Boschma & Weltevreden (2008); Birkin et al. (2018); Birkin et al. (2017); Beckers et al. (2018); Clarke et al. (2017); Dunne et al. (2008)
Establishment	 →	Sales floor area Parking facilities Number of Check-outs **Application of customer experience**	Roig-Tierno et al. (2013); Turhan et al. (2013); Kumar et al. (2017); Terblanche (2018); Pine & Gilmore (1998), Verhoef et al. (2009).
Location		Accessibility by car Accessibility by foot Urbanization (i.e. rural or urban)	Wood & Reynolds (2012); Roig-Tierno (2013); Kumar et al. (2017)

2.3 Conceptual model & hypotheses

By taking into account the parameters Roig-Tierno et al. (2013) suggest in combination with the trends *e-commerce* and *consumer shopping experiences*, the conceptual model (figure 4) is composed. On the left side, the current parameters *establishment, location, demographics* and *competition* are concentrated. These parameters directly explain supermarket turnovers. Between the parameters, there is a connection between *demographics* and *competition* because the type of market determines whether the attractiveness for more competitors (Kumar et al., 2017). Between *demographics* and *establishment,* the connection is indicated because the type of market determines the store-facilities. Between *demographics* and *location,* the connection indicates the relation between the demographics (e.g. density) and its relation to infrastructure and to the urbanisation rate. The model shows that *consumer shopping experience* is directly linked to the *establishment* since the experience, in this paper, always concerns the establishment itself. However, customer experience is not yet included in the parameter because the effects are still unknown in regard to explaining supermarket turnovers. A positive relation is expected when supermarkets add extra customer experience, this is indicated with the ‘+’. For the *use of e-commerce,* which is part of the *competition* a similar layout is used. The use of e-commerce in a supermarkets’ service area is expected to have a negative impact (-) on supermarket turnovers. The *demographics,* as concluded in Birkin et al. (2018) and Kirby-Hawkins et al. (2018), explain the adoption of e-commerce. Therefore, there is a line drawn from demographics to e-commerce. *The use of e-commerce* is not yet included in the parameter *competition* because the effects are still unknown in regard to explaining supermarket turnovers. In short, the parameters on the left summarises the current literature, whereas consumer shopping experience and e-commerce are yet to be investigated.

Figure 4. Conceptual model. On the left, the control variables are outlined, the independent variables are in the middle, the dependent variable is on the right.



Hypotheses 1a & b

The first hypothesis deducted from the theory concerns the impact of e-commerce on supermarket turnovers. Based on the results of Birkin et al. (2018) and Gorczynski & Kooijman (2015), it can be argued that an increase in online sales could have an impact on sales of physical stores. Therefore, the following hypothesis (1a) is formulated:

If online sales are high in a supermarket's service area, the supermarket's turnover will be lower.

As argued by Beckers et al. (2018), no spatial variation was found in the use of online sales in Belgium, however, Clarke et al. (2015), Birkin et al. (2017) and Boschma & Weltevreden (2008) argue that spatial differences have been observed. Therefore, the following hypothesis (1b) is formulated:

In rural areas, the impact of e-commerce on turnovers is less than in urban areas.

Hypotheses 2a & b

As suggested by Terblanche (2018), having more customer experience results in repatronage intentions of current and new customers. Furthermore, the experience is important for distinctiveness towards competitors in the highly competitive market. As a result, supermarkets that apply more experience to their stores are expected to see an increase in turnovers (Pine & Gilmore, 1998). Therefore, the following hypothesis (2a) is formulated:

If a supermarket's customer experience is higher, the supermarket's turnover will be higher.

Findlay & Sparks (2008) suggest there is a variation between the effects of customer experience between urban and rural areas. Urban supermarkets that score high on experience are expected to have relatively higher turnovers. Being distinctive in urbanised areas, with relatively high market saturation, is of more importance than supermarkets that are located in rural areas. The following hypothesis (2b) is therefore formulated:

In urban areas, the impact of "customer experience" on turnovers is larger than in rural areas.

3. Methodology

Panel data regression techniques have been employed to determine the impact of e-commerce and customer experience on supermarket turnovers over a time span of five years. Prior to presenting the results, the data are explained, then the dependent and independent variables are described and descriptive statistics are provided. In the final section of this chapter, the methods are elaborated upon.

3.1 Data description

The data that have been analysed in this paper, are restricted to data of full-service Albert Heijn supermarkets in the Netherlands that have been operational for the past five years ($N_{total} = 839$). The dataset is a combination of datasets from three sources: Dutch census data (CBS), Whooz-data on demographics and Ahold Delhaize on AH supermarket characteristics. Weltevreden (2007) indicates that, in order to overcome the subjective nature of most empirical studies concerning the impact of e-commerce on physical shopping, longitudinal data is required. Therefore, datasets from all three institutions are combined in a panel dataset spanning from 2015 to 2019. The timeframe of the use of e-commerce is five years because the intervention of home delivery and pick-up points have started in 2014 (Ahold Delhaize, 2017; FSIN, 2019). The data on customer experience is measured in a timeframe of four years, because the panel survey is held since January 2016. The panel data is *short, unbalanced* and *fixed*. The data are considered short because the span they cover is five years (Park, 2011). The data are unbalanced since not all data entities have the same number of observations, for e-commerce this is five years and for the customer experience this is four years (Wooldridge, 2008). Furthermore, the data are fixed since the same entities are observed for each period of time (Park, 2011).

3.2 Dependent variable

The dependent variable is the moving annual average supermarket turnover divided by the store size. The turnover by square metre offers a better cross-sectional comparison between a heterogeneous group of supermarkets (Turhan et al., 2013). The observations are independent of each other and linearity is confirmed. The logarithmic (log) approximation of the turnover per square metre is applied because this eliminates any skewness or heteroscedastic distributions (Wooldridge, 2008). Furthermore, the logarithm diminishes the effects of outliers and extreme observations, which makes the estimates more robust (Wooldridge, 2008).

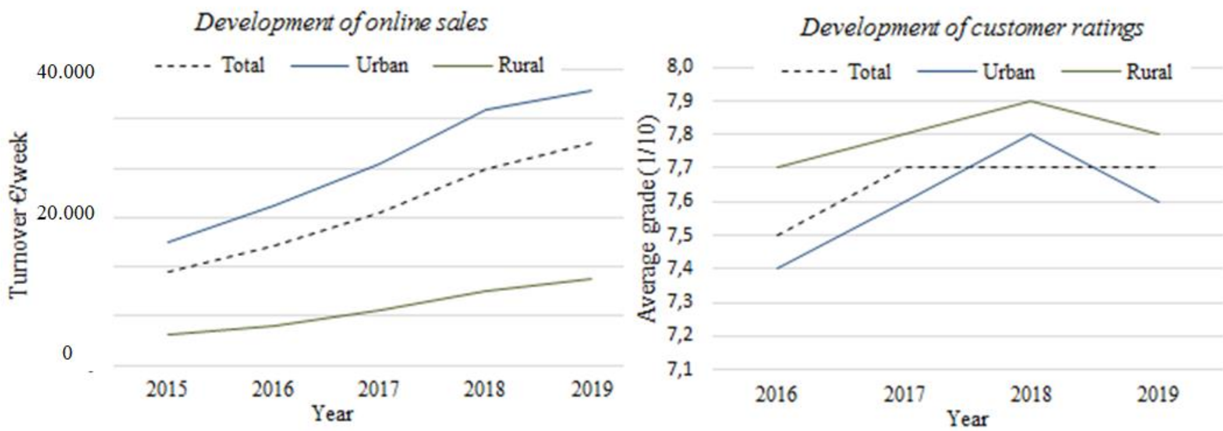
3.3 Explanatory variables

The variables *e-commerce* and *customer experience* are the explanatory variables that are at the main focus in this paper, therefore a detailed explanation is provided. Thereafter, a clarification of other variables is provided.

The aim of the variable *e-commerce* is to assess the magnitude of online sales that potentially affect supermarket turnovers. To measure this, data are based on the sales of AH.nl, the current online market leader (FSIN, 2019). Using AH.nl-data, online turnovers generated in a supermarket's consumer market area can be measured accurately. These service areas are geographically bounded areas where, on average, 70% of a supermarket's customers live, based on loyalty-card data. All supermarkets have unique service areas, although in urban areas some service areas overlap. In this case, some online turnover is taken into account more than once. Nonetheless, each service area reflects the customers of each supermarket specifically. E-commerce is measured in period 3 of the years 2015 to 2019. For similar considerations as the dependent variable, the log approximation is applied to online sales.

In figure 5 (left figure), the development of online sales is illustrated. In this graph, the general trend shows that spending has increased substantially, which complies with the literature (Gorczynski & Kooijman, 2015). In rural areas, online spending is much lower on average and the growth is less steep than in urban areas. About 70% of the researched supermarkets are located in the AH online service area.

Figure 5. Development of online spending AH online (left) development of customer ratings (right), ($N_{urban} = 566$) ($N_{rural} = 273$). (Due to confidentiality issues, the actual numbers have been transformed).



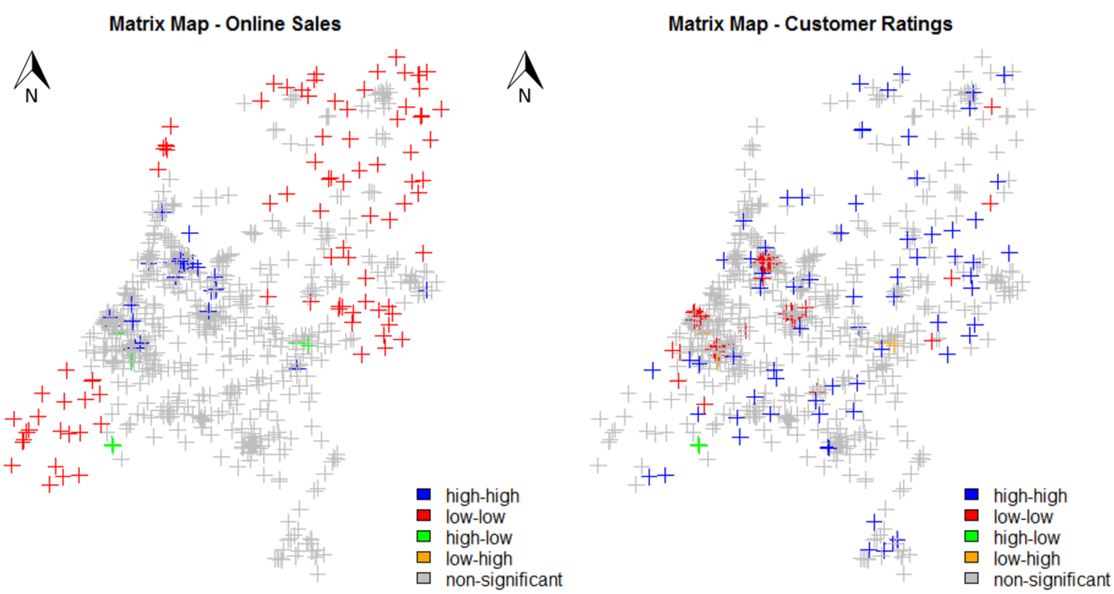
The aim of the variable *customer experience* is to assess the perceived customer experience for each supermarket. Verhoef et al. (2009) describe the customer experience as inherently subjective, which makes it complex to quantify. To overcome this problem, data on experience are based on *customer satisfaction research* questionnaires organised by Albert Heijn to obtain insights into the perception of customers. As a result, the experience is measured from the customer perspective, rather than physical elements in the supermarket, as suggested by Terblanche (2018). The surveys have been conducted six times a year with the same panel group since the beginning of 2016 in all supermarkets ($N_{total} = 839$). In each measurement, the respondents give a general score (scale = 1-10) to the supermarket in question. Contrary to *e-commerce,* this variable does not represent the service area but gives an indication of the development of customer experiences for each supermarket. The average rating in 2019 is 7.69/10 with a standard deviation of 0.49 ($\mu_{total} = 7.69, SD = 0.49$).

In figure 5 (right graph), the development of average customer ratings is illustrated. Striking in this graph is the general decrease in average scores in 2019 in both urban and rural areas. In rural areas, the average scores are higher than in urban stores. This applies to the literature where it is suggested that in rural areas experiences are more noticed (Packer & Ballentyne, 2016).

The distribution of supermarkets is illustrated in the map below (figure 6). The map shows that in the Randstad the density of AH supermarkets is higher than in other parts of the Netherlands. Nevertheless, AH has coverage across the whole country. The Moran’s I tests the spatial dependency between nearby observed values and thus measures whether supermarkets are independent of space or whether there are consistent relations between ‘neighbours’ (Croissant & Millo, 2019). The results of the Moran’s I suggest an insignificant spatial correlation in both (1) online sales ($p = 0.16$) and (2) customer ratings($p =$

0.16) (Appendix II). Figure 6 a matrix map is illustrated in which neighbouring supermarkets are compared with respect to both online sales (left) and customer ratings (right). Online sales show a cluster of high-high in online spending in the cities within the Randstad indicated in blue. This means that the observed mean is above the general mean and spatially lagged mean. This observation is in line with the *innovation-diffusion* hypothesis proposed by Beckers et al. (2018), where urban residents would be more inclined to buy e-groceries. Customer ratings mainly score high in rural areas, indicated in blue, suggesting a mean above the average scores and above the lagged average. The urban areas in the Randstad show substantially lower results compared to their neighbouring supermarkets. Despite the insignificant Moran's I, the maps show spatial patterns. Therefore, further investigation of spatial associations would be of interest.

Figure 6. LISA cluster map considering online sales (2016 – 2019) || (N_{total} = 839) (left) & LISA cluster map considering customer ratings (2016 – 2019) || (N_{total} = 839) (right)



In table 2, the general descriptive statistics of all explanatory variables are provided. In this table, a short description, the mean, standard deviation, the geographical unit and data sources are summarised for each variable. The explanatory variables are general indicators as suggested by Roig-Tierno et al. (2013). The data are available in three data frames, total (N_{total} = *839*), urban (N_{urban} = *566*)and rural (N_{rural} = *273*). The supermarket characteristics control for differences between supermarkets. Therefore, different types of supermarkets can be included in this analysis. For the explanatory variable *checkouts*, an additional quadratic variable is added. The quadratic variable (*checkouts*^{2}) estimates whether a parabolic curve is applicable, which means that after a certain number of checkouts the relationship could shift from negative to positive (Wooldridge, 2008). The quadratic relationship is expected since rural supermarkets generally have more checkouts, because rural stores are larger, but turnovers per square metre are lower. However, large stores (i.e. AH XL) with even more checkouts could have different functions and generate high turnovers per square metre. Thus, a negative relationship is expected first, then a positive relation. Demographic factors control for spatial differences and thus different spatial entities are analysed in this paper. Population size, for example, could explain higher online or offline turnovers just by the number of people living there. The log of population size is used in the analysis to overcome any skewness in the data. Income index is taken into account to check for differences within urban areas and between urban and rural areas. For example, demand can differ significantly between urban service areas with similar density but with contrasting income levels (Beckers et al., 2018). More lower-income regions are found in rural areas than in urban areas, therefore income indices contribute to a better comparison between urban and rural (Beckers et al., 2018). The locational characteristics control for offline competition and the local market share. In the analysis, the log of market share is taken into account to control for any skewness or heteroscedasticity. Table 2 describes the raw data. The appendix (1) contains the correlation matrix in which mutual relations are outlined and described.

Table 2. Descriptive statistics showing a description, the mean, standard deviation (SD), geographical unit and data source.

	Name	Description	Mean	SD	Geographical unit & data source
Dependent Variable	Supermarket turnover	Moving Annual Average weekly turnovers ($€/m^2$)	200	62	Supermarket level (*Ahold Delhaize*)
Explanatory variables					
Establishment	Check-outs	Number of checkouts	10	4	Supermarket level (*Ahold Delhaize*)
	Check-outs^2	Number of checkouts (Quadratic)	106	88	
	Parking space	Number of parking lots	184	221	Supermarket level (*Ahold Delhaize*)
Demographic factors	Population	The population living in a service area	18.975	17.600	Service Area (*CBS*)
	Income index	The index of income (100 is Dutch average)	103.5	19	Service Area (*CBS*)
	Education level	Level of education (high/low) High: (hbo) bachelor's degree or higher. Low: others.	194/642	0.42	Service Area (*Whooz-data*)

Location	Accessibility	The quality of accessibility (average/good, excellent)	558/278	0.47	Supermarket level (*Ahold Delhaize*)
Competition	Competition	Number of competitors	3.64	3.97	Service Area (Whooz-data)
	Market saturation	Competition density (total m^2 store size / population)	0.29	0.11	Service Area *(Ahold Delhaize)*
Hypothesised variables	Log(e-commerce)	Total AH online sales in supermarket's service area (€)	5.26	0.30	Service area (*Ahold Delhaize)*
	Experience	Customer rating (scale 1 to 10)	7.69	0.49	Service area (*Ahold Delhaize*)
	Interaction effect	Log((E-commerce)*Experience)	241		Service area

Source: Ahold Delhaize - Albert Heijn, Real Estate & Construction and Franchise (Including acquired data from the Dutch Bureau of Statistics (CBS) and Whooz-data).

3.4 Methods

The data tested in this paper is longitudinal, therefore, several panel data regressions have been employed. The hypotheses have been tested using panel data regressions as is explained in section 3.4.1. Then, a closer look into spatial relations has been analysed using a spatial panel data regression as is explained in section 3.4.2. Finally, validity and reliability will briefly be discussed.

3.4.1 Panel data regression

The impact of e-commerce has been investigated by analysing supermarket turnovers two-dimensionally. The first dimension contains data on supermarkets, their characteristics (*i)* and characteristics of their surrounding area (*r)*. The second dimension considers these variables over a time span of five years (t = 5). The data applied are thus cross-sectional time-series data (i.e. panel data) in which the impact of entities or trends are observed across time (Addison, Blackburn & Cotti, 2009). Having panel data, the effects of AH online usage can be measured by an econometric panel data regression technique (Houde, 2012). The panel regression offers insights into a potential causal relation between turnover growth/decline and the growth of an intervention (i.e. online grocery shopping) (Croissant & Millo, 2019). Donald and Lang (2007) suggest that using panel data is optimal for finding trends in sales. Furthermore, panel data regressions could identify effects that cannot be detected by just cross-sectional data (Anselin et al., 2008; Croissant & Millo, 2019). Panel data regressions are namely able to identify unobserved heterogeneity by leveraging the information on time variation for each variable (Wooldridge, 2008, pp. 488). Therefore, panel data regressions are most applicable to the research question of this paper. The regression equation is built up as follows:

$$(1)\quad log(\text{turnover})_{it} = \beta_0 + \beta_1 log(e - commerce)_{it} + \beta_2 log(experience)_{it} + \alpha \mathrm{X}_{it} + \gamma \mathrm{Z}_{rt} + \delta_{it} + error_{it}$$

In the equation above, the general layout of the panel regression is illustrated. The $turnover_{it}$ indicates the supermarket *i*, and *t*, which indicates the time in years. E-commerce, which is the second beta (after the intercept) in the formula ($\beta_1 log(e - commerce)_{it}$) is integrated as a time-dependent variable. The alpha ($\boldsymbol{\alpha} x_{it}$) controls for the supermarket characteristics. The $\boldsymbol{\gamma} Z_{rt}$ in the equation refers to demographic variables and competition variables, these variables are not supermarket dependent, but are about referring to the supermarket's surrounding area.

The aim of analysing the consumer shopping experience is to find relations between customer ratings over time and turnovers over time. Since the data are longitudinal, potential increases in-store experience can be measured by increasing average grades. A similar panel data regression is applied as shown in equation (1) for analysing the impact of the experience on average turnovers ($\beta_1 log(experience)_{it}$).

Potentially, the partial effect of an explanatory variable depends on the magnitude of yet another explanatory variable. As described in the literature, the increasing investments in customer experience are a counter-action of the increase in online grocery shopping (Grewal et al., 2010). Therefore, interaction is expected in the effects between both variables with regards to supermarket turnovers. The interaction effect can be measured by including a panel data regression model which multiplies the observations of e-commerce with the observations of customer experience (Lavrakas, 2008). Insights into the interactive effects of the two could, therefore, provide evidence for the expected relation between the two (Wooldridge, 2008, pp. 197).

For e-commerce, customer experience and the interaction effect, the *Fixed Effect Model* is applied. The Fixed Effect Model, part of the panel regression (δ_{it}), is the most common statistical method to obtain insights into the impact of a variable over time (Croissant & Millo, 2019). The model examines if intercepts differ across observations and time (Park, 2011). The fixed-effect model transforms the data by subtracting the average over time to every variable (Croissant & Millo, 2019). The Fixed Effect Model is defined as:

(2) $y_{it} - \bar{y}_i = \beta_1((e - commerce)_{it} - (e - commerce)_{\text{it}}) + \beta_2((experience)_{it} - (experience)_{\text{it}}) + \ldots + \beta_k x_{itk} + \alpha_i + \mu_{\text{it}}$

Where y_{it}- $\bar{y_i}$ is the time-demeaned data on y and similarly for $\beta_l((e - commerce)_{it} - (e - commerce)_i$ on the x. The Fixed Effects transformation is also referred to as the "within" transformation, because it takes the time variation within the cross-sectional data. Other panel data regression models, such as *random slopes model* and the *first difference model* were tested as well. The *Hausman test*, which estimates the optimal model ($\chi^2 = 354.22(7, N = 4{,}168), p < 2.2e - 16$), pointed out that the *Fixed Effect Models* in all panel data regressions in this paper is most powerful (Appendix II). Moreover, the Fixed Effect Model allows data to be unbalanced (Wooldridge, 2008 pp. 491), which is the case in this paper. Therefore, in the further extent of this paper, only Fixed Effect Models are illustrated.

3.4.2 Spatial analysis

As indicated in section 3.3, the spatial matrix maps (figure 6) indicate potential spatial patterns. Firstly, the question arises to what extent supermarket turnovers are influenced by the use of e-commerce of neighbouring service areas. Shi et al. (2018) suggested a potential modification effect of customer behaviour as a consequence of e-commerce. One aspect of the modification effect is that long-distance shopping would be replaced by e-commerce and short distance shopping would not (Weltevreden, 2007). In this case, large supermarkets with more long-distance customers could be negatively affected by the rise of e-commerce further away. Therefore, the spatial analysis aims to test the extent to which online sales in neighbouring service areas influence supermarket performance. Secondly, the question arises to what extent supermarket turnovers are influenced by customer ratings of neighbouring supermarkets. Terblanche (2018) suggests that stores with good customer experiences attract customers and will encourage these customers to revisit. Furthermore, as Turolla (2016) suggests, customer experience enhances a store's distinctiveness from competitors. As a result, the market position of a store would improve and potentially attract customers from a wider area. Therefore, the spatial analysis provides insights into supermarkets are influenced by the customer ratings of neighbouring supermarkets.

In order to quantify neighbouring supermarkets, a radius around each supermarket is drawn. When a supermarket is located in this radius, it is considered to be a neighbour (Croissant & Millo, 2019). Since the nature of the spatial analysis is of explanatory, three radiuses are measured. The first radius assesses the effects of supermarkets and their service areas within a range of one kilometre. The second and third radiuses assess supermarkets within a range of three and five kilometres, respectively. These radiuses are applied because it enables the analysis to include near neighbours, neighbours on a city or village level and neighbours on a large level. Regarding e-commerce, a spatial relation is expected in a 5-kilometre range, since an increase of online sales would be a substitute for long-distance shopping (Shi et al, 2018). Regarding customer experience, a spatial relation is expected with a 1-kilometre radius, since a supermarket surrounded by supermarkets with higher customer experiences could be substituted (Turolla, 2016). The method for the spatial analysis is a spatial panel data regression.

The spatial panel regression is similar to the panel data regression, as explained in the previous section. However, the spatial panel data regression includes e-commerce and customer experience in a matrix of weights **W**. This matrix considers the spatial effects of both online sales and customer rating, by calculating the following equation for every Albert Heijn supermarket:

$$(3)\quad \widehat{m}_i(x) = \sum\nolimits_{\mathrm{j}} w_{ij} x_j = \mathbf{w'}_{\boldsymbol{i}}\mathbf{x}$$

In this equation, the $\widehat{m}_i(x)$is the average of the values of $x$in the neighbouring supermarkets of supermarket i. The x represents either online sales or customer ratings. $w_{ij}$are the spatial weights that relate to a specific supermarket i to all other supermarkets j, and $x_j$represents the values of a variable of all supermarkets j. Equation (3) represents one row of the matrix **W**. In equation (4) the spatial-x model is outlined.

$$(4)\quad log(turnover)\ _{it} = \beta_0 + \beta_1 log(e - commerce)\ _{it} + \beta_2 log(experience)\ _{it} + \alpha X\ _{it} + \gamma Z\ _{rt} + \delta W x_{it} + \delta\ _{it} + error\ _{it}$$

In the spatial-x model, the general layout of the spatial panel regression is illustrated. The layout is similar to the equation of the panel data regression, but the $\delta W x_{it}$is added as a variable. The x represents either e-commerce or customer experience. E-commerce is measured on a service area level, whereas customer experiences are measured on a supermarket level (as defined in section 3.3).

Similar to the panel data regression, a Fixed Effect Model is applied. Also, all time-invariant variables are omitted. In contrast to the panel data regression, the spatial panel also omits all observations with missing values and observations without any neighbours. As a result, the non-spatial results of the analysis are less robust due to the compressed dataset. Therefore, the results concerning the impact of e-commerce and customer experience are more reliable in sections 4.1 and 4.2. Thus, the aim of the spatial analysis is exclusively to further analyse the spatial relations between online sales and customer ratings.

3.4.3 Reliability & Validity

This paper studies all Albert Heijn supermarkets, which is also the total population on which the results reflect. Consequently, the reliability of this paper is optimal. The methods applied in this paper are logically based on the objective of this paper since it focuses the supermarket performance growth over time (Houde, 2012). Customer experience is measured by a general customer rating. Arguably, this measurement does not reflect customer experience in its exact definition as meant by Healey et al. (2007). However, the data does reflect the perceived experience in general and is measured similarly across all supermarkets over four years. Therefore, its impact on turnovers does measure the objective of this paper. On the one hand, the internal validity might be problematic since the causal relation between supermarket performance developments could be explained by other affecting factors. For example, the local reputation of the supermarket, microeconomic conditions and the typology of the competition (i.e. budget or premium supermarkets). This limitation, on the other hand, is reduced by using longitudinal data (Bryman, 2012). This makes the data set more robust to external variables. Therefore, panel data is most suitable for analysing macro-level trends (Addison et al., 2009).

4. Outcomes

This section presents the outcomes of the panel data regressions and spatial analyses. The analyses and results are elaborated upon for each hypothesis outlined in section 2.3. Thereafter, the results of the spatial analysis are discussed further.

4.1 The impact of e-commerce

The first hypothesis concerns the impact of e-commerce on supermarket turnovers. Based on the results of Birkin et al. (2018) and Gorczynski & Kooijman (2015), it can be argued that an increase in online sales could have an impact on sales of physical stores. Therefore, the following hypothesis (1a) is formulated: *If e-commerce is actively used in a supermarket's service area, the supermarket's turnover will be lower.*

The findings are outlined in table 3. In model 1, a basic Ordinary Least Squares (OLS) model is shown. This model is not as robust as the Fixed Effects Models but indicates the basic relations of all control variables without taking time into account in its estimates. The assumptions are met since the distribution of residuals is homoscedastic, there is no multicollinearity (VIF < 2.3) and linearity is confirmed (Appendix II). The OLS model suggests that there is no relationship between customer experience and supermarket turnovers. Online turnover does positively relate to supermarket turnovers in this model ($\beta(online\ turnover) = 0.023, p\ =< 0.01$). This implies a complementary effect of 0.02% larger offline turnover when online sales grow with 1%. The small impact is in line with expectations, since the online sales form only 4% of total grocery sales (FSIN, 2019). However, the positive relation is striking, since a negative effect is often hypothesised between online sales and offline sales. Online sales were expected to be a substitute for offline sales in the case of supermarkets (Rietbergen & Weltevreden, 2009a). Though online sales do impact offline sales, online groceries could be considered to be complementary (Shi et al., 2019). Farag et al. (2007) suggest that online channels encourage sales in physical stores. Therefore, well-performing online channels improve the market position of their offline channels. In other words, if customers use AH online, those customers are more inclined to do their offline shopping in an Albert Heijn supermarket rather than competing supermarkets. Weltevreden (2007) confirms this phenomenon with two explanations *enhancement* and *efficiency.* Enhancement refers to the online marketing of sales or other incentives to visit the store. Efficiency refers to the situation where the physical store is part of the online transaction. For example, by providing the opportunity to pick up online orders in physical stores (Weltevreden, 2007). Both enhancement and efficiency are applied in the case of Albert Heijn. Furthermore, the model indicates that the supermarket's local market share is the strongest indicator ($\beta(market\ share) = 0.315, p \ =< 0.01$). Also, high education levels indicate higher supermarket turnovers than areas with lower education levels. Finally, the size of the population is a strong indication of the turnover. These results indicate that demographic factors are the best parameter for turnover estimations, which is all in line literature (Turhan et al., 2013). However, the OLS model does not take the time dimension into account. Therefore, the models 2, 3, 4 and 5 are added (table 3).

The findings in model 2 (table 3) show a Fixed Effect Model in which the impact of online sales on offline sales are examined (N_{total}). This model excludes independent variables that correlate highly, therefore the multicollinearity is controlled for (VIF < 5) (Wooldridge, 2008). The Breusch-Pagan test confirms the homoscedasticity of the residuals. The model also omits parking space, accessibility and education level as variables, because these characteristics are time-invariant. Secondly, this model shows a small positive impact of e-commerce on offline sales, which confirms the findings of model 1. The Fixed Effect Model namely suggests that a 1% increase in online sales leads to a 0.2% increase in offline sales ($\beta = 0.02, p < 0.01$). Therefore, the first hypothesis is rejected in favour of a complementary effect.

The second hypothesis considers spatial differences as follows, *in rural areas, the impact of e-commerce on turnovers is less than in urban areas.* In table 3, model 2, the second focus lies in supermarkets located in urban areas (the 48 largest cities in the Netherlands). The effect of e-commerce is similar to the general analysis, namely a positive relation ($\beta = 0.02, p \ < 0.01$). The third focus lies on supermarkets located in rural areas. The impact of online sales is larger than in urban areas ($\beta = 0.03, p \ < 0.01$). Therefore, the non-existent spatial variation that was suggested by Beckers et al. (2018) cannot be confirmed. Clarke et al. (2015), Birkin et al. (2017) and Boschma & Weltevreden (2008) argue that spatial differences have been observed, which applies to the results of this analysis. Though the differences between urban and rural areas are limited, urban areas have a smaller positive impact on offline sales than rural areas. Therefore, the hypothesis (1b) can be rejected. This could be explained by more competition in urban areas, which leads to being less inclined to revisit the same supermarket. In rural areas, with fewer competitors, online channels could enhance customer attachment more easily.

4.2 The impact of customer experience

As suggested by Terblanche (2018), scoring high on customer experience results in repatronage intentions of current and new customers. Furthermore, it does contribute to more diversification in terms of competition. Therefore, the following hypothesis (2a) was formulated: *If a supermarket's experience is higher, the supermarket's turnover will be higher.*

In model 3 (table 3), a significant result shows that customer experience positively relates to supermarket turnovers. This indicates that, in view of all explanatory parameters, the customer experience rate does add value to the model ($\beta = 0.04, p < 0.1$). This result is in line with the suggestion of Terblanche (2018), since customer experience would lead to intentions to revisit the same store. Findlay & Sparks (2008) suggest there is a spatial variation between the effects of customer experience on supermarket turnovers. Being more distinctive is namely of more importance in urban areas than in rural areas due to the fierce competition. The data show otherwise, therefore the second hypothesis (2b: *In urban areas, the impact of "customer experience" on turnovers is larger than in rural areas*) can be rejected. When zooming into the urban level, the model indicates a significant relation between turnovers and customer ratings ($\beta = 0.03\ p < 0.01$). This is in line with expectations, since a higher customer rating would presumably result in higher turnovers (Verhoef et al., 2009). In rural areas, however, a stronger positive relationship is observed ($\beta = 0.05, p < 0.01$). This means that, contrary to what was hypothesised based on the relevant literature, in rural areas supermarkets benefit more from high experience rates. This is in line with Findlay & Sparks (2008), who argue that customers in rural areas are affected more by customer experiences.

In model 4, the impact of e-commerce and experience is included. Strikingly, the relation between offline turnovers and experience becomes negative ($\beta = -0.0003, p < 0.01$), which means that when customer experience rates increase, supermarkets turnovers decrease. Thus, there is a bias in model 3 which is controlled in model 4 by the online turnovers. Therefore, the hypothesis (2a) can be rejected, despite the findings of model 3. A negative relation between supermarket turnovers and customer experience is contrary to what the literature proposed (Grewal et al, 2010; Terblanche, 2018). The negative relationship could be caused by supermarkets that have a decreased number of customers and thus turnovers, but in consequence score higher on experience ratings. Furthermore, supermarkets where experiences are high, might have different consumption purposes. For example, by selling mostly fresh products and products for direct consumption, rather than larger weekly groceries. Importantly, however, the negative impact is small. Therefore, the negative impact must be interpreted with caution and might not be of relevance for turnover estimations as proposed in section 2.

In model 5, the interaction effect between both e-commerce and customer experience is estimated. The results do not show substantially different results than the separate models. Therefore, no direct interaction between higher experience rates and use of e-commerce is observed. This means that the variables *log(online sales)* and *experience* do not depend on the magnitude of one and other. These results contradict expectations, the literature namely suggests that more experience is a consequence of omnichannel retailing (Grewal et al., 2010; Turolla, 2016). The non-existent relation between the two could be explained by the general store experience strategy of Albert Heijn supermarkets. Therefore, investments in customer experience do not necessarily differ between areas where e-commerce is prevalent and areas where it is absent.

The control variables show mostly significant positive results, which confirms the relevance of the four parameters proposed by Roig-Tierno et al (2013). However, income indices do not relate significantly to supermarket turnovers, which was expected (Turhan et al., 2013). The checkouts have a parabolic relation as was expected, since rural supermarkets generally have more checkouts because rural stores are larger but turnovers per square metre are lower. However, large stores (e.g. AH XL) with even more checkouts could have different functions and generate high turnovers per square metre. Furthermore, differences between urban and rural suggests a nuance to the parameters, mainly the impact of competition and market share differs between urban and rural areas. This is in line with expectations, since supermarket competition is fierce in urban areas (Dunne et al., 2008). Furthermore, the impact of market share of a supermarket relates stronger to supermarket turnovers in rural areas than it does in urban areas. This could be explained by the smaller number of supermarkets in rural areas. The model indicates an R^2 varying from 0.20 to 0.35 which indicate a fine quality for Fixed Effect Models (Wooldridge, 2008).

The results of this section suggest that online sales are complementary to offline sales. While in urban areas the use of online is higher than in rural areas, the complementary effects of e-commerce are larger in rural areas. Regarding customer experience, no substantial impact is observed in the mixed model. As an addition to this panel data regression, the analysis of the next section takes into account spatial associations on a micro level. These local associations are estimated with a spatial panel data regression.

Table 3. Multiple panel data regressions of supermarket turnover development and the impact of e-commerce. The table presents the data for NL, urban supermarkets and rural supermarkets.

Dependent variable: *(log)turnover / store size*	Model 1 OLS	Model 2 Online impact			Model 3 Experience impact			Model 4 Mixed	Model 5 Interaction
2015-2019	$N_{total(2019)}$	N_{total}	N_{urban}	N_{rural}	N_{total}	N_{urban}	N_{rural}	N_{total}	N_{total}
Control variables									
Parking space	-0.0002** (0.0002)								
Accessibility	0.033*** (0.003)								
Checkouts	-0.012*** (0.004)	-0.061*** (0.003)	-0.052*** (0.004)	-0.100*** (0.010)	-0.060*** (0.004)	-0.050*** (0.005)	-0.089*** (0.012)	-0.064*** (0.003)	-0.064*** (0.003)
Checkouts (quadratic)	0.0001 (0.0002)	0.001*** (0.0001)	0.001*** (0.0001)	0.003*** (0.001)	0.001*** (0.0001)	0.001*** (0.0002)	0.002*** (0.001)	0.001*** (0.0001)	0.001*** (0.0001)
Income index	-0.0002 (0.0002)	-0.0001 (0.0003)	0.0004 (0.0004)	-0.002** (0.001)	0.00000 (0.0004)	0.0004 (0.0004)	-0.001 (0.001)	-0.0002 (0.0003)	-0.0002 (0.0003)
(log) Population size	0.179*** (0.010)	0.046*** (0.006)	0.040*** (0.007)	0.049*** (0.011)	0.028*** (0.006)	0.008 (0.007)	0.039*** (0.012)	0.046*** (0.006)	0.045*** (0.006)
Education level	0.255*** (0.010)								
Number of competitors	-0.001 (0.002)	0.014*** (0.002)	0.014*** (0.002)	0.013** (0.006)	0.012*** (0.002)	0.005** (0.002)	0.008 (0.007)	0.013*** (0.002)	0.013*** (0.002)
(log)Market share	0.315*** (0.012)	0.181*** (0.011)	0.160*** (0.013)	0.239*** (0.021)	0.139*** (0.012)	0.119*** (0.014)	0.195*** (0.024)	0.193*** (0.011)	0.193*** (0.011)
Independent variables (log) Online turnover	0.023*** (0.002)	0.020*** (0.002)	0.016*** (0.002)	0.033*** (0.003)				0.012*** (0.002)	0.013*** (0.002)
Experience	-0.0001 (0.0001)				0.036*** (0.006)	0.028*** (0.007)	0.054*** (0.011)	-0.0003*** (0.00004)	-0.009* (0.0001)
log(online)* experience									0.00001 (0.000)
Constant (mean intercept)	2.182*** (0.103)	4.52***	4.61***	4.44***	4.72***	5.36***	4.38***	4.59***	4.59***
$\mathcal{X}^2$	276.069***	150.478***	81.582***	81.267***	103.527**	49.879***	52.323***	144.353***	128.276***
Fixed Effect	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.422	0.242	0.204	0.348	0.227	0.152	0.314	0.259	0.259
Hausman Test (p)	NA	2.2e-16	6.174e-16	2.2e-16	2.2e-16	1.276e-15	2.2e-16	2.247e-8	2.2e-16
N	4,168	4,168	2,818	1350	3,331	2,248	1,083	4,168	4,168

** Indicates a significance level < 0.1; ** Indicates a significance level < 0.05 *** Indicates a significance level < 0.01.*

4.3 Spatial analysis

Table 4 (next page) outlines the spatial panel data regression. The first model shows the reference model, as it was estimated in the previous section. The models 2, 3 and 4 give an overview of the panel regression including a spatial weight matrix as is explained in section 3.4.1. The difference between the models lies in the radius it takes into account. Model 2 includes supermarkets within a radius of one kilometre, model 3 includes a radius three kilometres and model 4 includes supermarkets that lie within a radius of five kilometres.

With respect to e-commerce, the weight matrix **W** shows no significant result for online sales. That being the case, it can be concluded that when online sales grow in a service area, this only contributes positively to the supermarket located in that service area, as was suggested in the previous section. On the one hand, this result contradicts expectations of Shi et al. (2018), since no modification effect between short-distance and long-distance shopping is observed. On the other hand, supermarket shopping in general could be considered to be short-distance, due to its daily or weekly consumption frequencies (Findly & Sparks, 2008). This means that the modification effect, in terms of distance, could not be relevant to grocery retailing.

By way of contrast, the weight matrix **W** for customer experiences shows significant positive results for all radiuses. Most explanatory power is observed with a radius of three kilometres (= 0.018, $p < 0.01$). The results suggest that a supermarket performance is positively affected by an increase in customer ratings at neighbouring Albert Heijn supermarkets. These results are quite contrary to what would be expected based on Terblanche (2018), Grewal et al. (2010) and Tsai & Yang (2013), that suggest that having better customer experiences, this would result in subtracting customers from other stores. However, the results only take into account Albert Heijn supermarkets. Therefore, an explanation for the positive relation could be that the performance of an Albert Heijn improves when other Albert Heijn supermarkets improve their customer experience. In line with this, the suggestions of Tsai & Yang (2013) could be still be the case, since an improved customer experience results in a better market position. However, the nuance that must be made is that considering a supermarket chain, the customer experiences are not solely dependent on one supermarket. This confirms the assumption of Parker & Ballantyne (2016), who argue that customer experiences relate to local experience perceptions. Which also indicates that customer experiences are dependent on local conditions and therefore, customer experiences do not solely depend on supermarkets themselves.

Table 4. Panel spatial data regressions of supermarket turnover development and the impact of e-commerce/ customer ratings. The table presents the data for NL from 2016 – 2019 for three radiuses with a distance (d) of one, three and five kilometres.

Dependent variable: log(turnover) / store size	Model 1 Spatial panel	Model 2 Spatial panel	Model 3 Spatial panel	Model 4 Spatial panel
Characteristics				
Parking space				
Accessibility				
Checkouts	-0.06*** (0.004)	-0.061*** (0.004)	-0.061*** (0.004)	-0.061*** (0.004)
Checkouts (quadratic)	0.001*** (0.0001)	0.001*** (0.0001)	0.001*** (0.0001)	0.001*** (0.0001)
Income index	0.001 (0.0001)	0.001 (0.0001	0.001 (0.0001	0.001 (0.0001
(log) Population size	0.026*** (0.006)	0.026*** (0.006)	0.026*** (0.006)	0.026*** (0.006)
Education level				
Number of competitors	0.009*** (0.002)	0.009*** (0.002)	0.009*** (0.002)	0.009*** (0.002)
(log)Market share	0.028*** (0.003)	0.028*** (0.003)	0.028*** (0.003)	0.028*** (0.003)
Independent variables				
(log) Online turnover	0.028*** (0.003)	0.024*** (0.003)	0.026*** (0.003)	0.027*** (0.003)
Experience	0.022*** (0.006)	0.025*** (0.007)	0.026*** (0.006)	0.026*** (0.006)
WOnline turnover (d=1)		-0.000 (0.000)		
WOnline turnover (d=3			-0.000 (0.0000)	
WOnline turnover (d=5)				-0.000 (0.00)
Wexperience (d=1)		0.011*** (0.004)		
Wexperience (d=3)			0.018*** (0.004)	
Wexperience (d=5)				0.014*** (0.006)
χ^2	100.622***	82.274***	82.615***	81.466***
R^2	0.25	0.26	0.26	0.25
N	3.212	3.071	3.195	3.212

** Indicates a significance level < 0.1; ** Indicates a significance level < 0.05 *** Indicates a significance level < 0.01.*

5. Limitations and further research

First of all, the goal of this research is to analyse developments on a macro level, which in consequence has its limitations. As for the spatial analysis, in which all Albert Heijn supermarkets with near neighbouring supermarkets have been reviewed. Future research should focus on a micro level in order to better understand and compare the spatial relations in both urban and rural areas.

Secondly, the results suggest a complementary effect between online sales and offline sales. However, these conclusions only reflect on Albert Heijn as an omnichannel retailer. This means that the impact of online sales on turnovers of physical supermarkets in general might differ (Weltevreden, 2007). Future research into this topic should focus on the effects of e-commerce on single-channel supermarket chains. This would complement this research with a broader view of the market.

Thirdly, the different store concepts of Albert Heijn (e.g. AH XL, City Premium, City Budget) have not been taken into consideration. Future research within Albert Heijn should consider differences between these store concepts to analyse what type of supermarket benefits most or least from e-commerce.

Finally, data on consumer experiences has been measured based on a panel survey that does not solely measures customer experience. The survey provides general scores to the supermarket, which makes the score vulnerable to biases, like availability of products or queues for checkouts. Furthermore, the survey does not necessarily aim to provide a statistical reflection of all customers. Moreover, Terblanche (2018) suggests that research into customer experiences must be conducted apart from one supermarket chain. Therefore, future research requires a more in-depth qualitative analysis into the impact of consumer shopping experiences on turnover developments in diverse supermarket chains.

6. Conclusions

This paper seeks to examine the impact of two contemporary developments in supermarket turnover assessments. (1) The impact of e-grocery sales on offline grocery sales and (2) the impact of the perceived customer experience on supermarket turnovers. This research contributes to the literature by extending the existing parameters that explain supermarket turnovers. Foremost in the limited body of literature concerning e-commerce in grocery shopping in the Netherlands. Literature suggests that e-commerce would be a substitute for offline sales in supermarkets (Birkin et al., 2018; Gorczynski & Kooijman, 2015). Therefore, a negative relationship is expected between growth in online sales and offline sales. The second trend, customer experience, is the effect of contemporary omnichannel retailing, because supermarkets must differentiate themselves to stay relevant and competitive (Pine & Gilmore, 2011; Grewal et al., 2010).

Literature suggests that high scores on customer experiences would result in higher turnovers (Terblanche, 2018).

Data of 839 supermarkets are used for the sample period of 2015 to 2019. In the data, online sales are matched to each supermarket as well as an annual customer experience score. Other supermarket characteristics, demographic and competition data were added as control variables as suggested by Roig-Tierno et al. (2013). Panel data regressions have been employed to turn the data into results.

The research question is: *to what extent do e-commerce and shopping experience affect supermarket performance growth and to what extent does the impact differ between urban and rural areas in the Netherlands?* The findings of this paper are not quite in line with previous literature. The impact of e-commerce on supermarket performances namely has a positive effect, suggesting a complementary nature of e-commerce rather than a substitutional nature (Farag et al., 2007). Therefore, the results suggest that e-commerce enhances physical supermarket sales (Weltevreden, 2007). The enhancement could be caused by reaching customers online and provide (personalised) advertisements (Weltevreden, 2007). Consequently, AH online customers could be more inclined to be attached to the supermarket chain, which explains the complementary effect. Furthermore, in rural areas, the complementary effect of e-commerce is higher than in urban areas. This could be explained by more competition in urban areas, which leads to being less inclined to visit the same supermarket (Kumar et al., 2017). In rural areas, with fewer competitors, online channels could enhance customer attachment more easily.

On a micro level, the question has risen whether supermarket performances are influenced by the use of e-commerce of neighbouring service areas. Which could, according to the modification effect, be expected (Shi et al., 2018). Results suggest no spatial dependency between neighbouring service areas regarding online sales. Therefore, the debate on e-commerce and its impact on offline turnovers should not be expanded to a wider spatial scope than its service area.

Regarding the impact of customer experience on supermarket turnovers, the analyses suggest conflicting results with the literature. The panel data regression suggests a small negative relation, which indicates that an increase in customer ratings would results in lower turnovers. Based on the *progression of economic values* as proposed by Pine & Gilmore (1998), a positive relation was expected. Moreover, literature suggests that investing in customer experience enhances its market position (Tsai & Yang, 2013; Packer & Ballantyne, 2016). The negative relation could be explained by supermarkets that have high turnovers, but as a result, score low on customer ratings.

The spatial analysis suggests that there is a positive association between customer ratings of neighbouring supermarkets. This could mean that customer experiences depend on local perceptions of good experiences as suggested by Parker & Ballantyne (2016). Another justification could be that an investment in customer experience in one Albert Heijn store, improves the general intention to visit an Albert Heijn supermarket. The results indicate that customer experiences are partly dependent on local conditions and, therefore, customer experiences do not solely depend on supermarkets themselves.

In short, e-commerce has a complementary effect on supermarket performance growth. The complementary effect is the strongest in rural areas. Customer experience does not have a substantial relation to supermarket performances, which is neither observed in urban or rural areas. Having summed up the outcomes, there are future challenges in this field of research. Firstly, the spatial analysis could be executed on a micro level, which would provide a better understanding of the spatial relations. Secondly, different Albert Heijn store concepts must be taken into consideration. Thirdly, the results on e-commerce should be verified in the case of a single-channel retailer. As a final suggestion, the role of experience in grocery shopping behaviour should be verified using qualitative research.

6.1 Managerial implications

In this paper, besides the theoretical discussion, some managerial implications are suggested. First of all, an e-commerce platform has a complementary function for Albert Heijn. To illustrate this for Albert Heijn, an approximate increase of €1000 online sales (1% of average online sales per service area) results in a €60 (0.02% of average offline sales per service area) increase of weekly turnovers for supermarkets located in that service area (Appendix II, table 2).

(1) Therefore, as the first recommendation, Albert Heijn should consider doing an experiment promoting AH.nl where supermarkets perform unsatisfactorily. Investing in its online channel could enhance that market position of its offline business operations. Especially in rural areas, where Albert Heijn's market share is under pressure, it potentially is an effective growth strategy.

Secondly, regarding the customer experience, the impact of increasing customer ratings on turnovers is not substantial. Therefore, investing in customer experience might not be lucrative, as has been assumed. More strikingly, the impact of customer ratings positively relates to the customer ratings of neighbouring supermarkets. This means that investing in the customer experience of one supermarket could enhance the turnover performance of neighbouring Albert Heijn supermarkets.

(2) As the second recommendation, Albert Heijn should consider investing in customer experience as an investment in its local market position. Regardless of the direct returns on investment of one supermarket, the gains of customer experience have a broader impact.

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Appendix

Supermarket turnover assessments: The impact of omnichannel retailing

Table of contents

Appendix I - Correlation table

Table 1. Correlation table

	Supermarket Turnover	Accessibility	Parking Spaces	Nr. Check-outs	Income index	Population 500m	Education binary	Competition	Market share	Online turnover	Custmer experience
Supermarket Turnover	1	[1] 0,53***	0,30****	[2] 0,80****	0,13***	0,068*	0,12***	[3] 0,48***	0,0013	[4] 0,61***	0,077*
Accessibility		1	0,27***	0,46***	0,12***	0,028	0,036	0,21***	0,019	0,29***	0,051
Parking Spaces			1	0,34***	-0,09	-0,068	-0,072	0,38***	-0,26***	0,29***	0,055
Nr. Check-outs				1	0,07*	0,03	0,054	0,47***	-0,074	0,52***	0,045
Income index					1	0,007	0,50***	-0,18***	0,21***	0,33***	-0,10***
Population 500m						1	0,34***	0,099**	-0,30***	0,24***	[5] -0,46***
Education binary							1	-0,6	0,008	0,30***	-0,25***
Competition								1	-0,56***	0,58***	-0,079*
Market share									1	-0,32***	0,27***
Online turnover										1	-0,19***
Custmer experience											1

** Indicates a significance level < 0.1; ** Indicates a significance level < 0.05 *** Indicates a significance level < 0.01.*

In the correlation table above (table 1), correlations between the dependent (maa_turnover), all control variables and independent variables are outlined. The upper left square is the supermarket turnover, the two most right variables are *online turnover* and *customer rating.* There are five striking correlations observed, these have been indicated with a number in the table.

1. Firstly, accessibility-scores correlates positively with supermarket turnovers, which is an expected relationship. However, the accessibility seems to have a stronger correlation than demographic variables, like income index, population size and education. Based on the parameters proposed by Roig-Tierno (2017), demographics would be most important.
2. Checkouts and turnovers correlate strongly. This correlation is expected, since there is a direct causal relation between the number of checkouts necessary to facilitate the number of customers in a supermarket.
3. Competition correlates moderately positive with turnovers, which is a striking relation since more competition would result in a smaller market share. However, an agglomeration effect could be the case. Many supermarkets nearby could be the result of a good environment for supermarkets.
4. Online turnovers and offline turnovers are positively correlated. This is a striking result, since a substitution effect is expected between on- and offline sales. The correlation is a supervisual measurement, but it does indicate a positive relationship. An explanation is that in areas where AH online obtains high turnovers, are also places where Albert Heijn supermarkets are most popular.
5. Finally, a negative relation is observed between population size and customer ratings, which indicates that a larger population has a negative effect on customer ratings.

Appendix II - Tests and assumptions

Hypothesis 1a & 2a
1a. *If online sales are high in a supermarket's service area, the supermarket's turnover will be lower.*
2a. *If a supermarket's customer experience is higher, the supermarket's turnover will be higher.*

Hausman Test
The Hausman test gives an indication of what model to use for a panel data regression (Park, 2011). Two models were possible in the case of this paper, the Fixed Effect Model and the Random Effects Model. A significant result in the Hausman tests indicates that the Fixed Effect Model is better.

Model 2 general:	chisq = 354.22,	df = 7,	p-value < 2.2e-16***
Model 2 urban:	chisq = 61.942,	df = 7,	p-value = 6.174e-11***
Model 2 rural:	chisq = 297.38,	df = 7,	p-value < 2.2e-16***
Model 3 general:	chisq = 233.01,	df = 7,	p-value < 2.2e-16***
Model 3 urban:	chisq = 82.163,	df = 6,	p-value = 1.276e-15***
Model 3 rural:	chisq = 302.89,	df = 7,	p-value < 2.2e-16***
Model 4:	chisq = 51.35,	df = 8,	p-value = 2.247e-08***
Model 5:	chisq = 206.93,	df = 9,	p-value < 2.2e-16***

Conclusion: Hausman test indicates a significant result when it both a *Random Effects Model* and a *Fixed Effects Model.* This indicates that the Fixed Effects Model is more robust to apply.

Breusch-Godfrey/Wooldridge test
The Wooldridge test, tests for serial correlation. For panel data spanning long ranges of time, are important to have no serial correlation. For short panel data, as is the case in this paper, no precautions need to be taken, since short panel data often shows serial correlation.

data: Panel Data Albert Heijn
chisq = 41.136, df = 1, p-value = 1.42e-10
alternative hypothesis: serial correlation in idiosyncratic errors

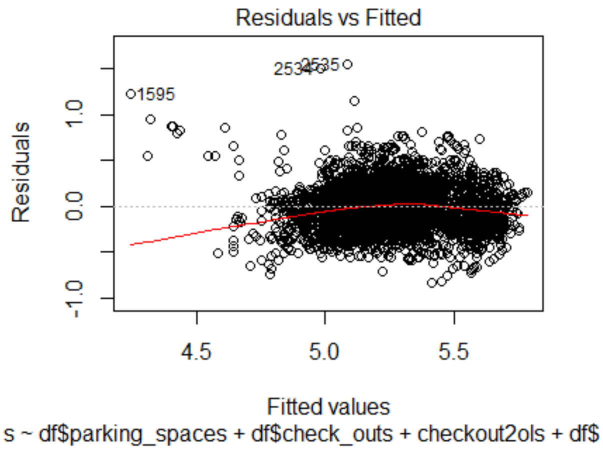
Conclusion: Significant result indicating a serial correlation. This is in line with expectations. Wooldridge (2008, pp. 419).

Breusch-Pagan test
Homoscedasticity in panel regression can be confirmed with the Breusch-Pagan test.
BP = 7286.7, df = 864, p-value < 2.2e-16
Conclusion: The significant result indicates that homoscedasticity is confirmed.

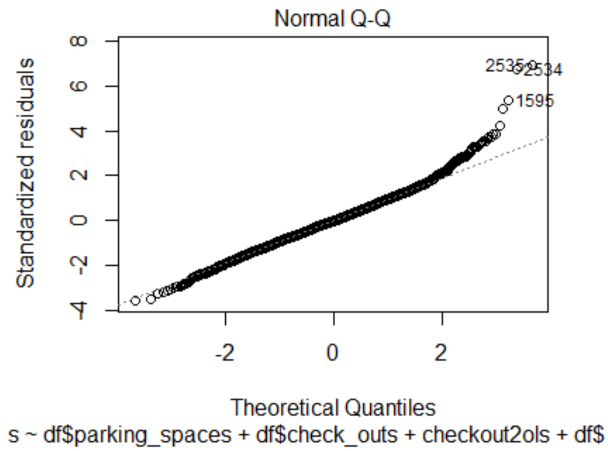
Assumptions for OLS section 4.1

Table 2. OLS model for table 3, model 1.

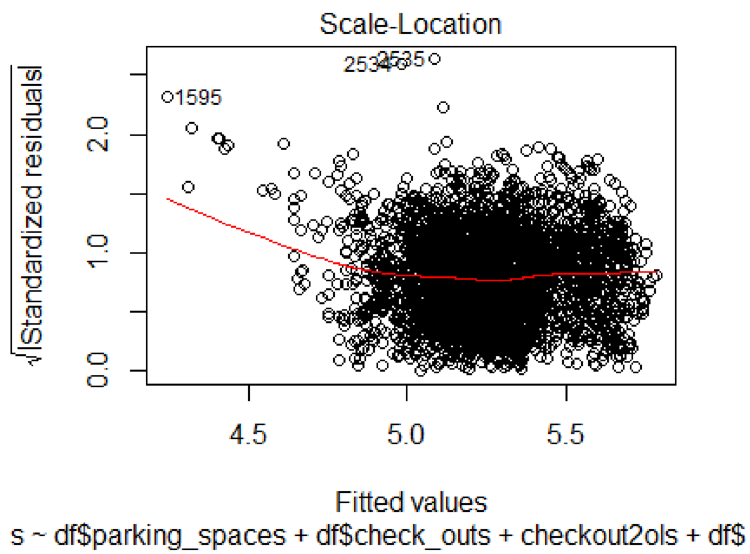
Linearity & Homoscedasticity



Normality of residuals



Regression model



The OLS model applied in the results requires 6 assumptions. These need to be checked prior to carrying out the analysis.

1. Independent observations - Yes
2. Both variables have an interval or ratio scale of measurement - Yes
3. The relation is theoretically causal: independent X influences independent Y; not vice versa. - Yes
4. The relation is linear. Check with scatter plot. - Yes, see table 2 (normality of residuals)
5. The residuals are normally distributed. - Yes, see table 2 (normality of residuals)
6. The residuals have a consistent variance. - Yes, see table 2 (Regression model)

7. Multicollinearity (table 3)

Table. 3 Overview of multicollinearity

Variable	*VIF (<5)*
Parking space	1.29
Nr. of checkouts	2.02
Accessibility	1.20
Income Index	1.56
Population size	3.99
Educ binary	1.39
Nr. of competitors	2.84
Market share	2.94
Customer rating	1.04
Online sales	1.62

Hypothesis 1b & 2b

1b. *In rural areas, the impact of e-commerce on turnovers is less than in urban areas.*

2b. *In urban areas, the impact of "shopping experience" on turnovers is larger than in urban areas.*

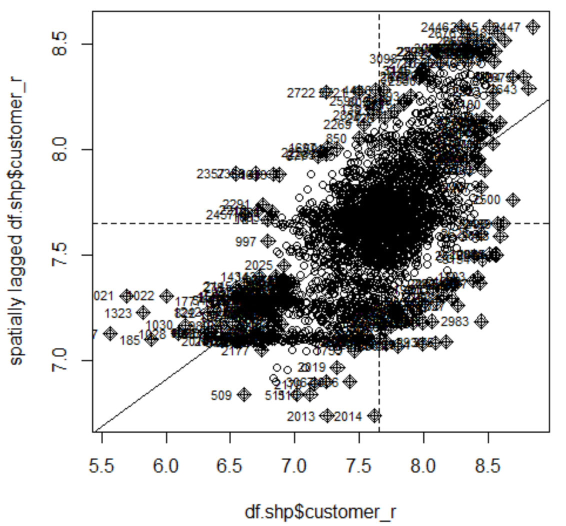
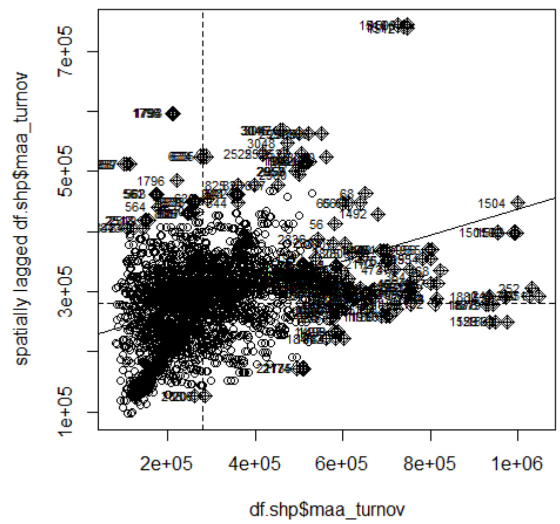
Monte-Carlo simulation of Moran I data: Customer Rating weights: list number of simulations + 1: 6 Statistic = 0.44684, observed rank = 6, p-value = 0.1667 alternative hypothesis: greater	**Monte-Carlo simulation of Moran I** data: Online Sales weights: list number of simulations + 1: 6 statistic = 0.07322, observed rank = 6, p-value = 0.1667 alternative hypothesis: greater
Customer rating, Moran's I scatterplot 2015-2019  	**Online Sales, Moran's I scatterplot 2015-2019** 

Table 4. The impact of online sales on offline sales for AH supermarkets in the Netherlands
(Due to confidentiality issues, actual numbers have been omitted)

Calculating the impact of online sales

	General	Urban	Rural
Mean online (DIS)	€ XXXX	€ XXXX	€ XXXX
Mean offline (supermarket)	€ XXXXX	€ XXXX	€ XXXX
General	Impact*	Standardised	/10
Online increase in SA	€ XXXX	€ 1.000,00	€ 100,00
Offline increase per supermarket	€ XXXX	€ 60,00	€ 5,60
Urban	Impact**	Standardised	/10
Online increase in SA	€ XXXX	€ 1.150,00	€ 115,00
Offline increase per supermarket	€ XXXX	€ 46,00	€ 4,60
Rural	Impact***	Standardised	/10
Online increase in SA	€ XXXX	€ 350,00	€ 35,00
Offline increase per supermarket	€ XXXX	€ 75,00	€ 7,50

* for every 1% increase in online turnover, an increase of 0.02% is expected in offline turnovers (general)
** for every 1% increase in online turnover, an increase of 0.016% is expected in offline turnovers (urban)
*** for every 1% increase in online turnover, an increase of 0.033% is expected in offline turnovers (rural)

Appendix III - Rstudio

```
# Libraries for PDR
library(car)
library(PerformanceAnalytics)
library(cluster.datasets)
library(stargazer)
library(lmtest)
library(plm)
library(ggplot2)
library(ggmap)
library(raster)
library(spdep)
library(maptools)
library(RColorBrewer)
library(classInt)
library(spatialreg)
library(rgdal)
library(randomForest)

# Basic dataset
      attach(data_set_13_6_)
      data_19 <- subset(data_set_13_6_, year == 2019)
data_cor <- data.frame(data_19$maa_turnover2, data_19$accessibility_score,
      data_19$parking_spaces, data_19$check_outs, data_19$income_index_sa,
      data_19$pop_500m,data_19$educ_bin, data_19$competition_sa,
      data_19$market_share_sa, data_19$online_turnover,
      data_19$customer_rating)
chart.Correlation(data_cor, histogram=TRUE)
plot <- ggplot(data_cor, aes(y = data_cor$online_turnover,
x=data_cor$urban_category))

# Welch Test
      df_tt <- subset(data_set_13_6_, customer_rating < 10)
      df_ttt <- subset(data_set_13_6_, turnover_online_pp < 50)
  t.test(df_ttt$turnover_online_pp ~ df_ttt$urban_rural)
  t.test(df_tt$customer_rating ~ df_tt$urban_rural)


# identifying missing values
  is.na(df$online_turnover) <- 99
  is.na(df$online_week_dis) <- 99
  is.na(df$customer_rating) <- 99
  is.na(df$parking_spaces)  <- 0
# identifying more missing values
  Df_online_urban       <- subset(df, urban_rural == 1)
  df_online_rural       <- subset(df, urban_rural == 0)
  df_ex                 <- subset(df, year != 2015)
  df_ex_urban           <- subset(df_ex, urban_rural == 1)
```

```
  df_ex_rural  <- subset(df_ex, urban_rural == 0)

## Creating a logarithm for dependent & independent variables (not for
control variables)
  # log | moving annual average turnover (inf = not applicable)
  # dependent variable dataframes
y_ols <- log(df$maa_turnover2/df$store_size)
         is.na(y_ols) <- do.call(cbind,lapply(y_ols, is.infinite))

y_online <- log(df$maa_turnover2/df$store_size)
          is.na(y_online) <- do.call(cbind,lapply(y_online, is.infinite))

y_turnover_online_urban <- log(df_online_urban$maa_turnover2/
                               df_online_urban$store_size)
          is.na(y_turnover_online_urban) <-
          do.call(cbind,lapply(y_turnover_online_urban, is.infinite))

y_turnover_online_rural <- log(df_online_rural$maa_turnover2/
                               df_online_rural$store_size)
          is.na(y_turnover_online_rural) <-
          do.call(cbind,lapply(y_turnover_online_rural, is.infinite))

y_turnover_ex <- log(df_ex$maa_turnover2/df_ex$store_size)
          is.na(y_turnover_ex) <- do.call(cbind,lapply(y_turnover_ex,
          is.infinite))

y_turnover_ex_urban <- log(df_ex_urban$maa_turnover2/df_ex_urban$store_size)
          is.na(y_turnover_ex_urban) <-
          do.call(cbind,lapply(y_turnover_ex_urban, is.infinite))

y_turnover_ex_rural <- log(df_ex_rural$maa_turnover2/df_ex_rural$store_size)
          is.na(y_turnover_ex_rural) <-
          do.call(cbind,lapply(y_turnover_ex_rural, is.infinite))

    # (log)experience dataframes
x_experience_ols <- log(df$customer_rating)
          is.na(x_experience_ols) <- do.call(cbind,lapply(x_experience_ols,
          is.infinite))

x_experience_panel <- log(df_ex$customer_rating)
          is.na(x_experience_panel) <-
          do.call(cbind,lapply(x_experience_panel, is.infinite))


x_experience_panel_u <- log(df_ex_urban$customer_rating)
        is.na(x_experience_panel_u) <-
        do.call(cbind,lapply(x_experience_panel_u, is.infinite))

x_experience_panel_r <- log(df_ex_rural$customer_rating)
```

```
        is.na(x_experience_panel_r) <-
        do.call(cbind,lapply(x_experience_panel_r, is.infinite))

    # (log)online dataframes
x_ols <- log(df$online_turnover)
        is.na(x_ols) <- do.call(cbind,lapply(x_ols, is.infinite))

x_online <- log(df$online_turnover)
        is.na(x_online) <- do.call(cbind,lapply(x_online, is.infinite))

x_online_urban <- log(df_online_urban$online_turnover)
        is.na(x_online_urban) <- do.call(cbind,lapply(x_online_urban,
        is.infinite))

x_online_rural <- log(df_online_rural$online_turnover)
        is.na(x_online_rural) <- do.call(cbind,lapply(x_online_rural,
        is.infinite))

   # (log)population dataframe
x_population <- log(df$pop_sa)
          is.na(x_population) <- do.call(cbind,lapply(x_population,
          is.infinite))

x_population_panel <- log(df$pop_sa)
          is.na(x_population_panel) <-
          do.call(cbind,lapply(x_population_panel, is.infinite))

x_population_urban <- log(df_online_urban$pop_sa)
          is.na(x_population_urban) <-
          do.call(cbind,lapply(x_population_urban, is.infinite))

x_population_rural <- log(df_online_rural$pop_sa)
          is.na(x_population_rural) <-
          do.call(cbind,lapply(x_population_rural, is.infinite))

x_population_ex <- log(df_ex$pop_sa)
          is.na(x_population_ex) <- do.call(cbind,lapply(x_population_ex,
          is.infinite))

x_population_ex_u <- log(df_ex_urban$pop_sa)
          is.na(x_population_ex_u) <- do.call(cbind,lapply(x_population_ex_u,
          is.infinite))

x_population_ex_r <- log(df_ex_rural$pop_sa)
          is.na(x_population_ex_r) <- do.call(cbind,lapply(x_population_ex_r,
          is.infinite))

    # (log)market share dataframes
x_marketshare <- log(df$market_share_sa)
```

```
          is.na(x_marketshare) <- do.call(cbind,lapply(x_marketshare,
          is.infinite))

x_marketshare_panel <- log(df$market_share_sa)
          is.na(x_marketshare_panel) <-
          do.call(cbind,lapply(x_marketshare_panel, is.infinite))

x_marketshare_urban <- log(df_online_urban$market_share_sa)
          is.na(x_marketshare_urban) <-
          do.call(cbind,lapply(x_marketshare_urban, is.infinite))

x_marketshare_rural <- log(df_online_rural$market_share_sa)
          is.na(x_marketshare_rural) <-
          do.call(cbind,lapply(x_marketshare_rural, is.infinite))

x_marketshare_ex <- log(df_ex$market_share_sa)
          is.na(x_marketshare_ex) <- do.call(cbind,lapply(x_marketshare_ex,
          is.infinite))

x_marketshare_ex_u <- log(df_ex_urban$market_share_sa)
          is.na(x_marketshare_ex_u) <-
          do.call(cbind,lapply(x_marketshare_ex_u, is.infinite))

x_marketshare_ex_r <- log(df_ex_rural$market_share_sa)
          is.na(x_marketshare_ex_r) <-
          do.call(cbind,lapply(x_marketshare_ex_r, is.infinite))

    # Creating an interaction effect between customer ratings and turnover
      online
interaction <- (x_online*df$customer_rating)

    # Quadratic variables
checkout2ols      <- df$check_outs^2
checkout2         <- (df$check_outs^2)
checkout2_urban   <- (df_online_urban$check_outs^2)
checkout2_rural   <- (df_online_rural$check_outs^2)
checkout2_ex      <- (df_ex$check_outs^2)
checkout2_ex_u    <- (df_ex_urban$check_outs^2)
checkout2_ex_r    <- (df_ex_rural$check_outs^2)

## Fixed Effect Models - all other models are not valid -> hausman test was
insignificant
    # Model 1 OLS
model1_ols <- lm(y_ols ~ df$parking_spaces + df$check_outs + checkout2ols +
      df$accessibility_bin + df$income_index_sa + x_population + df$educ_bin
      + x_marketshare +df$competition_sa + df$customer_rating + x_ols, df)

stargazer(model1_ols, type="text")
```

```
 # Model 2 FE model - ONLINE IMPACT
model1_general  <- plm(y_ols ~ df$parking_spaces + df$check_outs +
checkout2ols + df$accessibility_bin + df$income_index_sa + x_population +
df$educ_bin + x_marketshare + df$competition_sa + x_ols, df, index=c
("store_nr", "year"), model = "within")

stargazer(model1_general, type = "text")
mean(fixef(model1_general)) # estimating the "mean fixed effect" as constant

model1_random  <- plm(y_ols ~ df$parking_spaces + df$check_outs +
checkout2ols + df$accessibility_bin + df$income_index_sa + x_population +
df$educ_bin + x_marketshare + df$competition_sa + x_ols, df,
index=c("store_nr", "year"), model = "random")

stargazer(model1_random, type = "text")
phtest(model1_general, model1_random)
pbgtest(model1_general)
bptest(y_ols ~ df$parking_spaces + df$check_outs + checkout2ols +
df$accessibility_bin + df$income_index_sa + x_population + df$educ_bin +
x_marketshare + df$competition_sa + x_ols + factor(df$store_nr), data = df,
studentize=F)

     # Model 2 FE Model - ONLINE IMPACT (URBAN)

model1_urban  <- plm(y_turnover_online_urban ~ df_online_urban$parking_spaces
      + df_online_urban$check_outs + checkout2_urban +
      df_online_urban$accessibility_bin + df_online_urban$income_index_sa +
      x_population_urban + df_online_urban$educ_bin + x_marketshare_urban +
      df_online_urban$competition_sa + x_online_urban, Df_online_urban,
      index=c("store_nr", "year"), model = "within")

stargazer(model1_urban, type = "text")
mean(fixef(model1_urban))

     # Model 2 FE Model - ONLINE IMPACT (URBAN)

model1_rural    <- plm(y_turnover_online_rural
~df_online_rural$parking_spaces
      + df_online_rural$check_outs + checkout2_rural +
      df_online_rural$accessibility_bin + df_online_rural$income_index_sa +
      x_population_rural + df_online_rural$educ_bin + x_marketshare_rural +
      df_online_rural$competition_sa + x_online_rural,
      df_online_rural,index=c("store_nr", "year"), model = "within")

stargazer(model1_rural, type = "text")
mean(fixef(model1_rural))

    # Model 3 FE Model - EXPERIENCE IMPACT (GENERAL)
```

```
model2_general <- plm(y_turnover_ex ~ df_ex$parking_spaces + df_ex$check_outs
      + checkout2_ex + df_ex$accessibility_score + df_ex$income_index_sa +
      x_population_ex + df_ex$educ_bin + x_marketshare_ex +
      df_ex$competition_sa + df_ex$customer_rating, df_ex,index=c("store_nr",
      "year"), model = "within")

stargazer(model2_general, type = "text")
mean(fixef(model2_general))

     # Model 3 FE Model - EXPERIENCE IMPACT (URBAN)
model2_urban <- plm(y_turnover_ex_urban ~ df_ex_urban$parking_spaces +
      df_ex_urban$check_outs + checkout2_ex_u + df_ex_urban$
accessibility_score + df_ex_urban$income_index_sa + x_population_ex_u +
      df_ex_urban$educ_bin + x_population_ex_u + df_ex_urban$competition_sa +
      df_ex_urban$customer_rating, df_ex_urban,index=c("store_nr", "year"),
      model = "within")

stargazer(model2_urban, type="text")
mean(fixef(model2_urban))

       # Model 3 FE Model - EXPERIENCE IMPACT (RURAL)
model2_rural <- plm(y_turnover_ex_rural ~ df_ex_rural$parking_spaces +
df_ex_rural$check_outs + checkout2_ex_r +df_ex_rural$accessibility_score +
df_ex_rural$income_index_sa + x_population_ex_r +df_ex_rural$educ_bin +
x_marketshare_ex_r + df_ex_rural$competition_sa +
df_ex_rural$customer_rating,
df_ex_rural,index=c("store_nr", "year"), model = "within")

stargazer(model2_rural, type = "text")
mean(fixef(model2_rural))

     # Model 4 FE Model - ONLINE- & EXPERIENCE IMPACT (GENERAL)

model3_general <- plm(y_online ~ parking_spaces + check_outs + checkout2 +
accessibility_score + income_index_sa + x_population_panel + educ_bin
+ x_marketshare + competition_sa + x_online + df$customer_rating, df
,index=c("store_nr", "year"), model = "within")
stargazer(model3_general, type = "text")
mean(fixef(model3_general))

     # Model 4 FE Model - ONLINE- & EXPERIENCE IMPACT + INTERACTION
EFFECT(GENERAL)

model4_general <- plm(y_online ~ parking_spaces + check_outs + checkout2 +
accessibility_score + income_index_sa + x_population_panel + educ_bin
+ x_marketshare + competition_sa + x_online + df$customer_rating +
interaction, df, index=c("store_nr", "year"), model = "within")
stargazer(model4_general, type = "text")
mean(fixef(model4_general))
```

```
 # stargazer combined
stargazer(model1_ols, model1_general, model1_urban, model1_rural,
model2_general, model2_urban, model2_rural, model3_general,
model4_general, type="html", out="table_total.html")

-----------------------------------------------------------------------------
          #SPATIAL ANALYSIS
-----------------------------------------------------------------------------

#load data
    df.shp <- (readOGR("C:\\Spatial", "balanced"))

#distance based neighbors
    coords <- coordinates(df.shp)
    neighbours <- dnearneigh(coords,-5,5, longlat = T)
    list <- nb2listw(neighbours, glist = NULL, style = "W", zero.policy = TRUE)

    coords1 <- coordinates(df.shp)
    neighbours1 <- dnearneigh(coords1,-1,1, longlat = T)
 list1 <- nb2listw(neighbours1, glist = NULL, style = "W", zero.policy = TRUE)

  coords3 <- coordinates(df.shp)
  neighbours3 <- dnearneigh(coords3,-3,3, longlat = T)
        list3 <- nb2listw(neighbours3, glist = NULL, style = "W", zero.policy =
TRUE)

moran.mc(datp$online_tur, list, nsim = 5, na.action=na.exclude,zero.policy = T)
moran.plot(df.shp$maa_turnov, list,nsim = 5,na.action=na.exclude,zero.policy = T)
moran.mc(df.shp$customer_r, list, nsim = 5, na.action=na.exclude,zero.policy = T)
moran.plot(df.shp$customer_r,list,nsim = 5, na.action=na.exclude,zero.policy = T)

  # Making the data panel data
    dat=df.shp@data
    class(dat)
    datp = pdata.frame(dat,c("store_nr","year"))
    datp<-datp[order(dat$year),]
    class(datp)

  #lagged variables
    wONLINE <- lag.listw(list, df.shp$online_tur, zero.policy = NULL)
    wEXPERIENCE <- lag.listw(list, df.shp$customer_r, zero.policy = NULL)

    wONLINE1 <- lag.listw(list1, df.shp$online_tur, zero.policy = NULL)
    wEXPERIENCE1 <- lag.listw(list1, df.shp$customer_r, zero.policy = NULL)

    wONLINE3 <- lag.listw(list3, df.shp$online_tur, zero.policy = NULL)
    wEXPERIENCE3 <- lag.listw(list3, df.shp$customer_r, zero.policy = NULL)
```

```
    # Images of distance link plots 1,3,5 k
      png("NN 5k.png",width = 1200, height = 1200)
      plot(df.shp,border="blue")
      plot(list,coords,add=TRUE)
      title("Distance link plot - Radius 5 kilometre",cex.main = 3)
      dev.off()

      ## === Creating a logarithm for dependent & independent variables (not for
      control variables)
      # dependent variable dataframes
      y.sols <- log(datp$maa_turnov/datp$store_size)
      is.na(y_ols) <- do.call(cbind,lapply(y_ols, is.infinite))

    # (log)experience dataframes
      x.ex.sols <- log(datp$customer_r)
 is.na(x_experience_ols) <- do.call(cbind,lapply(x_experience_ols, is.infinite))

    # (log)online dataframes
      x.on.sols <- log(datp$online_tur)
      is.na(x_ols) <- do.call(cbind,lapply(x_ols, is.infinite))

    # (log)population dataframes
      x.pop.sols <- log(datp$pop_sa)
      is.na(x_population) <- do.call(cbind,lapply(x_population, is.infinite))

    # (log)market share dataframes
      x.markets <- log(datp$market_sha)
      is.na(x.markets) <- do.call(cbind,lapply(x.markets, is.infinite))

    # Creating an interaction effect between customer ratings and turnover online
      x.interaction.sols <- (x.on.sols*datp$customer_r)
      summary(x.interaction.sols)

    # Quadratic variables
      checkout2sols <- datp$check_outs*datp$check_outs

    # ======== Spatail panel regression ==========
ref <- k1 <- plm(y.sols ~ datp$parking_sp + datp$check_outs + checkout2sols +
datp$accessibil + datp$income_ind + x.pop.sols + x.markets + datp$educ_bin  +
datp$competitio + x.on.sols + datp$customer_r, datp, index = c("store_nr", "year"),
model = "within")

k1 <- plm(y.sols ~ datp$parking_sp + datp$check_outs + checkout2sols +
datp$accessibil + datp$income_ind + x.pop.sols + x.markets + datp$educ_bin  +
datp$competitio + x.on.sols + datp$customer_r + wONLINE1 + wEXPERIENCE1, datp,
index = c("store_nr", "year"), model = "within")
```

```
3 <- plm(y.sols ~ datp$parking_sp + datp$check_outs + checkout2sols +
datp$accessibil + datp$income_ind + x.pop.sols+ x.markets + datp$educ_bin +
datp$competitio + x.on.sols + datp$customer_r + wONLINE3 + wEXPERIENCE3, datp,
index = c("store_nr", "year"), model = "within")

k5 <- plm(y.sols ~ datp$parking_sp + datp$check_outs + checkout2sols +
datp$accessibil + datp$income_ind + x.pop.sols + x.markets + datp$educ_bin +
datp$competitio + x.on.sols + datp$customer_r + wONLINE + wEXPERIENCE, datp, index
= c("store_nr", "year"), model = "within")

stargazer(ref,k1,k3,k5, type = "html", out = "spatialols.html")

   # making LISA maps based on customer rating & online spending
        lisa_e <- localmoran(df.shp$customer_r, list, zero.policy = T)
        lisa_o <- localmoran(log(df.shp$online_tur), list, zero.policy = T)

        cCUSTOM <- (df.shp$customer_r) - median(df.shp$customer_r)
        cONLINE <- (log(df.shp$online_tur)) - mean(log(df.shp$online_tur))
        mI_e <- lisa_e[, 1]
        mI_o <- lisa_o[, 1]
        E_mI <- mI_e - mean(mI_e)
        O_mI <- mI_o - mean(mI_o)

        quadrant1 <- vector(mode="numeric",length=nrow(lisa_e))
            quadrant1[cCUSTOM >0 & E_mI>0] <- 1
            quadrant1[cCUSTOM <0 & E_mI>0] <- 2
            quadrant1[cCUSTOM >0 & E_mI<0] <- 3
            quadrant1[cCUSTOM <0 & E_mI<0] <- 4

        quadrant2 <- vector(mode="numeric",length=nrow(lisa_o))
            quadrant2[cONLINE >0 & O_mI>0] <- 1
            quadrant2[cONLINE <0 & O_mI>0] <- 2
            quadrant2[cONLINE >0 & O_mI<0] <- 3
            quadrant2[cONLINE <0 & O_mI<0] <- 4

         signif <- 0.05

      # places non-significant Moran's in the category "5"
           Quadrant1[lisa_e[, 5]> signif] <- 5
           Quadrant2[lisa_o[, 5]> signif] <- 5

# Map Online
png(file="MAP_online.png", width = 800, res = 125, bg = "transparent")
         colors <- c("blue", "red", "green", "orange", "grey", rgb(.95, .95, .95))
         par(mar=c(0,0,1,0))
         plot(df.shp, border="green", col=colors[quadrant2], main = "Matrix Map -
         Online Sales", bg = "transparent", cex.main = 0.75) legend("bottomright",
         legend=c("high-high","low-low","high-low","low-high",              "non-
         significant"), fill=colors,bty="n",cex=0.75,y.intersp=1,x.intersp=1)
```

```
dev.off()

# Map Experience
png(file="MAP_experience.png", width = 800, res = 125, bg = "transparent")
       colors <- c("blue", "red", "green", "orange", "grey", rgb(.95, .95, .95))
       par(mar=c(0,0,1,0))
         plot(df.shp, border="green", col=colors[quadrant1], main = "Matrix Map -
         Customer Ratings", bg = "transparent", cex.main = 0.75)
          legend("bottomright",legend=c("high-high","low-low","high-low","low-
         high",  "non-significant"),  fill=colors,    bty="n",cex=0.75,y.intersp=1,
         x.intersp=1)
dev.off()
```