Estimating Effects of Changes in Relative Price Positions and Relative Delivery Promise Positions on Product Sales Utilising Finite Mixture Poisson Models

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Abstract

In this paper, we use a heterogeneous longitudinal dataset of approximately 10.000 products spread over 11 different shop categories and followed during two distinct time periods of the year 2021 to estimate how changes in relative price positions and relative delivery promise positions have an influence on product sales. To this end, we introduce the variables sigmoid relative price position and sigmoid relative delivery promise position, two variables which are scale independent and measure how competitive one retailer is compared to the market based on respectively the price and the delivery promise. By utilising a Finite Mixture Poisson model architecture, we estimate for which type of products sales are more affected by changes in the sigmoid relative price position and for which type of product sales this holds true for changes in the sigmoid relative delivery promise position. In addition, we introduce the novel concepts of Rational Choice, Willingness to Pay (more for receiving a faster delivery promise) and Unwillingness to Pay (more for receiving a faster delivery promise) to estimate for which type of products we find evidence that consumers are on aggregate willing to pay a higher price in case they receive a faster delivery promise. We estimate these effects also by means of a Finite Mixture Poisson model architecture.

We find that for a large majority of the products sales are more sensitive to changes in the sigmoid relative price position compared to changes in the sigmoid relative delivery promise position. Furthermore, we find strong evidence that on aggregate consumers are accepting slow delivery promises in case they can buy the product at a lower price.

Keywords: Sigmoid Relative Price Position, Sigmoid Relative Delivery Promise Position,

Rational Choice, Willingness to Pay, Unwillingness to Pay, Finite Mixture Poisson Models

The content of this thesis is the sole responsibility of the author and does not reflect the view of the supervisor, second assessor, Erasmus School of Economics or Erasmus University.

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1. Introduction

In the current era of online shopping, consumers can easily compare offers from different online retailers. Consequently, for online retailers it is important to provide product offers which are competitive. At a first glance, one might think that online retailers want to compete on price only. However, this neglects other factors which can make the offers of online retailers competitive. One of these factors is the promised delivery time of an offer, or the delivery promise for short. By including this second factor, the problem becomes two-dimensional, making it possible to measure the interaction between prices and delivery promises. This might lead to previously unobtained insights if only the price dimension would be considered.

In order to illustrate the above concept, take the hypothetical situation in which a consumer faces two offers for one product he is interested in. Offer A has a lower price compared to offer B, but a delivery promise which results in a later delivery than that of offer B. Only considering prices, offer A would be preferred over offer B. However, since the company behind offer B promised to deliver faster, it might be the case offer B is actually preferred over offer A. Therefore, based on these offers, an interesting question is to what extent the consumer is willing choose offer B over offer A.

Generalizing from the above example, we are interested in studying how the purchase decision of consumers for consumer products is influenced by the product offers which differ in price and/or delivery promise. As a starting point of researching this topic, we need to choose an appropriate theoretical framework. In our opinion, two types of methodologies are worth considering. First, we could take the perspective from individual consumers. The idea behind this approach is to study the choices of individual consumers (over time) and estimate what types of consumers are more susceptible for products with better price propositions or better delivery promise propositions. For example in Marino et al. (2018) the effect of increasing delivery rates on consumer purchase decisions is studied using logistic regression with fixed effects from the individual consumer level. Two other studies which use this approach are Cui et al. (2020b) and Chen and Cui (2021). In both studies a difference-in-difference is used to estimate consumer preferences for faster delivery speed at the individual consumer level. Another approach is the discrete choice model setting. Using a discrete choice model design, we estimate the preferences of consumers based on different offer propositions. For this we can consider generally two methods. In the first method, we rely on the intention of choices that customers make (stated preferences). This is mostly measured by means of surveys. These surveys are set-up by knowledge experts which provide a set of options, in which the participants need to select the option which provides them the highest utility. A study which comes close to this design is that of Saha et al. (2020). Another way in which the choices of customers can be quantified is by looking at the decisions customers make (revealed preferences). Within this approach we take data from which the decisions of customers can be derived. Compared to the stated preferences approach, in this approach no experimental design is used and the decision behavior is learned from the data. To our knowledge this approach has not yet been used directly in the literature for estimating consumer sensitivities to prices and delivery promises.

Using another methodology, we do not consider the individual preferences of consumers, but rather look at the aggregate product level. In this approach, we confine ourselves to a metric which is able

to capture aggregated product sensitivities. The most suitable metric here is the one which includes some type of sales information (conversion or simply just sales) for a specified unit of time (say one day). Based on this metric, the goal is to model how changes in the sales metric are affected by changes in the relative price, the relative delivery promise, and/or some interaction between these two. Compared to the individual study designs, we ignore individual consumer preferences and want to estimate systematic preferences instead. Using this research design, nuances can be found by considering different types of products, for example based on product popularity, price proposition, delivery promise proposition or product type. In this way we can categorise products into different effect types. However, under this approach it is not possible to differentiate the consumer behaviour, estimate preferences of smaller groups of consumers which deviate from the larger groups, or to directly model trade-offs using binary outcomes. To the best of our knowledge there is no study which estimates changes in relative prices, relative delivery promises and the interaction between these two using aggregated product levels.

In this study we consider the latter methodology. Using this approach, we develop a framework with two goals in mind. First, we want to make prices and delivery promises comparable on the same scale. Second, we want to be able use a relative study design. This implies that we want to be able to measure how the offer of some retailer deviates in terms of price and delivery promise from the market. Ultimately, our framework leads to the creation of two novel variables: sigmoid relative price positions and sigmoid relative delivery promise positions, or $\sigma_{9.21}(\text{RP}_p)$ and $\sigma_{9.21}(\text{RP}_d)$ for short. Here p and d respectively denote the price and delivery promise, RP is an abbreviation for relative position, and $\sigma_{9.21}$ a sigmoid transformation of the relative position with scale parameter which we set equal to 9.21. These two variables are scale independent and measure how competitive one retailer is compared to the market based on respectively price and the delivery promise.

Within the framework of this study, we use $\sigma_{9.21}(\text{RP}_p)$ and $\sigma_{9.21}(\text{RP}_d)$ to estimate how sales are affected by changes of these two variables. What is more, we transform $\sigma_{9.21}(\text{RP}_p)$ and $\sigma_{9.21}(\text{RP}_d)$ to capture two kinds of behaviour. The first type of behaviour relates to the extent to which consumers behave rationally in case both the relative price position and relative delivery promise position of one particular retailer outperforms the market. We denote the variable which measures this behavior as Rational Choice (RC). For the second type of behaviour, we are interested in determining sensitivity of willingness/unwillingness to pay more for a faster delivery promise, respectively denoted by Willingness to Pay (WTP) and Unwillingness to Pay (UTP).

Over the course of this study, we want to find the answer to questions related to two different topics. First of all, we want to study to what extent sales of consumer products are more sensitive to changes in the relative delivery promise position ($\sigma_{9.21}(\text{RP}_d)$) compared to changes in the relative price position ($\sigma_{9.21}(\text{RP}_p)$). The second question relates to what extent consumers are willing to pay a higher price for a consumer product provided that they receive a faster delivery promise in return. By rephrasing the first statement as a question, we obtain the first research question of this study:

To what extent are sales of consumer products more sensitive to changes in the relative delivery promise position ($\sigma_{9.21}(RP_d)$) compared to changes in the relative price position ($\sigma_{9.21}(RP_p)$)?

As a starting point to answer this question, we aim to estimate what the effects of changes in $\sigma_{9.21}(\mathrm{RP}_p)$ and $\sigma_{9.21}(\mathrm{RP}_d)$ are on sales. An immediate consequence of this estimation is that we can compare the magnitude of the two coefficients to see which of the two has a larger effect on sales of consumer products. We make the estimation more heterogeneous by dividing the population of products into different shop categories. We estimate how $\sigma_{9.21}(\mathrm{RP}_p)$ and $\sigma_{9.21}(\mathrm{RP}_d)$ influence sales using Poisson regression, a regression model suitable for modelling non-negative count data. In addition, we allow for heterogeneity by using a Finite Mixture model architecture. This is a framework which assumes that the population consists of multiple latent (unobserved) subpopulations and allows for the estimation of separate regression models for every subpopulation. We use this framework to allow for heterogeneity within a shop category.

For the second topic of this study, we intend to answer the following research question:

To what extent do consumers prefer product offers which are more expensive in terms of the price proposition, but faster in terms of the delivery promise proposition?

In order to answer this second research question we can take two different perspectives. From the first perspective, we consider the situation in which consumers have a general preference to pay more for receiving a faster delivery promise, without the need to receive the product before a certain date. The main focal point here is to determine to what extent consumers exhibit the behaviour in which they want to receive products as fast as possible and therefore are willing to pay more if this means that they receive the product earlier. From the second perspective, we relax this assumption somewhat. In this case, we confine ourselves to situations in which consumers generally might not be willing to pay more for receiving a faster delivery promise. However, this preference might change if they need to have the product delivered before a certain date. For example, if the consumer buys one product as a birthday/holiday present, it is plausible to assume that the consumer wants to have the product delivered before the birthday/holiday takes place. Therefore, within this perspective we want to determine to what extent consumers are willing to pay more for receiving a faster delivery promise in case it is plausible to assume that they want to have the product received before a certain date.

In this study, we apply variants taken from both perspectives using the concepts of RC, WTP and UTP. For the first perspective, we use the same modeling approach as for the answering the first research question, with the difference that we replace $\sigma_{9.21}(\mathrm{RP}_p)$ and $\sigma_{9.21}(\mathrm{RP}_d)$ with RC, WTP and UTP. Hence, we allow for heterogeneity within our data by estimating the effects over different shops and by applying a Poisson Finite Mixture model architecture. Furthermore, we consider both the regular and holiday period.

For the second perspective, we utilise a slightly different setting. The idea here is to consider willingness to pay around two specific dates: Sinterklaas (5 December) and Christmas (25 December). The reason why we select these two particular dates is that during this period some of the products which are bought by consumers are bought as gifts. As a result, if a consumer buys a product to give away as a present, we suspect that the consumer prefers to receive the product before one of the holidays. Therefore, we use this period to estimate to what extent consumers are willing to pay more

for products around Sinterklaas and Christmas. Similar to the other two model approaches, we allow for heterogeneity by means of shop categories and a Poisson Finite Mixture model framework.

The structure of this paper is as follows. We introduce the reader to the topic of prices and delivery promises by means of Section 2, in which we provide a literature overview of different studies related to price sensitivity estimation, delivery promises, and joint estimation of prices and delivery promises. For completeness, we consider approaches from the absolute (only using data of one retailer) and relative (also taking competitor data into account) perspectives. In Section 3 we develop the theoretical framework which forms the foundation of the remainder of this study. Here we introduce the concepts of $\sigma_{9.21}(\mathrm{RP}_p)$, $\sigma_{9.21}(\mathrm{RP}_d)$, RC, WTP and UTP. This section is followed up by Section 4, in which the reader becomes familiar with the data used in this study. In Section 5 we explain the methodology of this study. Moving to Section 6 we present the concrete results aiding us to answer the research questions. We conclude this paper in Section 7 in which we summarise our main findings. For the reader which is interested in more background behind the set-up of this study, we have included an extensive set of appendices which respectively explain the methodology of imputing missing data of delivery promises (Appendix A), a more extensive overview of the used data (Appendix B), the methodological explanation of Poisson Finite Mixture Models (Appendix C), and a more extensive overview of the results (Appendix D).

2. Literature Overview

For studying the effects of changes in prices and delivery promises on purchase decisions of customers (of consumer products in an e-commerce setting), we can distinguish studies which only study price effects, only delivery promise effects, or studies which take both variables into account. Within the study field of prices, we can decompose these studies into studies which consider absolute prices, or relative (compared to other competitors or the market) prices. From a methodological point of view, we can distinguish studies which use observational data, questionnaires, or qualitative approaches.

Based on these characteristics, we next provide a general description of the current state of the literature.

2.1. Studies Related to Prices

For studies related to estimating the effects of changing prices on the purchase behaviour, we find a vast amount of different studies, both in the field of absolute prices and relative prices. Additionally, we can distinguish studies which apply constant price effects, or varying price effects. One study in this field is that of Tellis (1988), in which the researcher provides a meta-analysis of price elasticities in an absolute price setting for different product markets. In this meta-analysis, it is shown that price elasticities are highly varying between different product categories. A little bit more recently, Bijmolt et al. (2005) has done a similar analysis. For studies within the realm of relative prices, we can mention Mazumdar et al. (2005), which uses reference prices as focus point. Here reference prices relate to prices of competitors, or prices observed in the past. Another range of pricing studies is the field of dynamic pricing (in an e-commerce setting), which can amongst others be derived from a

game-theoretic- (Hinz et al. (2011)), machine learning- ((Gupta and Pathak (2014)), or econometric (Cope (2007)) point of view.

2.2. Studies Related to Delivery Promises

Studies about delivery times (and delivery promises) are generally closely related to studies about the effect of overall service quality on purchasing behaviour of customers , such as that of Cox and Dale (2001), Lin et al. (2016), and Thakur et al. (2017). We also find studies which study the effect of changing delivery times (delivery rates) on the purchase behaviour of consumers, without taking the delivery promise into consideration. In addition, these studies do not take relative delivery rates into account. For instance, in the study of Marino et al. (2018) the effect of increasing delivery rates on consumer purchase decisions is studied using logistic regression with fixed effects. The conclusion of this study is that consumers value faster delivery rates (in absolute sense), and this additionally holds true for industries with high lead times, such as furniture.

More closely related to estimating the effect of changing delivery promises to the purchase decision of customers, we find a couple of recently published studies. These studies share a methodological set-up in the sense that these are based on a difference-in-difference design. Additionally, these studies only take the delivery promise of one online retailer into account, and therefore ignore relative delivery promises compared to the market. Within this area we can mention for example the study of Cui et al. (2020b), in which a difference-in-difference approach based on observational data for an American e-commerce company showed that reducing the delivery promise has a positive effect on sales. Another study is that of Fisher et al. (2019), in which the opening op a new American distribution center allows them to see what effect the faster delivery promises have on sales. By taking a difference-in-difference approach, the conclusion of the researchers of this paper is that online store sales increased, on average, by 1.45% for every work day reduction of the delivery promise. As a third example, we find Cui et al. (2020a), in which a study was done around a natural experiment. This natural experiment involved the clash between SF Express (a Chinese logistics company with a high reputation regarding delivery quality) and Alibaba (an e-commerce company). As a result of this clash, Alibaba decided to remove SF Express as a logistics partner for 42 hours in June 2017. Given this time-gap the researchers applied a difference-in-difference approach in order to study the effect of a loss of a high quality logistics partner on sales. The researchers concluded that as a result of the clash sales on Alibaba were reduced by 14.56%.

Regarding more relative approaches of delivery promises, we are not able to find remarkable empirical studies. However, we are able to mention the study of Ho and Zheng (2004), which takes a game-theoretic approach. In this study, the researchers develop a market share model to capture the impact of delivery-time commitment and delivery quality on the firm's market share for duopolistic competition. The researchers prove the existence of Nash equilibria, and show that this is analogous to a Prisoners' Dilemma.

2.3. Studies Related to a Joint Estimation of Prices and Delivery Promises

We find different studies in which prices are compared to the overall service quality of products. Here we can mention qualitative studies (Gans, 2003), theoretical studies (So, 2000, Hill et al., 2000),

or empirical studies (Allon et al., 2011).

When we consider the delivery promise more in particular, we see that the current level of research between the trade-off of prices and delivery promises is lacking in terms of quantity. Additionally, we could not find any study which considers this trade-off from a relative perspective. Keeping this in our mind, we were able to find a couple of studies which try to investigate the trade-off between prices and delivery promises. For instance, in Saha et al. (2020), a study based on questionnaires was conducted which aims to study the willingness to pay for a faster delivery promise. This was done using hierarchical regression analysis. The researchers of this study concluded that consumers are willing to pay more for a faster delivery promise in case consumers also have a positive perception of the e-commerce company they buy from, the customer satisfaction is positive, and the delivery is efficient. To mention another study within this field, we have the study of Chen and Cui (2021). In this study, the direct trade-off between prices and delivery times is studied based on transaction-level data. The researchers of this paper used a mixed logit model to estimate the price and delivery promise sensitivities between males and females. The researchers concluded that males have a higher sensitivity to changes in the delivery promise than females, and are willing to pay more for faster delivery.

2.4. Contribution to the Literature

Overall, we see that the literature for price effects on purchase decisions of customers is well covered both from the absolute and relative price perspectives. For studies regarding delivery promises, we currently find a clear gap of empirical studies which relate relative delivery promises to the purchase decision of customers. More directly related to this study, when we consider the trade-off between prices and delivery promises within absolute settings, we observe studies which use policy changes of individual companies to study the trade-off between prices and delivery promises, mainly using difference-in-difference approaches. However, we were not able to find any published research in the field of the trade-off between prices and delivery promises in a relative setting. Therefore, to the best of our knowledge, this is the first study which attempts to study the trade-off between prices and delivery promises from a relative perspective.

Additionally, we consider the effects of sales on a product aggregation level, which is different from approaches such as that of Marino et al. (2018), Saha et al. (2020), or Chen and Cui (2021) in the sense that these consider purchase behaviour on the individual consumer level. Comparing these two approaches, we should note that using data on the individual consumer level has two major advantages over the approach we propose in this study. First of all, a purchase decision based on trade-offs can more directly be modelled, for instance as a binary decision. Secondly, by making consumers the focal point, rather than products, we can study how trade-offs might differ between different types of consumers. In our study design it is not possible to take these considerations into account. Instead, we are only able to measure trade-offs in case consumers systematically prefer prices over delivery promises (or vice versa) and only in an indirect setting. This implies that if a small group of consumers deviates from the main stream in terms of preferences, we neglect their purchase considerations. From a practical point of view, we want to mention two disadvantages of

using individual consumer level data, namely the lack of available data which makes it possible to estimate effects for individual consumers, and the cost of setting up a setting in which it is possible to measure effects from the individual consumer level.

As a direct application of a study design in which we can utilise data from the perspective of individual consumers, we can mention two Discrete Choice Model settings. First, we could measure trade-offs by holding a survey in which consumers need to state their preferences under a set of alternatives (stated preferences). Alternatively, we estimate the the preferences of customers using data from which we can directly derive the purchase behaviour (revealed choices). To the best of our knowledge, estimating the trade-offs between prices and delivery promises from using a discrete choice model with revealed choices has not yet been applied in the literature.

Another difference between the current literature and the approach we take, is that of the number of included products in the study. Since we allow for different types of products by means of shop categories, and products of all popularity levels per shop category, we consider a more heterogeneous set of products compared to the earlier mentioned studies which study the trade-off between prices and delivery promises.

Besides these general observations, we also provide a novel framework to define relative positions of prices and delivery promises, which makes these two variables comparable, and usable to express willingness to pay. We introduce these concepts in Section 3.

3. Theoretical Framework

In this section we develop the theoretical framework which we use in the remainder of this paper. In order to clarify the intuition behind this framework, we consider a toy example throughout this section, which we will adapt according to the illustration we want to make. In this illustration, we consider two offer positions, one of the internal retailer, and one of the market. We allow these offers to vary based on price and later on also on delivery promise. The goal of this section is to determine in what way we can quantitatively relate the offer of the internal retailer to that of the market offer. For this reason, let us have a look at Table 1 where we have different instances of the offer (here only in terms of price) for both the internal retailer and the market. For one identical product, we distinguish four situations. In instance A, both offers are exactly the same, while in instances B and C the the internal retailer is more competitive than the market, and in instances D and E the offer of the internal retailer is less competitive than that of the market.

Situation	Internal price	Market price	Relative price position
A	€10	€10	neutral
B	€10	€11	neutral/good
C	€10	€30	good/outstanding
D	€11	€10	neutral/bad
E	€30	€10	bad/awful

Table 1: Different offer propositions for some product of the internal retailer compared to the market. Note that for all situations we consider the same product.

Assuming that the definition of the market price is correct, the first question we want to answer is that of how to quantify the dispersion between the offer of the internal retailer compared to that

of the market, and in what way to scale this dispersion for larger differences. To illustrate this, take situations B and D where we find that the price of the internal retailer only differs by one euro. The question we can raise here is to what extent we should threat this deviation as a significant deviation from the market (from a neutral position to a good/bad situation). For larger deviations, such as shown by means of situations C and E, the question becomes whether these deviations are only moderate or large (good/bad versus awful/outstanding). It should be noted here that the difference between the internal price and market price does not only depend on the absolute difference, but also the scale of the prices themselves. To make this concrete, a 1 euro difference makes most likely a much larger impact for products which are on the cheaper end, in contrast to products which are more expensive.

Given that we have obtained a metric which is able to capture behaviour which reflects a relative position, the following question we want to answer is in what way we can express a willingness to pay more for a faster delivery promise. Here we confine ourselves to those instances in which the offer of the internal retailer is better in terms of the proposed delivery promise, but worse in terms of the price. Additionally we would like to add here the other theoretical situations which can occur.

In order to build the framework to answer these questions, we start in Section 3.1, by developing and illustrating concepts which ultimately lead to the definition of relative positions which will be used throughout this paper. Subsequently, in Section 3.2 we use this definition to introduce and define the concepts of Willingness to Pay (WTP), Unwillingness to Pay (UTP), and Rational Choice (RC).

3.1. Defining Relative Positions

3.1.1. Mathematical Definition

Definition Relative Position. In order to derive the relative position of two variables, let $x, y \in \mathbb{R}^+$ be two positive real numbers for which we calculate the level of dispersion. In this context, we compare the value of x to that of y, that is we let x vary and take y as given. We can distinguish three different positions x can take for a given y:

1. $x = y$: In this situation we say that we have no dispersion and that the relative position of x compared to y needs to be neutral. We denote this situation by the point of symmetry s.
2. $x < y$: In this situation we say that we have positive dispersion and that the relative position of x compared to y needs to be exceeding the point of symmetry s, the point in which $x = y$.
3. $x > y$: In this situation we say that we have negative dispersion and that the relative position of x compared to y and needs to be smaller than needs to the point of symmetry s, the point in which $x = y$.

These situations imply that the relative position of x increases the lower x becomes compared to y. Based on the three positions, we want to define a the relative position between x and y by means of a transformation which satisfies the three positions x can take compared to a given value of y. In this thesis, we define the relative position by means of a two-step procedure. First, we apply a transformation between x and y to obtain a fixed range of values. Then we transform these values by means of the sigmoid function. All-in-all, we obtain the following two formulas:

$$\text{Relative Position}(x, y) = -\frac{(x - y)}{(x + y)} \text{ for } x + y > 0 \tag{1}$$

$$\sigma_k[\text{Relative Position}(x,y)] = \frac{1}{1+e^{-k*\text{Relative Position}(x,y)}} \tag{2}$$

Where we set $k = 9.2103 \approx 9.21$ at Equation 2, which ensures that Relative Position$(x,y) \in [-1,1]$ is entirely covered in the range $[0,1]$. The definition of Equation 1 allows us to satisfy the following set of conditions on top of the basic conditions we have already set:

1. **Symmetrical Dispersion**: For some positive real numbered scalar $c \in \mathbb{R}^+$, let $x_1 = cy$, and $x_2 = \frac{y}{c}$. Then $|\text{Relative Position}(x_1,y) - s| = |\text{Relative Position}(x_2,y) - s|$. This condition implies that the distance around the point of symmetry s should be the same in case x exceeds y by a proportionate amount c, or y exceeds x by the same proportionate amount c. We require this property such that we can easily compare situations in which x exceeds y or y exceeds x. We can easily check that this condition is satisfied for Formula 1 by replacing x with x_1, and x_2, using the fact that $s = 0$, such that we have that
   $|\text{Relative Position}(x_1,y)| = |\frac{-(c-1)}{c+1}| = |\frac{(c-1)}{c+1}| = |\text{Relative Position}(x_2,y)|$
2. **Bounded Positions**: We want that Relative Position(x,y) takes on a bounded range of values Relative Position$(x,y) \in [N,M]$. This implies that the following conditions are satisfied:
   (a) For given y, $\lim_{x\to\infty}$ Relative Position$(x,y) \leq M$
   or for given x, $\lim_{y\to 0}$ Relative Position$(x,y) \leq M$ for some $M \in \mathbb{R}$
   (b) For given y, $\lim_{x\to 0}$ Relative Position$(x,y) \leq N$
   or for given x, $\lim_{y\to\infty}$ Relative Position$(x,y) \leq N$ for some $N \in \mathbb{R}$

   We want to have this property such that interpretations of high levels of dispersion between x and y are possible in a fixed range. For the formula of Equation 1, we have that
   Relative Position$(x,y) \in [-1,1]$.

In order to amplify small deviations from x to y compared to larger deviations, we transform the formula of Equation 1 by the sigmoid function of Equation 2. The idea here is that small deviations from the point of symmetry s (which equals 0 using Equation 1) result in larger changes compared to changes further away from this point. Furthermore, the sigmoid function is a monotonic transformation which preserves the property of symmetrical dispersion and is bounded on some interval given that Relative Position$(x,y) \in [-1,1]$. Given this interval for Relative Position(x,y), we want that for $\lim_{\text{Relative Position}(x,y)\to -1}$, $\lim_{\sigma_k(\text{Relative Position}(x,y))\to 0}$ and for $\lim_{\text{Relative Position}(x,y)\to 1}$, $\lim_{\sigma_k(\text{Relative Position}(x,y))\to 1}$ in such a rate that whenever
Relative Position$(x,y) = -1$, $\sigma_k(-1) = e^{-5}$ and whenever Relative Position$(x,y) = 1$, $1 - \sigma_k(1) = e^{-5}$. We set $k = 9.2103 \approx 9.21$ such that this holds.

In Figure 1 we have plotted the mappings from Relative Position(x,y) to $\sigma_k[\text{Relative Position}(x,y)]$. In this plot, we see that s of Relative Position(x,y) is mapped to a value of 0.5, and that relative small deviations from this point correspond to larger deviations in $\sigma_k[\text{Relative Position}(x,y)]$ compared to values farther away from s. In fact, we have that for Relative Position$(x,y) \in [-0.5,0.5]$ we cover 98% of the range of $\sigma_k[\text{Relative Position}(x,y)]$.

Graphical Illustration Relative Position. In order to illustrate the behaviour of our chosen transformation, we compare values of Relative Position(x,y) and $\sigma_k[\text{Relative Position}(x,y)]$ to the ratio between

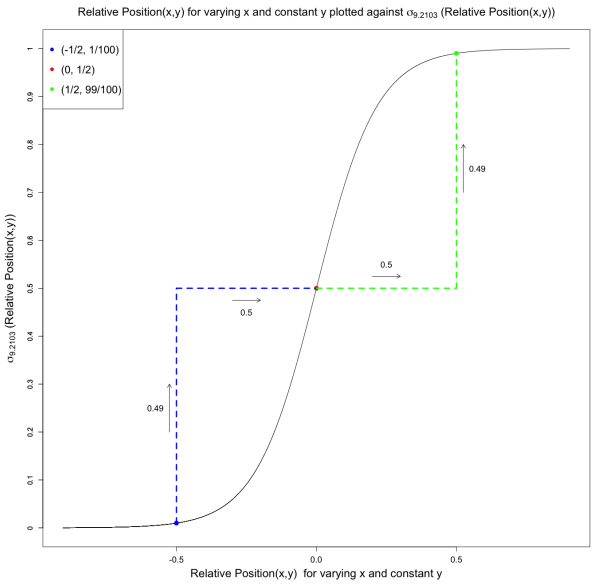

Figure 1: Mappings from Relative Position(x, y) to σ_k[Relative Position(x, y)]

x and y, $R(x, y)$. Here $\mathrm{R}(x, y)$ has a simple interpretation. For some scalar $c \in \mathbb{R}^+$ if $y = cx$ then $\mathrm{R}(x, y) = c$, whereas for Relative Position$(x, y) = -\frac{(c-1)}{(c+1)}$, and σ_k[Relative Position(x, y)] $= \frac{1}{1+e^{k\frac{(c-1)}{(c+1)}}}$. In Figure 2 we have plotted $R(x, y)$ against Relative Position(x, y) (left plot) and σ_k[Relative Position(x, y)] (right plot) respectively on the interval $\mathrm{R}(x, y) \in (0, 4]$. Note that the $\mathrm{R}(x, y)$ has a negative association with both Relative Position(x, y) and σ_k[Relative Position(x, y)], since the higher x becomes compared to y, the more dispersion we have.

In the plots of Figure three values of $R(x, y)$ highlighted. First $\mathrm{R}(x, y) = \frac{1}{3}$ in green, second $R(x, y) = 1$ (point s) in red, and lastly $R(x, y) = 3$ in blue. The dashed lines with the corresponding colors represent the ratio between of Relative Position(x, y), and σ_k[Relative Position(x, y)] compared to s over that of $R(x, y)$. Based on these ratios we see that $\mathrm{R}(x, y)$ has asymmetric differences around s, while both Relative Position(x, y), and σ_k[Relative Position(x, y)] behave symmetrically around this point. Furthermore, we see that for $\mathrm{R}(x, y) \in [\frac{1}{3}, 3]$ we cover for 98% of the range of σ_k[Relative Position(x, y)].

Motivation for Inclusion σ_k. We decide to transform Relative Position(x, y) by means of σ_k in order to let small deviations around s have a larger impact on the relative position than larger ones. As can be seen in Figure 1, changes of the relative position around the midpoint s result in much steeper curves than changes in the farther corners. This implies that whenever changes of x in the neighbourhood of y have much larger impact on the relative position compared to changes of x for which the dispersion between x and y is already large. As a result, the relative position stabilises for changes farther away from the midpoint s.

In the set-up of this thesis, we prefer this behavior. We compare the relative position (in terms of price and delivery promise) of the internal retailer to that of the rest of the market in the context of e-

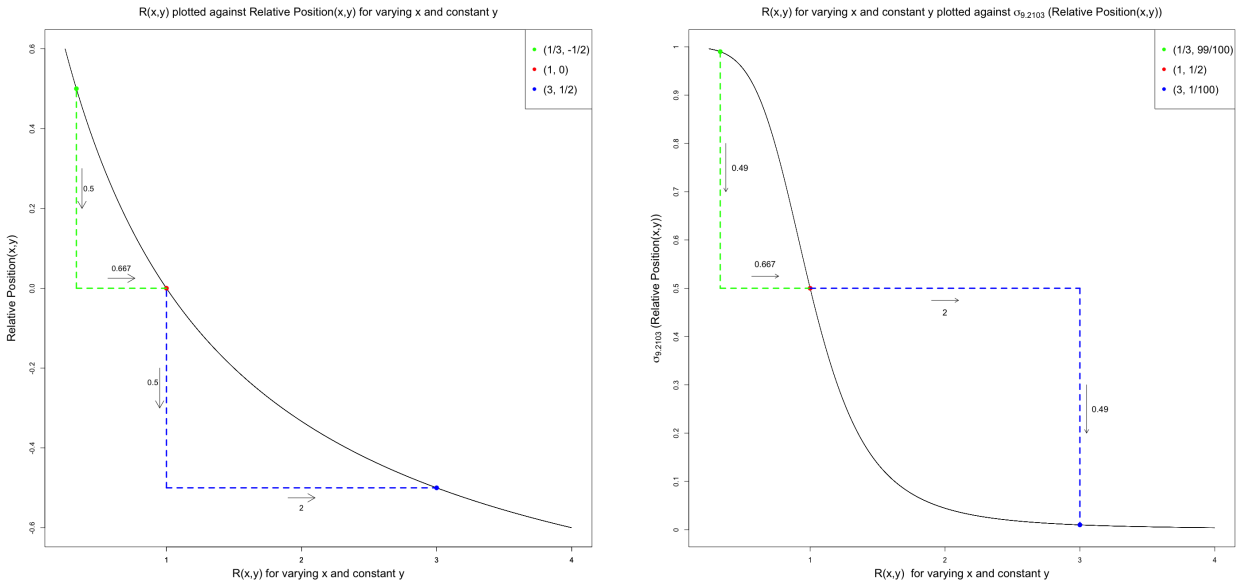

Figure 2: Mapping $R(x, y)$ to Relative Position(x, y) and σ_k[Relative Position(x, y)]

commerce. As this is an extremely competitive market in which the information barrier for consumers is low for finding products which suits their needs best, only small changes from the market price and/or delivery promise can already result in large deviations in the relative position.

Additionally, using the definition of Equation 1, we observe that 99 per cent of all observations within our dataset has a an absolute relative price position below $\frac{1}{2}$. This corresponds to R(Internal Price, Market Price) $\in (\frac{1}{2}, 2)$. For the delivery promise we find that 93 percent of all absolute relative delivery promise positions are below $\frac{1}{2}$, which corresponds to R(Internal Delivery Promise, Market Delivery Promise) $\in (\frac{1}{3}, 3)$. This illustrates that the dispersion of price and delivery promise between the internal retailer and the market generally is bounded by a couple of factors. The additional transformation of σ_k allows us capture almost all variability within these bounds.

3.1.2. Application of Relative Position

In Table 2 we find the ratio $R(x, y)$, the first variant of relative position of (1), and the sigmoid transformation by means of (2). For brevity we call internal price $= x$ and market price $= y$.

Situation	Internal price	Market price	$R(x, y)$	Relative Position(x, y)	$\sigma_{9.21}$(Relative Position(x, y))
A	€10	€10	1	0	0.5
B	€10	€11	0.91	0.05	0.61
C	€10	€30	0.33	0.5	0.99
D	€11	€10	1.1	-0.05	0.39
E	€30	€10	3	-0.5	0.01

Table 2: Applying different concepts of relative position on the different instances of the toy example

Using these definitions, we can make a couple of observations. First, we see that $\sigma_{9.21}$ (Relative Position(x, y)) has the largest difference in case we move from situation A to situations B/D. Here it should be noted that once we account for the range of values all metrics

can take we have that the impact of moving from situation A to B/D has even larger impact for $\sigma_{9.21}$ (Relative Position(x, y)) compared to the other metrics. This implies that
$\sigma_{9.21}$ (Relative Position(x, y)) is most sensitive to small changes in the price position of the internal retailer compared to the market. By moving from situation B to situation C, we see that the for $\sigma_{9.21}$ (Relative Position(x, y)) the relative difference is much smaller than for Relative Position(x, y)) (62% versus 900%), and relatively the same for $R(x, y)$ (62% versus 63%). However as $R(x, y)$ is not symmetric around its midpoint, we find that if we move from situation D to E the relative difference of $R(x, y)$ is much larger compared to that of $\sigma_{9.21}$ (Relative Position(x, y)) (62% versus 173%).Hence, once the relative price position of the internal retailer is already deviating from the market, larger differences tend to have a more dampening effect in case we apply definition $\sigma_{9.21}$ (Relative Position(x, y)) in compared to Relative Position(x, y) and $R(x, y)$.

3.1.3. Notation and Moving Forward

Given the introduced concept of the relative position, let us now introduce the notation we use when we consider relative positions. For some product i measured at day t, we define the relative price position of the internal retailer compared to the market as $\sigma_{9.21}(\text{RP}_{pit})$, and the relative delivery promise position of the internal retailer compared to the market as $\sigma_{9.21}(\text{RP}_{dit})$. Here p denotes the price, d denotes the delivery promise, RP the relative position formula of Equation 1, and $\sigma_{9.21}()$ the sigmoid transformation of the relative position as defined in Equation 2.

During the development of this paper, $\sigma_{9.21}(\text{RP}_{pit})$ and $\sigma_{9.21}(\text{RP}_{dit})$ can be considered as the foundation on which all other theory, and model estimation is based. First of all, we use $\sigma_{9.21}(\text{RP}_{pit})$ and $\sigma_{9.21}(\text{RP}_{dit})$ to estimate the effects of changes in prices and delivery promises from a relative perspective. Secondly, we use the concepts of $\sigma_{9.21}(\text{RP}_{pit})$ and $\sigma_{9.21}(\text{RP}_{dit})$ to build the theory around WTP, UTP and RC. We do this in Section 3.2.

3.2. Defining RC, WTP, UTP

In this subsection we introduce the concepts of Rational Choice (RC), Willingness to Pay (WTP) and Unwillingness to Pay (UTP) in two steps. First we expand the example of Table 1 by the inclusion of delivery promises leading to the example of Table 3 and explain which different situations can occur. Based on the nature of every scenario, we add one of the labels RC, WTP and UTP. Based on these labels, we then introduce more formally (mathematically and economically) the different concepts.

In Table 1 we see that in total, for one identical product there are four different offer combinations which can occur. In the first instance, denoted by I in Table 3, we find that the offer of the internal retailer is better than the market both in terms of price and the delivery promise. Consequently, $\sigma_{9.21}(\text{RP}_{pit}) > 0.5$ (green in Table 3 for I) and $\sigma_{9.21}(\text{RP}_{dit}) > 0.5$ (green in Table 3 for I) . If we hold all other purchase considerations of consumers constant (such as other service quality factors, or the perceived reputation of the internal retailer), in this situation the rational choice from a consumer perspective would be to buy from the internal retailer, since both the price and delivery promise are better than the market. The exact opposite rationale is true for situation II, where both the market price and market delivery promise are better than that of the internal retailer. Therefore, we have that $\sigma_{9.21}(\text{RP}_{pit}) < 0.5$ (red in Table 3 for II) and $\sigma_{9.21}(\text{RP}_{dit}) < 0.5$ (red in Table 3 for II).

Consequently in this situation it would be an *irrational* decision to buy from the internal retailer, holding all purchasing considerations constant.

Situation	Internal price	Market price	$\sigma_{9.21}(\text{RP}_{pit})$	Internal promise	Market promise	$\sigma_{9.21}(\text{RP}_{dit})$	Offer Position
I	€10	€30	**0.99**	1	3	**0.99**	RC
II	€30	€10	**0.01**	3	1	**0.01**	RC
III	€30	€10	**0.01**	1	3	**0.99**	WTP
IV	€10	€30	**0.99**	3	1	**0.01**	UTP

Table 3: An offer for the internal retailer in terms of price and delivery promise (internal promise) for a product compared to the market price and market delivery promise (market promise). Note that under all scenarios we consider the same product.

Since situations I and II are each others opposites, and both imply similar positions of the relative price and relative delivery promise around the point of symmetry (if $\sigma_{9.21}(\text{RP}_{pit}) > 0.5$ then $\sigma_{9.21}(\text{RP}_{dit}) > 0.5$, and when $\sigma_{9.21}(\text{RP}_{pit}) < 0.5$ then $\sigma_{9.21}(\text{RP}_{dit}) < 0.5$), we can combine these two instances under one umbrella. We denote this umbrella by the name of *Rational Choice* (RC), which implies that for those offer combinations which fall under this type, it is rational (I) or irrational (II) to buy from the internal retailer, holding all other purhcase considerations constant.

For situations III and IV of Table 3 this reasoning does not hold. For situation III we have that the price of the internal retailer is worse than that of the market because $\sigma_{9.21}(\text{RP}_{pit}) < 0.5$ (red in situation III), while the delivery promise is more competitive than the market since $\sigma_{9.21}(\text{RP}_{dit}) > 0.5$ (green in situation III). Therefore, the concept of a rational choice does not apply here. However, we can introduce another concept. Since $\sigma_{9.21}(\text{RP}_{pit}) < 0.5$, but $\sigma_{9.21}(\text{RP}_{dit}) > 0.5$, we can argue that in this situation it could be the case that consumers are still considering to buy from the internal retailer in case they prefer a faster delivery promise over a lower price. We shall denote situations like these as *Willingness to Pay* more for a faster delivery promise (WTP).

Using a similar reasoning for IV, we can define a concept in which consumers prefer to buy from the internal retailer whenever the price of the internal retailer is lower than the market ($\sigma_{9.21}(\text{RP}_{pit}) > 0.5$), but the delivery promise is worse than the market ($\sigma_{9.21}(\text{RP}_{dit}) < 0.5$). We call this *Unwillingness to Pay* more for a faster delivery promise (UTP), although the interpretation of this variable is slightly different than the name does suggest. Rather than measuring unwillingness to pay for a faster delivery promise, what this variable captures is the extent to which that consumers are accepting a slower delivery promise in case they can buy at a lower price (compared to the market).

We want to stress that our definition of (un)willingness to pay is different from the definitions more commonly found in the literature. In the literature, willingness to pay usually refers to the absolute monetary amount a consumer is willing to pay more to receive additional benefits for some attribute which increases its utility, while unwillingness to pay indicates the opposite. As we show more formally in Section 3.2.2, in this paper we use (un)willingness to pay as continuous positions in a tradeoff space with fixed range (between 0 and 1) between relative price positions and relative delivery promise positions. For situations in which willingness to pay is applicable, the tradeoff to make is to buy one product from a competitor at a higher price, but receive a lower delivery promise in return, while for unwillingness to pay the consumer is accepting that the delivery promise of the retailer he/she is buying from is higher than the market, but can buy the product at a lower price. Within the tradeoff space (un)willingness to pay indicates how large the tradeoff is to make.

In the next subsections we derive our definitions for RC, WTP and UTP. First, we provide the mathematical definition for these variables, which we complement with economic interpretations.

3.2.1. Deriving RC

Mathematical Definition RC. We express RC for product i at time t , denoted as RC_{it}, by means of the following formula

$$\mathrm{RC}_{it}(\sigma_{9.21}(\mathrm{RP}_{pit}), \sigma_{9.21}(\mathrm{RP}_{dit})) = 2\left(\frac{n\cdot\sigma_{9.21}(\mathrm{RP}_{pit})+m\cdot\sigma_{9.21}(\mathrm{RP}_{dit})}{n+m} - 0.5\right) * \mathbf{1}_{((\sigma_{9.21}(\mathrm{RP}_{pit})-0.5)\cdot(\sigma_{9.21}(\mathrm{RP}_{dit})-0.5)\geq 0)} \tag{3}$$

Where n and m are weights which determine the relative importance between $\sigma_{9.21}(\mathrm{RP}_{pit})$ and $\sigma_{9.21}(\mathrm{RP}_{dit})$. In this study, we set $n = m = 1$. This assumes that we treat $\sigma_{9.21}(\mathrm{RP}_{pit})$ and $\sigma_{9.21}(\mathrm{RP}_{dit})$ as being equally important. By changing n and m from, this baseline, we can put more weight on either $\sigma_{9.21}(\mathrm{RP}_{pit})$ or $\sigma_{9.21}(\mathrm{RP}_{dit})$. By doing so, $RC_{it}(\sigma_{9.21}(\mathrm{RP}_{pit}), \sigma_{9.21}(\mathrm{RP}_{dit}))$ depends more on the variable on which we put more weight. For instance, if we believe that rational choice is more determined by price than delivery promises, we can (slightly) increase n such that rational choice reflects more changes in $\sigma_{9.21}(\mathrm{RP}_{pit})$. In case we set $m = 0$, or we set n sufficiently high given a value for m such that $\sigma_{9.21}(\mathrm{RP}_{dit})$ has no contribution in $RC_{it}(\sigma_{9.21}(\mathrm{RP}_{pit}), \sigma_{9.21}(\mathrm{RP}_{dit}))$, rational choice reflects all situations in which the internal retailer has better price propositions than the market and we set situations in which the internal retailer has worse prices than the market equal to 0. For brevity we denote $RC_{it}(\sigma_{9.21}(\mathrm{RP}_{pit}), \sigma_{9.21}(\mathrm{RP}_{dit}))$ as RC_{it}.

The definition of RC_{it} as given in Equation 3 satisfies the following mathematical properties:

- **Fixed Range**: Given that $\sigma_{9.21}(\mathrm{RP}_{pit}) \in [0, 1]$ and $\sigma_{9.21}(\mathrm{RP}_{dit}) \in [0, 1]$, we have that $\mathrm{RC}_{it} \in [-1, 1]$.

- **Symmetrical Dispersion**: For RC_{it} the point of symmetry, denoted as RC_s equals 0. Based on RC_s, we can show that the behavior of RC_{it} based on the definition of Equation 3 is symmetrical around this point.

  In order to do this, let us introduce some terminology. Let c_1 denote a first coordinate pair of ($\sigma_{9.21}(\mathrm{RP}_{pit})$, $\sigma_{9.21}(\mathrm{RP}_{dit})$), and c_2 a second coordinate pair of ($\sigma_{9.21}(\mathrm{RP}_{pit})$, $\sigma_{9.21}(\mathrm{RP}_{dit})$) which is symmetrically the opposite of c_1 in terms of $\sigma_{9.21}(\mathrm{RP}_{pit})$ and $\sigma_{9.21}(\mathrm{RP}_{dit})$. That is if $\sigma_{9.21}(\mathrm{RP}_{pit})_{c_1}$ belongs to the coordinate pair c_1, then $1 - \sigma_{9.21}(\mathrm{RP}_{pit})_{c_1}$ belongs to coordinate pair c_2. Given this property, it holds that $|\mathrm{RC}_{it}(c_1) - \mathrm{RC}_s| = |\mathrm{RC}_{it}(c_2) - \mathrm{RC}_s|$.

  This statement can easily be proven by using the properties of c_1 and c_2 (that is writing c_2 in terms of c_1), substituting them into Equation 3, and observing what role the indicator function $\mathbf{1}_{(\sigma_{9.21}(\mathrm{RP}_{pit})-0.5)*(\sigma_{9.21}(\mathrm{RP}_{dit})-0.5)\geq 0)}$ plays. In order to support this claim, we will now provide the derivation by means of a case-distinction.

  1. Take a coordinate pair of c_1 such that $\mathbf{1}_{\left((\sigma_{9.21}(\mathrm{RP}_{pit})_{c_1}-0.5)*(\sigma_{9.21}(\mathrm{RP}_{dit})_{c_1}-0.5)\geq 0\right)} = 0$: In this case $|\mathrm{RC}_{it}(c_1) - \mathrm{RC}_s| = |\mathrm{RC}_{it}(c_2) - \mathrm{RC}_s| = 0$
  2. Take a coordinate pair of c_1 such that $\mathbf{1}_{\left((\sigma_{9.21}(\mathrm{RP}_{pit})_{c_1}-0.5)*(\sigma_{9.21}(\mathrm{RP}_{dit})_{c_1}-0.5)\geq 0\right)} = 1$: In this

case Formula 3 can be simplified to

$$2*\left(\frac{n*\sigma_{9.21}(\mathrm{RP}_{pit})+m*\sigma_{9.21}(\mathrm{RP}_{dit})}{n+m}-0.5\right)=2*\frac{n*\sigma_{9.21}(\mathrm{RP}_{pit})+m*\sigma_{9.21}(\mathrm{RP}_{dit})}{n+m}-1$$

This implies that

$$|\mathrm{RC}_{it}(c_1)-\mathrm{RC}_s|=\left|2*\frac{n*\sigma_{9.21}(\mathrm{RP}_{pit})_{c_1}+m*\sigma_{9.21}(\mathrm{RP}_{dit})_{c_1}}{n+m}-1\right|=|G-1|$$

Where we set $2*\frac{n*\sigma_{9.21}(\mathrm{RP}_{pit})_{c_1}+m*\sigma_{9.21}(\mathrm{RP}_{dit})_{c_1}}{n+m}=G$ in the last step. If we use the relation between coordinate pairs c_1 and c_2, we obtain for coordinate c_2 that

$$\begin{aligned}|\mathrm{RC}_{it}(c_2)-\mathrm{RC}_s|&=\left|2*\frac{n*(1-\sigma_{9.21}(\mathrm{RP}_{pit})_{c_1})+m*(1-\sigma_{9.21}(\mathrm{RP}_{dit})_{c_1})}{n+m}-1\right|\\&=\left|1-2*\frac{n*\sigma_{9.21}(\mathrm{RP}_{pit})_{c_1}+m*\sigma_{9.21}(\mathrm{RP}_{dit})_{c_1}}{n+m}\right|=|1-G|\end{aligned}$$

Based on these derivations we then have that

$$|\mathrm{RC}_{it}(c_1)-\mathrm{RC}_s|=|G-1|=|1-G|=|\mathrm{RC}_{it}(c_2)-\mathrm{RC}_s|$$

Economic Interpretation RC. Given the expression for RC_{it} as provided in Formula 3, let us next provide an economic intuition of what RC_{it} represents. For this, it helps to plot RC_{it} for the different values of $\sigma_{9.21}(\mathrm{RP}_{pit})$ and $\sigma_{9.21}(\mathrm{RP}_{dit})$, which we do in Figure 3.

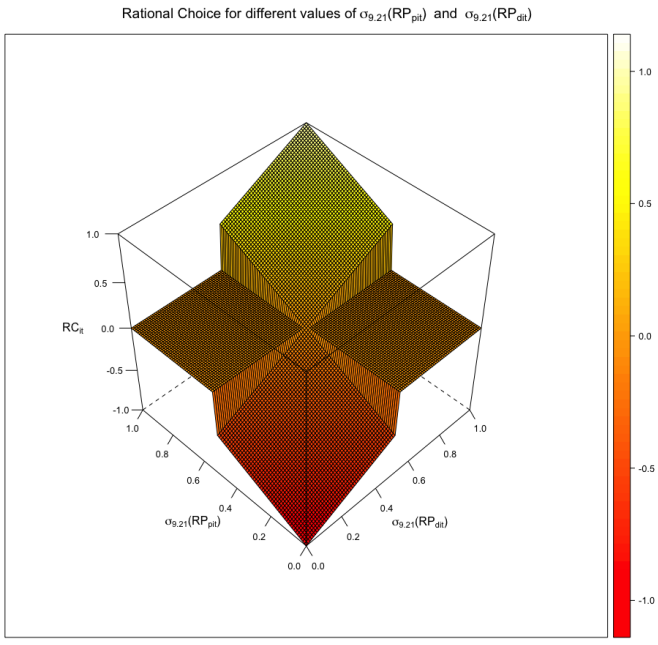

Figure 3: RC_{it} for the different values of $\sigma_{9.21}(\mathrm{RP}_{pit})$ and $\sigma_{9.21}(\mathrm{RP}_{dit})$

In Figure 3 we can distinguish four different areas. First we have upper diagonal area, covered in

the orange to yellow colors. Within this area we find that $\sigma_{9.21}(\text{RP}_{pit}) \geq 0.5$ and $\sigma_{9.21}(\text{RP}_{dit}) \geq 0.5$. Economically, this area represents all possible offer combinations for which the internal retailer is more competitive than the market both in terms of price and delivery promise. In terms of the covered space of RC_{it}, we observe here that $\text{RC}_{it} \in [0, 1]$. This implies that whenever positive values of RC_{it} are associated with offer positions for which it is rational to buy from the internal retailer based on price and the delivery promise, holding all other purchase considerations fixed. Additionally, we see that the maximum value of the rational choice, $\text{RC}_{it} = 1$ implies that $\sigma_{9.21}(\text{RP}_{pit}) = 1$ and $\sigma_{9.21}(\text{RP}_{dit}) = 1$. Consequently, it is most rational to buy from the internal retailer in case both the relative price position and relative delivery promise position are maximised.

In the lower diagonal area, represented by the colors ranging from orange to red, we observe that $\sigma_{9.21}(\text{RP}_{pit}) \leq 0.5$ and $\sigma_{9.21}(\text{RP}_{dit}) \leq 0.5$. From an economic perspective, we see that this area represent all possible offer combinations in which the internal retailer is less competitive than the market in terms of price and delivery promise. In numerical terms, this implies that in this area $\text{RC}_{it} \in [-1, 0]$, where a value of -1 indicates that $\sigma_{9.21}(\text{RP}_{pit}) = 0$ and $\sigma_{9.21}(\text{RP}_{dit}) = 0$. Hence, it is the least rational to buy from the internal retailer whenever the relative price position and relative delivery promise position of the internal retailer obtain their minimum values compared to the market.

Besides the two diagonal planes, we also observe two flat planes. These areas are flat because of the inclusion of the indicator function $\mathbf{1}_{(\sigma_{9.21}(\text{RP}_{pit})-0.5)*(\sigma_{9.21}(\text{RP}_{dit})-0.5)\geq 0)}$, which makes the rational choice inactive in these areas. Within these areas, we cannot speak of a rational choice, since either $\sigma_{9.21}(\text{RP}_{pit}) > 0.5$ but $\sigma_{9.21}(\text{RP}_{dit}) < 0.5$ (left horizontal square), or $\sigma_{9.21}(\text{RP}_{dit}) > 0.5$ but $\sigma_{9.21}(\text{RP}_{pit}) < 0.5$ (right horizontal square). For the right flat area, we therefore observe the region which represents willingness to pay, while the left flat area represents unwillingness to pay.

3.2.2. Deriving WTP and UTP

In order to derive the formulas of WTP, and UTP, let us recall the example of Table 3, by means of Table 4, and adapt it slightly to highlight between trade-offs and no trade-offs. In Table 4 we now find that situations I and II now represent the no trade-off situation, whereas situations III and IV still respectively represent WTP and UTP. The formulas we derive should satisfy these different situations. Additionally, since WTP and UTP are each others complements in the trade-off space, we want to derive the equations in such a way that this principle is preserved. With this in our minds, let us now move to the derivations and interpretation.

Situation	Internal price	Market price	$\sigma_{9.21}(\text{RP}_{pit})$	Internal promise	Market promise	$\sigma_{9.21}(\text{RP}_{dit})$	Offer Position
I	€10	€30	**0.99**	1	3	**0.99**	No trade-off
II	€30	€10	**0.01**	3	1	**0.01**	No trade-off
III	€30	€10	**0.01**	1	3	**0.99**	WTP
IV	€10	€30	**0.99**	3	1	**0.01**	UTP

Table 4: Four different offer propositions for the internal retailer in terms of price and delivery promise (internal promise) for a product compared to the market price and market delivery promise (market promise), where we have two trade-off situations and two situations which do not reflect any trade-off.

Mathematical Definitions WTP and UTP. .

We express WTP and UTP for product i at time t , respectively denoted by WTP_{it} and UTP_{it}, by means of the following formulas:

$$\text{WTP}_{it}(\sigma_{9.21}(\text{RP}_{pit}), \sigma_{9.21}(\text{RP}_{dit})) = \frac{\sigma_{9.21}(\text{RP}_{dit}) - \sigma_{9.21}(\text{RP}_{pit})}{\sigma_{9.21}(\text{RP}_{dit}) + \sigma_{9.21}(\text{RP}_{pit})} * \mathbf{1}_{(\sigma_{9.21}(\text{RP}_{dit})-0.5\geq 0)} * \mathbf{1}_{(\sigma_{9.21}(\text{RP}_{pit})-0.5\leq 0)} \tag{4}$$

$$\text{UTP}_{it}(\sigma_{9.21}(\text{RP}_{pit}), \sigma_{9.21}(\text{RP}_{dit})) = \frac{\sigma_{9.21}(\text{RP}_{pit}) - \sigma_{9.21}(\text{RP}_{dit})}{\sigma_{9.21}(\text{RP}_{pit}) + \sigma_{9.21}(\text{RP}_{dit})} * \mathbf{1}_{(\sigma_{9.21}(\text{RP}_{pit})-0.5\geq 0)} * \mathbf{1}_{(\sigma_{9.21}(\text{RP}_{dit})-0.5\leq 0)} \tag{5}$$

Where we denote $\text{WTP}_{it}(\sigma_{9.21}(\text{RP}_{pit}), \sigma_{9.21}(\text{RP}_{dit}))$ as WTP_{it} and $\text{UTP}_{it}(\sigma_{9.21}(\text{RP}_{pit}), \sigma_{9.21}(\text{RP}_{dit}))$ as UTP_{it}. When we investigate Equations 4 and 5 more closely, we can see that these equations reflect similar behavior as that of Equation 1, with one slight deviation: we set the areas where the functions would attain negative values equal to 0 by means of the indicator functions. Consequently, $\text{WTP}_{it} \in [0, 1]$ and $\text{UTP}_{it} \in [0, 1]$.

Furthermore, based on the way Equations 4 and 5 are created, we observe that these two formulas can be regarded as each others complements in the trade-off space. The reason for this is twofold. First, we can express the fraction $\frac{\sigma_{9.21}(\text{RP}_{dit})-\sigma_{9.21}(\text{RP}_{pit})}{\sigma_{9.21}(\text{RP}_{dit})+\sigma_{9.21}(\text{RP}_{pit})}$ of Equation 4 in terms of the fraction of Equation 5 (and vice-versa) by multiplying it by minus one. Second, the two indicator functions of Equation 4 can be expressed as the complements of the indicator functions of Equation 5. Therefore, if we apply these two transformations simultaneously to Equation 4, we obtain the result of Equation 5:

$$\begin{aligned} &- \frac{\sigma_{9.21}(\text{RP}_{dit}) - \sigma_{9.21}(\text{RP}_{pit})}{\sigma_{9.21}(\text{RP}_{dit}) + \sigma_{9.21}(\text{RP}_{pit})} * (1 - \mathbf{1}_{(\sigma_{9.21}(\text{RP}_{dit})-0.5\geq 0)}) * (1 - \mathbf{1}_{(\sigma_{9.21}(\text{RP}_{pit})-0.5\leq 0)}) \\ =_{(2)} &\frac{\sigma_{9.21}(\text{RP}_{pit}) - \sigma_{9.21}(\text{RP}_{dit})}{\sigma_{9.21}(\text{RP}_{pit}) + \sigma_{9.21}(\text{RP}_{dit})} * \mathbf{1}_{(\sigma_{9.21}(\text{RP}_{pit})-0.5\geq 0)} * \mathbf{1}_{(\sigma_{9.21}(\text{RP}_{dit})-0.5\leq 0)} = \text{UTP}_{it} \end{aligned}$$

In $_{(2)}$, it should be noted that for $\sigma_{9.21}(\text{RP}_{dit}) = \sigma_{9.21}(\text{RP}_{dit}) = 0.5$ we have $\text{WTP}_{it} = \text{UTP}_{it} = 0$. As a result, we can replace the $>$ and $<$ symbols of the indicator functions $\mathbf{1}_{(\sigma_{9.21}(\text{RP}_{pit})-0.5>0)}$ and $\mathbf{1}_{(\sigma_{9.21}(\text{RP}_{dit})-0.5<0)}$ by $\geq$ and $\leq$.

Economic Interpretation WTP and UTP. In Figure 4 we have plotted the spaces of WTP_{it} (left plot) and UTP_{it} (right plot) for all different combinations of $\sigma_{9.21}(\text{RP}_{pit})$ and $\sigma_{9.21}(\text{RP}_{dit})$. Based on these two plots, let us now explain the economic intuition of these two variables.

We first consider the plot related to WTP_{it} (left). Here we can distinguish two different areas, one flat area with only zeros, and one upward moving area where WTP_{it} is active. Within the active part, the blue area indicates all combinations of $\sigma_{9.21}(\text{RP}_{pit})$ and $\sigma_{9.21}(\text{RP}_{dit})$ which are close to the point of symmetry (0.5). From an economic perspective, these combinations indicate that the offer of the internal retailer is a little better in terms of delivery promise and a little worse in price. Therefore, in these situations, the trade-off is relatively small. Moving towards the areas of the plot which are represented by the green and orange colors, we observe that the relative price position of the the internal retailer becomes worse and worse compared to the market ($\sigma_{9.21}(\text{RP}_{pit})$ moves closer to 0), while the relative delivery promise starts outperforming the market offer more and more ($\sigma_{9.21}(\text{RP}_{dit})$

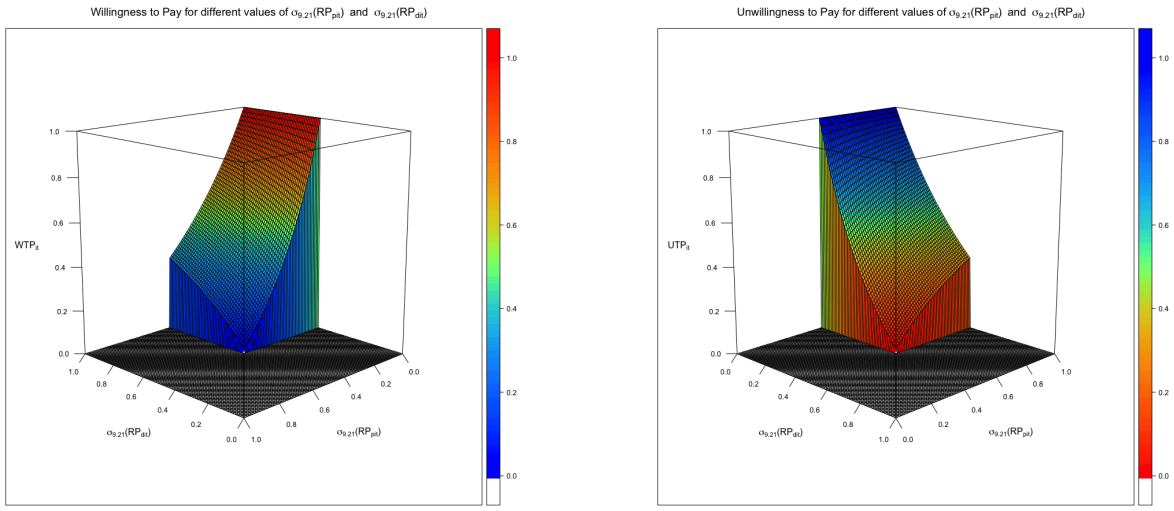

Figure 4: Plots of WTP_{it} (left) and UTP_{it} (right) for all different combinations of $\sigma_{9.21}(\text{RP}_{pit})$ and $\sigma_{9.21}(\text{RP}_{dit})$

moves closer to 1). Therefore in this area the trade-off between prices and delivery promises starts to increase. For all values in the red area, we find that the trade-off becomes even more stringent, in the sense that the values of $\sigma_{9.21}(\text{RP}_{pit})$ here are very close to 0, while the values of $\sigma_{9.21}(\text{RP}_{dit})$ are very close to 1. In the top left corner of the plot, we then observe the largest possible trade-off, since $\sigma_{9.21}(\text{RP}_{pit}) = 0$ and $\sigma_{9.21}(\text{RP}_{dit}) = 1$. In short, the larger the value of WTP_{it}, the more we observe trade-offs between price and delivery promise in which consumers need to pay a higher price compared to the market in order to receive a faster delivery promise.

Next, let us have a closer look at the plot related to UTP_{it} (right). Similarly to the plot of WTP_{it}, we here can distinguish an active and inactive area. For the active part of the plot, we start in the red area, where both the price and delivery promise are relatively close to the market offer. Therefore, the trade-off between prices and delivery promises is not larger here. By considering the areas of the plot covered in the orange and green colors, we see that the trade-off between prices and delivery promises start to increase. The reason for this, is that $\sigma_{9.21}(\text{RP}_{pit})$ starts moving closer to 1, while $\sigma_{9.21}(\text{RP}_{dit})$ starts moving closer to 0. Within the blue area, we then see that $\sigma_{9.21}(\text{RP}_{pit})$ is close to 1, while $\sigma_{9.21}(\text{RP}_{dit})$ is close to 0. From an economic perspective, this indicates that the offer of the internal retailer is relatively cheap compared to the market, but has delivery promises which are relatively much higher than the market. In the top right corner we find the most extreme trade-off, with $\sigma_{9.21}(\text{RP}_{pit}) = 1$ and $\sigma_{9.21}(\text{RP}_{dit}) = 0$. To summarize this explanation: the larger the value of UTP_{it}, the more we observe trade-offs between price and delivery promise for which holds that consumers can buy the product at a lower price from the internal retailer compared to the market, but receive a slower delivery promise in return.

4. Data

In this section we elaborate on the data we use for the estimating the effects. During this study we make use of a dataset of approximately 10,000 products, measured at a daily interval during

two periods of the year 2021. The data is provided by one of the largest e-commerce companies of the Netherlands. The e-commerce company of interest sells products and allows third-parties to sell products on their platform, leading to a wide variety of products offered. To be more specific, the products are allocated over 23 different product categories, ranging from books to computers and from clothing to furniture.

In this study we estimate how changes in $\sigma_{9.21}(\mathrm{RP}_p)$, $\sigma_{9.21}(\mathrm{RP}_d)$ RC, WTP, and UTP have an influence on daily sales measured at the individual product level, controlling for other factors. We define daily sales as the number of distinct purchases on a day. Hence, we count situations in which a consumers purchases multiple copies of a product as one sale. For determining the values of $\sigma_{9.21}(\mathrm{RP}_p)$, $\sigma_{9.21}(\mathrm{RP}_d)$ RC, WTP, and UTP, we use aggregated daily prices and delivery promises of the internal retailer. Here aggregation is needed since prices and delivery promises of the product can change during the course of a day. In addition, we include the market price and market delivery promise of the competition (excluding the internal retailer). For this, we use prices and delivery promises of approximately 1000 different online competitors. This data is also offered by the e-commerce company. We control for daily sales by including information about whether the product was for sale on a given day, product discount, display of the product, daily temperature and day dummies.

The remainder of this section is as follows. First, we provide a motivation for the chosen time frame. Second, we explain our selection process for determining which products are used in this study. Third, we summarise the products over the different product categories, which are denoted as shops throughout this paper. Lastly, we provide an overview of all variables used in this study.

4.1. Selected Time Frame

For the time frame, we consider the year 2021. The motivation to select this year is that for the variable related to the delivery promise of the competitors, we have high proportions of incomplete/ missing data. This implies that the delivery promises of competitors are incorrect or simply missing. As a result, we apply a (semi)-manual imputation scheme to recover the delivery promises of the competitor data. For this make use of delivery promise information which is competitor specific (the postal service used, how delivery promises are different during the weekends etc.). For the year 2021 we have manually checked this information is correct and included this information to adjust delivery promises. However, we have no guarantees that these corrections also are correct for other years than the year 2021. Therefore, we have decided only use data for the year 2021. For a more thorough explanation of our imputation scheme, we refer to Appendix A. Within the year 2021, we separate the timeframe into three distinct periods, which we have plotted in Figure 5 by means of aggregated sales over all products of interest. We define the lockdown period in red, the regular period in green, and the holiday period in orange. The regular period is chosen in such a way to represent usual off-holiday season market conditions. Between December 2020 and the end of April of 2021 the country of the internal retailer, the Netherlands, was in a lockdown. Consequently, most physical stores were closed. Although not directly observed from the plot of Figure 5, the market conditions before May 2021 may have influenced the purchase behavior of customers in unforeseen ways. As the goal of this thesis is not to study this effect, we decide not to use this time period in our model.

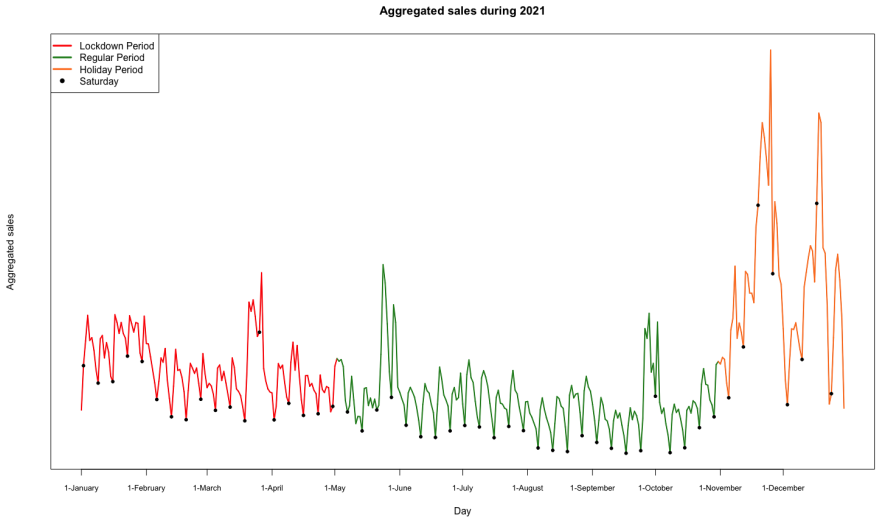

Figure 5: Aggregated sales for 2021

The months November and December deviate from the months before October due to the start of the holiday season. Additionally, in the year 2021, there was again a lockdown which started at December 19. During the total holiday season (including the lockdown), we have observed different sales patterns compared to the period May 2021 to October 2021. On aggregate, this can also be seen by comparing the holiday period to the model period, in which we observe much higher and volatile sales during the holiday period compared to the model period. For this reason, we decide not to combine these two periods in one model, but rather apply two model specifications for these two time frames. Therefore, the goal of this thesis is to study effects during an off-holiday and holiday period.

For the holiday period, we also consider a specific model specification around two holidays in which many consumers buy consumer products as gifts in the Netherlands (December 5 and Christmas). The set-up around these days is to test whether we can observe deviating purchase patterns in the days around December 5 or December 24. We explain this set-up in more detail in Section 4.4.3.

4.2. Product Selection Criteria

The products used in this thesis are selected using four criteria conditioned on a given time frame, being the percentage of days with at least one sale, the release date of the product, the availability of market data, and the variability for the variables RC, WTP and UTP.

Percentage of Days with at Least One Sale. We have only selected products which have a minimum of one sale in at least 50 percent of the days within the time frame. Based on this selection, we refine ourselves to a raw-data pool of approximately 500.000 products. These products also correspond to the 500.000 most popular products (in terms of sales) of the internal retailer. We have set this threshold for two reasons. First and foremost, the internal retailer has the most accurate market information for the most popular products. Second, we have observed that these products have low variability in sales. As a consequence of our choice to confine ourselves to the 500.000 most popular

products, we believe that it is likely that we neglect products with general lower sensitivities to changes in $\sigma_{9.21}(\mathrm{RP}_p)$ and $\sigma_{9.21}(\mathrm{RP}_d)$.

Release Date of Products. We only include products which have a release date at least two weeks before May 3 2021 for three reasons. First, a couple of products have different sales patterns around the release period. Second, the delivery promise is here of less interest. Thirdly, we want to have a balanced dataset.

Availability of Market Data. We only consider products for which we observe market data. Since the goal of this thesis is to study the effect of changes in the relative position of price and the delivery promise, we rely on competitor data. Therefore, we exclude all products for which we do not have any market data (either because there are no competitors, or because we do not observe them). As a result of this condition we lack products in a couple of shops, as can be seen by considering Table 5, in which we have that for the shops *Dutch Books* and *International Books* we only consider a very small proportion of all possible products within these shops. This can be explained once we know the results of our imputation approach, which we explain in Appendix A. As a result of the lack of products in these two shops, we believe that it is not possible to make specific claims for products related to books. This claim is supported if we compare the distribution of prices of products considered in this study to the initial data pool of 500.000 products. By doing so we find an underrepresentation for more expensive books, and an overrepresentation for books in the cheap to middle price ranges (€10-€20). For a more detailed discussion on this topic, we refer to Appendix B.

Variability in RC, WTP and UTP. We exclude all products which do not have at least observation for all cases of RC, WTP and UTP. This means that we only include products which have at least one day in which RC is active, at least one day for which WTP is active and at least one day for which UTP is active. The motivation behind this choice is that the architecture we are using cannot deal with situations in which we do not have any variability in one of our variables. Without this selection criterion we would have obtained approximately 40.000 products, while with this criterion being activated, around different 10.000 products remain. As a consequence of this criterion, we require every product to have at least observation with in which the price of the internal retailer is better than the market ($\sigma_{9.21}(\mathrm{RP}_p) > 0.5$) and at least one observation for which this is worse than the market ($\sigma_{9.21}(\mathrm{RP}_p) < 0.5$). Similarly, every product needs to have at least one observation for which the delivery promise of the internal retailer is better than the market ($\sigma_{9.21}(\mathrm{RP}_d) > 0.5$) and at least one observation for which this is worse than the market ($\sigma_{9.21}(\mathrm{RP}_d) < 0.5$). Compared to the initial data pool of 500.000 products, the addition of this criterion leads to a disproportionately high removal of products which are only rarely sold (median daily sales of less than 1). As a result, we have an overrepresentation of products which have a median daily sales in the range of 5 to 20 units sold. However, in terms of prices and delivery promises we do not find any disproportional changes if we contrast the data pool of 500.000 products to the set of products we obtain once we apply this selection criterion. For a more detailed discussion on how the used data in this study relates to the initial set of products, we refer to Appendix B.2.

4.3. Product Overview

Based on the selection criteria, we obtain products distributed over 23 shops, as depicted in Table 5. In this table we show the number of products we use during the regular period, the holiday period (with a separate column for products which we use for the willingness to pay around Sinterklaas and Christmas), and the number of distinct competitors per shop. In the last row, the numbers related to the number of products are the sum over all shops, whereas the total number of competitors are the total number of unique competitors. In Table 5, we can see that we have most products of the shop Toys during both the regular period and the holiday period, while the number of products for the shops Dutch Books, Home Interior and International Books is lowest. What is more, we see that for the holiday period we have more products than during the regular period.

Shop	# Products Regular Period	# Products Holiday Period	# Products WTP Holiday	# Unique Competitors	Shop category
Baby	539	438	108	353	Drugs and Baby
Computer	380	654	243	548	Hardware
Daily Care	364	601	193	366	Personal Care
DIY	930	955	188	691	DIY
Dutch Books	81	7	1	112	Other
Entertainment	475	908	334	321	Entertainment
Fashion Accessories	155	184	36	468	Other
Fashion and Footwear	212	294	44	369	Other
Garden and Lighting	325	398	121	593	Other
Health	453	424	74	414	Drugs and Baby
Home Interior	27	58	16	589	Other
International Books	27	25	0	23	Other
Kitchen and Household	575	774	176	511	Kitchen and Household
MDA	99	110	25	391	Domestic Appliances
Mobile	350	600	217	495	Hardware
Outdoor and Mobility	424	354	72	630	Sports and Activity
Perfumery	396	401	108	279	Personal Care
Pet	127	201	34	314	Other
SDA	753	1,156	409	504	Domestic Appliances
Sound and Vision	386	736	259	589	Sound and Vision
Sports	179	261	72	466	Sports and Activity
Supermarket	389	431	145	476	Drugs and Baby
Toys	1,681	3,075	694	505	Toys
Total	**9,327**	**13,045**	**3,569**	**1,135**	Not Applicable

Table 5: The shops of interest in this study, complemented with the number of products per considered timeframe and the total number of distinct competitors

DIY = Do It Yourself
MDA = Medium Domestic Appliances
SDA = Small Domestic Appliances

In this thesis, we aggregate the products of the different shops into 11 different shop categories. The choice whether we combine shops or threat them separately depends on the number of products we have available per shop. In case a shop accounts for at least 5% of all products for all datasets, we threat them as a separate shop category. Otherwise, we combine them with other shops which offer similar products. In the last column of Table 5 we show to which shop category the shop belongs.

4.4. Overview Variables

The structure of this subsection is as follows. First we provide the raw variables which we have available. Second, we summarise how we aggregate the data based on the most important variables (sales, price, delivery promise) to the product level. Lastly, we provide an overview of the cleaned and well-defined variables used during this thesis.

4.4.1. Overview Raw Variables

Over the course of this study, we make use of the following raw variables:

1. *Sales*: The number of times a product is bought on a day between May 3 2021 and December 31 2021. In case one customer purchases multiple copies of the product, we count one sale.

Furthermore, we only count consumer purchases which do not make use of any subscription models offered by the internal retailer. We disregard these purchases from the number of sales, since consumers with subscriptions possibly receive a discounted price or a faster delivery promise. For the same reason we disregard purchases from the total number of sales which pay more to receive a faster delivery promise.

2. *Internal Price*: The aggregated product price offered by the e-commerce company. This price includes possible shipping costs.
3. *Competitor Prices*: The prices offered by the competitors during a day. We use one snapshot of a competitor's price per day. This price includes possible shipping costs.
4. *Raw Internal Delivery Promise*: The default delivery promise made by the e-commerce company. The unit of measurement for the delivery promise is in days.
5. *Raw Competitor Delivery Promises*: The delivery promises offered by the competitors during a day. We use one snapshot of a competitor's delivery promise per day. The delivery promises unit of measurement is days. Note that many competitors provide different delivery promises. Usually the promise to deliver faster is made in case an additional fee is paid. In this situation , we only consider the default promise, the delivery promise without any additional fees, or subscriptions.
6. *Ultimate Order Time (of Competitors)*: The ultimate order time for which the delivery promise of the competitor holds. In case no explicit ultimate order time is provided we set the value equal to 23:59 (end of day).
7. *For Sale Proportion*: The proportion of time the product is for sale on a day. A value of zero indicates that the product was not for sale during the day, a value of 1 that is was for sale for the entire day. This variable is used to account for sudden drops in sales in case the product is not in stock.
8. *Monthly Page Visits Competitor Sites*: We weight the relative size of different competitors by means of the number of page visits to every website per month. As we do not have any information about the sales data of competitors, this is the closest metric we have to determine the size of different competitors. These numbers are derived from an external source which is specialized in tracking web traffic of Dutch websites.
9. *Weather Information*: We include average daily temperature to account for seasonal weather patterns. The source of this information is the Koninklijk Nederlands Meteorologisch Instituut (KNMI). As a point of reference we use the average daily temperature of De Bilt.
10. *Daily Discounts*: We add a daily discount boolean to our model to account for days in which a product receives a discount. This variable serves as a control variable.
11. *Display*: We create a display boolean for products which receive extra attention on the site of the internal retailer. Whenever this boolean is active, it implies that the product was part of some promotional activity during a day. As a result, the product could be more easily be found compared to other products in the same shop. We add this variable to function as a control variable.
12. *Day Dummies*: We include daily dummies for several situations. First of all, we have weekday

dummies. Second we have holiday dummies for official holidays. Third, we have a dummy for Black Friday, and lastly we have dummies to account for the lockdown period (19 December 2021 to 31 December 2021).

We account for weekdays since the number of sales of the internal retailer tend to differ depending on the day of the week. For example in Figure 5, we can see that on Saturday the sales tend to be systematically lower than all other days of the week. The inclusion for the holidays is two-fold. First the number of sales can follow different patterns at these days. Secondly, the delivery promises is different at these days for most shops. We add a dummy for Black Friday to account for the different sales patterns on this day. This can also be seen when we consider Figure 5, where the day with maximum sales is on Black Friday. Lastly, we add dummies for the lockdown period, to account for the fact that offline stores were closed during this period, and we therefore might expect that online sales increase.

Most of the raw variables can already be used for our model. However, for the creation of the relative price position, relative delivery promise position, RC, WTP, and UTP, we first need to apply some product cleaning and aggregation. This will be the topic of the next part of this subsection.

4.4.2. Cleaning and Aggregation of Data

Internal Retailer. For the internal data we have that a particular product can be sold by multiple sellers, either being the e-commerce partner itself or external partners. The offers of the sellers can deviate in terms of price and/or delivery promise. A consumer can buy the product from all sellers which have placed a product offer. However, only one seller gets the most attention for a product. This is the seller which provides the most competing offer in terms of price and/or delivery promise. This seller gets the so-called buy-box, which is the easiest way in which a consumer can buy the product. In case the consumer wants to buy from a different seller, he/she needs to perform additional actions before the product can be bought.

The determination of the best offers occurs in real time, which implies that most competitive offer can change during the course of the day. Consequently, it is not possible to select one offer as being the best for the entire day. We account for this issue in two ways:

1. When a product has sales on a given day: In case a product is sold, we aggregate the price and delivery promise by the amount of sales the product has had under the different offers.

2. When a product does not have any sales: In case the product is not sold on a given day, we cannot use sales as weights. Instead, we consider the amount of time on this day each offer was best and use this as weights to determine the delivery promise and price.

Therefore, the price and delivery promise of the internal retailer are in fact aggregated numbers. For the delivery promise this implies that we convert it from a discrete variable to a continuous variable.

Competitor Data. For the data of competitors, we rely on scraped data. This data is either directly scraped from the site of a competitor, or indirectly by using an intermediary. These intermediaries

are price competitor sites, which scrape prices and delivery promises for given products on different platforms and summarise this information on their own website.

For the scraped data, we find that the prices (and shipping costs) in nearly all instances are provided. Therefore, besides (expected) random measurement error, we have no problems with using this data. For the delivery promise of competitors we observe that for many products on certain days the delivery promise is missing. As this accounts for a majority of all data, we decide to apply a semi-manual imputation scheme to replace the missing values with values which are very likely to be the actual delivery promise. For a thorough explanation of this process, we refer to Appendix A.

Completing Delivery Promises. For the delivery promise, we combine the information of the raw delivery promise and the ultimate order time to obtain a value for the delivery promise. For this we take the raw delivery promise and add the ultimate order time as a penalty, according to the following rule:

$$\text{Delivery Promise} = \begin{cases} \text{Raw Delivery Promise} + \frac{24 - \text{Ultimate Order Time}}{24} & \text{If Raw Delivery Promise} \leq 14 \\ 14 & \text{Otherwise} \end{cases} \tag{6}$$

The rule of Equation 6 allows us to add a penalty of the ultimate order time proportional to time of the day. Second, we place an upper bound to the delivery promise of 14 days. We select this particular threshold value to account for almost all different delivery promises of the internal retailer (rounded this accounts for 100% of all different delivery promises), which is in the range of 1 day to 14 days.

Defining Market Weights. We define the market price and market delivery promise by means of weighted information aggregation over all observed competitors. The weights are determined based on the magnitude of every competitor. As proxies for magnitude, we have web traffic data of the 120 most popular competitors of the internal retailer in the Netherlands. We use this web traffic to calculate the weights for every competitor, by taking the square root of the number of monthly page visits and dividing this by the square root of the competitor with the fewest page visits in this month. We divide by the minimum in order to have a base weight of 1, which we can apply to all other competitors outside the top 120.

More formally, let q denote one competitor for which we want to obtain a market weight for some month m, where $m = 5, 6, 7, 8, 9, 10, 11, 12$. We say that $q \in Q_m$ in case we have web traffic data of the competitor in month m, while $q \in Q_m^{\mathsf{c}}$ implies that we do not have any web traffic data of this competitor in month m. Additionally, let v_{qm} be the number of page visits for the competitor in one month, and $\min(v_{Q_m,m})$ be the minimum amount of page visits we observe in month m. Then we define the market weight of competitor q in month m as follows:

$$\text{MW}_{qm} = \begin{cases} \frac{\sqrt{v_{qm}}}{\sqrt{\min(v_{Q_m,m})}} & \text{If } q \in Q_m \\ 1 & \text{Otherwise} \end{cases} \tag{7}$$

Given MW_{qm} as defined in Equation 7, we calculate the market price and market delivery promise of a product i at day t as the weighted average of the prices and delivery promises of all competitors

which offer product i at day t and for which we have data. That is, $q \in Q^{it}$ denotes if competitor q offers product i at day t. Furthermore, p_{qit} denotes the price of competitor q for product i at day t, and d_{qit} corresponds to the delivery promise of competitor q for product i at day t. Using these notations, we define the market price and market delivery promise of product i at day t by means of Equations 8 and 9:

$$\text{Market Price}_{it} = \frac{\sum_{q \in Q^{it}} \text{MW}_{qm} * p_{qit}}{\sum_{q \in Q^{it}} \text{MW}_{qm}} \tag{8}$$

$$\text{Market Delivery Promise}_{it} = \frac{\sum_{q \in Q^{it}} \text{MW}_{qm} * d_{qit}}{\sum_{q \in Q^{it}} \text{MW}_{qm}} \tag{9}$$

Here it should be noted that MW_{qm} changes on a monthly basis. For example for all days t, for which we have $m = 5$ we have have slightly different values of MW_{qm} for some of the competitors compared to all values of t which belong to $m = 6$.

4.4.3. Overview of Cleaned Variables

In Table 6 we have summarised the variables after cleaning, along with the variable abbreviation which we use to denote the variable in the remaining of this paper, possible additional subscripts and their range, the variable type, the variable role and the range of values the variable has based on the data in our dataset. We use sales as the dependent variable, $\sigma_{9.21}(\text{RP}_p)$, $\sigma_{9.21}(\text{RP}_d)$, RC, WTP, and UTP as variables to study, and all other variables as control variables. For a more detailed overview of the variability of these variables over the different shops we refer to Appendix B.1.

Variable	Variable Abbreviation	Additional Subscript	Subscript Range	Type	Variable Role	Variable Range
Sales	Sales	None	*	Count	Dependent Variable	$[0, 10^4]$
$\sigma_{9.21}(\text{RP}_p)$	$\sigma_{9.21}(\text{RP}_p)$	None	*	Continuous	Variable to Study	$[0, 1]$
$\sigma_{9.21}(\text{RP}_d)$	$\sigma_{9.21}(\text{RP}_d)$	None	*	Continuous	Variable to Study	$[0, 1]$
RC	RC	None	*	Continuous	Variable to Study	$[-1, 1]$
WTP	WTP	None	*	Continuous	Variable to Study	$[0, 1]$
Willingness to pay around Sinterklaas and Christmas	WTPSC	None	*	Continuous	Variable to Study	$[0, 1]$
UTP	UTP	None	*	Continuous	Variable to Study	$[0, 1]$
Shop Category	SC	g	$\in [1, 11]$	Categorical	Interaction Variable	11 levels
For Sale Proportion	FSP	None	*	Continuous	Control Variable	$[0, 1]$
Weekday Dummy	WD	w	$\in [1, 7]$	Categorical	Control Variable	$\{0, 1\}$
Holiday Dummy	Hol	None	*	Categorical	Control Variable	$\{0, 1\}$
Black Friday	BF	None	*	Categorical	Control Variable	$\{0, 1\}$
Lockdown Period	Lock	None	*	Categorical	Control Variable	$\{0, 1\}$
Average Daily Temperature in Degrees Celsius	Temp	None	*	Continuous	Control Variable	$[-5.8, 24.0]$
Discount	Disc	None	*	Categorical	Control Variable	$\{0, 1\}$
Display	Disp	None	*	Categorical	Control Variable	$\{0, 1\}$

Table 6: Variables of interest in this study

In this study, we consider two different time frames. Depending on the time period, the included control variables can be different. To be more specific, during the holiday period we add day dummies for Black Friday and a lockdown period (19 December to 31 December), which are absent during the regular period. Additionally, we remove the variables *Display* and *Temperature* from the holiday period. We remove *Display* because this variable is not well quantified during this period and *Temperature* because the time holiday period is too short to consider seasonal effects.

Note on Variable Willingness to Pay around Sinterklaas and Christmas. We aim to estimate willingness to pay around Sinterklaas and Christmas by considering a subset of products from the holiday period which satisfy a special condition. The condition states that in the week before Sinterklaas (5 December) and/or Christmas (24 December) the internal retailer is the only observed e-commerce

shop which promises to deliver the product before Sinterklaas or Christmas. Additionally, the price of the product is higher than that of the other observed prices, which implies that there is a mark-up for receiving this promise. Based on this condition we want to estimate whether we observe a willingness to pay for these offers.

We can view willingness to pay around Sinterklaas and Christmas (WTPSC) from a relative or absolute perspective. From the relative perspective the willingness to pay around Sinterklaas and Christmas might be higher than general situations for which WTP is active. From the absolute perspective, we disregard the general situation for which WTP is active and only want to determine whether willingness to pay around Sinterklaas and Christmas is positive. We deem that making claims from the absolute perspective is much more difficult than from the relative perspective. The reason for this is that we observe a general declining sales pattern in the week before Sinterklaas and Christmas (recall the aggregated sales plot of Figure 5). Therefore as most products under consideration follow this similar sales pattern, it is expected that in an absolute sense the coefficients of willingness to pay around Sinterklaas and Christmas will be negative. Therefore, we are more interested in considering the effects from a relative perspective.

The relative perspective can also be seen from another view. Rather than comparing willingness to pay around Sinterklaas and Christmas to general situations in which WTP is active, we compare the sales of products for which we observe an opportunity to measure willingness to pay around Sinterklaas and Christmas to products for which also other e-commerce shops promise to deliver the product before one of these holidays. If we denote the first group of products by G_1 and the second group of products by G_2, the idea behind this approach would be to determine to what extent the sales of G_1 follow a different pattern than those of G_1. Although this theoretically might sound as an interesting approach to take, in practice it is difficult to find a suitable control group G_2 which has comparable traits as that of the study group G_1. Therefore, we disregard this approach from this study.

Given that only a small proportion of products satisfies the condition in which we can estimate WTPSC, the question arises to what extent we can make claims about the products as a whole. If we compare the products which we use to estimate WTPSC to the population of 500.000 products based on price, delivery promise and sales, we find levels of over- and underrepresentation for these three variables, which differ depending on the shop category. In general, in terms of prices we find that products with cheaper prices (median price below €10) are a little underrepresented, while relatively more expensive products (median price above €50) are a little overrepresented. With regards to sales, we see relative high levels of overrepresentation for products which have a median daily sales of at least 5 units sold per day. However, for most shops these deviations from the population are not problematic. For a more detailed overview of this, we refer to Appendix B.2.

5. Methods

In this section we explain the methodology which we use in order to answer the research questions. The goal of this paper is to study how changes in the study variables ($\sigma_{9.21}(\text{RP}_p)$, $\sigma_{9.21}(\text{RP}_d)$, RC, WTP, and UTP) have an influence on daily sales patterns of various products. For this we consider a

Poisson regression model, a regression specification suitable for non-negative count data (see Cameron and Trivedi (2005) section section 20.2). Within our research design, we want to take the heterogeneity of different effect types into account. We define an effect type as the combination of parameter estimates of study variables for a specific product. For instance, for product A the parameter estimates for $\sigma_{9.21}(\text{RP}_p)$ might be significantly larger than the parameter estimates of $\sigma_{9.21}(\text{RP}_d)$ implying that we have found evidence that for this product changes in the relative price position have on average a larger influence on sales holding all other factors constant. For product B on the other hand, we might find evidence in the opposite direction. We define these two different instances as two different effect types. We allow for heterogeneity in terms of different product types with the inclusion of 11 different shop categories, which we summarise in a categorical variable abbreviated as SC_g, where $g \in [1, 11]$ is a subscript which denotes the specific shop category. We include SC_g as an interaction term in our model with one shop category as a baseline, being *DIY*.

In addition, we want to be able to estimate heterogeneity within a shop category. For this, we apply the Finite Mixture model framework, which makes it possible to divide a population into a finite number of latent (unobserved) subpopulations (also denoted as clusters or segments) and allows us to estimate a regression model for every subpopulation. Furthermore, this framework allows for group membership uncertainty by the inclusion of the posterior probability, which is the probability that a product belongs to a given segment. By the inclusion of the Finite Mixture model architecture, we can discover possible different effect types within a shop category in case products are allocated to different segments, and the effect types deviate from segment to segment. Therefore, the main motivation why we include the Finite Mixture model framework is to make it possible detect possible different effect types within a shop category.

In total we run five different model specifications. First of all, we have two different time periods. Second, we use a different model specification to estimate willingness to pay around Sinterklaas and Christmas. Third, we split the estimation of $\sigma_{9.21}(\text{RP}_p)$, $\sigma_{9.21}(\text{RP}_d)$, RC, WTP, and UTP into two different models given a time period. In the first model, we only obtain estimates of the parameters corresponding to $\sigma_{9.21}(\text{RP}_p)$, $\sigma_{9.21}(\text{RP}_d)$, while the goal of the second model is to obtain parameter estimates for RC, WTP, and UTP. The reason why we split the estimation into two parts is twofold. First, RC, WTP, and UTP are derived from the values of $\sigma_{9.21}(\text{RP}_p)$, $\sigma_{9.21}(\text{RP}_d)$, which means that we would have high correlation between these two variable types if we would run them simultaneously. Secondly, the estimation of these two types of variables are related to two different research questions. By estimating the effects of all the coefficients in a jointly matter the interpretation of the obtained parameter estimates possibly becomes more difficult. Therefore, we believe it is more convenient to use two different models conditioned on a time period.

The remainder of this section is as follows. First we unfold the Finite Mixture Poisson framework. Second we discuss limitations of our model framework. Third, we show the training strategy to obtain parameter estimates. Lastly, we explain in more detail how we define different effect types.

5.1. Finite Mixture Poisson Model Framework

5.1.1. Poisson Regression Model

In this study, we model the daily sales of product i, for $i = 1, 2, ..., N$ measured at day t for $t = 1, 2, ..., T$, or $Sales_{it}$ for short, by means of a Poisson regression model. Hence, for random variable $SALES_{it}$, $SALES_{it} \sim \text{Pois}(\lambda_{it})$ which implies the following probability mass function (PMF)

$$\text{P}(SALES_{it} = Sales_{it}) = \frac{e^{-\lambda_{it}} \lambda_{it}^{Sales_{it}}}{Sales_{it}!} \tag{10}$$

We say that conditioned on a set of regressors x'_{it} and parameter vector β, the conditional mean of $Sales_{it}$ can be expressed using a log-link, resulting in the following form

$$E(Sales_{it}|x_{it}) = \lambda_{it} = \exp(x'_{it}\beta) \tag{11}$$

Based on the PMF of (10) and the log-link of (11), we write the log-likelihood as

$$\begin{aligned} \mathcal{L}(\beta) =& \log\left(\prod_{i=1}^{N} f(Sales_i|x_i, \beta)\right) = \log\left(\prod_{i=1}^{N}\prod_{t=1}^{T} f(Sales_{it}|x_{it}, \beta)\right) \\ =& \sum_{i=1}^{N}\sum_{t=1}^{T}\left[Sales_{it}x'_{it}\beta - e^{x'_{it}\beta} - \log(Sales_{it}!)\right] \end{aligned} \tag{12}$$

We can find estimates for β by solving the first order condition of (12) with respect to β, which in this case needs to be done using Gauss-Newton or Newton-Raphson algorithms, since the first order condition has no closed form solution (see Cameron and Trivedi (2005) section 20.2.2).

5.1.2. Finite Mixture Model Architecture

In this study we use the Finite Mixture Model framework to allow for heterogeneity within shop categories. For this we assume that a sample of products can be segmented in a finite number of smaller components (mixtures) for which can estimate different conditional means. If we assume that there exist S different segments, then we can write the conditional mean for one segment s given (11) as

$$\lambda_{its} = \exp(x'_{it}\beta_s) \tag{13}$$

Note that in (13) we have added the subscript s to β to allow for the estimation of λ_{its}. We assume that product i belongs to one of S_i clusters, where $S_i \in \{1, 2, ..., S\}$, for some $S \in \mathbf{N}$. We denote the probability of product i belonging to S_i as $\text{P}(S_i = s) = \pi_s$. Since we state that π_s is a probability, we implicitly set the following conditions:

$$\pi_s \geq 0 \tag{14}$$

$$\sum_{s=1}^{S} \pi_s = 1 \tag{15}$$

Using these conditions along with (13), we can now start to write the S-finite mixture model for product i. For this let $\psi = (\pi_1, \pi_2, ..., \pi_S, \beta'_1, \beta'_2, ..., \beta'_S)$ be the vector of all parameters, such that we

have the S-finite mixture

$$h(Sales_i|x_i,\psi) = \sum_{s=1}^{S} \pi_s \prod_{t=1}^{T} f(Sales_{it}|x_{it},\beta_s) = \sum_{s=1}^{S} \pi_s f(Sales_i|x_i,\beta_s) \tag{16}$$

Where $f(Sales_{it}|x_{it},\beta_s)$ corresponds to the likelihood function under a Poisson density. For the remainder of the discussion we use the equality $f(Sales_i|x_i,\beta_s) = \prod_{t=1}^{T} f(Sales_{it}|x_{it},\beta_s)$. The authors of Wedel and DeSarbo (1995) have shown how (16) can be estimated under generalised linear models (to which Poisson regression belongs). In order to obtain estimates for all parameters the Expectation Maximization (EM), first derived by Dempster et al. (1977), is usually used. In this study we will also make use of the EM-algorithm. Within the EM-algorithm, the posterior probability p_{is} is derived and can be interpreted as the probability of product i belonging to segment s. In the next paragraph we formulate the steps needed to derive a general EM-algorithm, while in Appendix C.3 we show the specific derivations under the Poisson density.

Derivation EM-Algorithm. We derive the EM-algorithm in two steps. First we show a formula for the complete likelihood function for some arbitrary density function. Given this complete likelihood function, we then derive the EM-algorithm.

We start the derivation of the complete log-likelihood by means of (16) which we extend by including all N products. This gives us the likelihood-function

$$h(Sales|x,\psi) = \prod_{i=1}^{N} \sum_{s=1}^{S} \pi_s f(Sales_i|x_i,\beta_s) \tag{17}$$

Taking logs with respect to (17) results in the log-likelihood function

$$\mathcal{L}(Sales|x,\psi) = \sum_{i=1}^{N} \log(\sum_{s=1}^{S} \pi_s f(Sales_i|x_i,\beta_s)) \tag{18}$$

The log-likelihood function as defined in equation (18) makes it hard to find estimates for ψ, due to the sum over the segments s in the log. Therefore, we define the complete likelihood function, by assuming that the segment S_i is known. By doing so we obtain the formula

$$L_c(Sales, s|x,\psi) = \prod_{i=1}^{N} \prod_{s=1}^{S} (\pi_c f(Sales_i|x_i,\beta_s))^{\mathbb{I}(S_i=s)} \tag{19}$$

Taking logs, we obtain the complete log-likelihood function

$$\mathcal{L}_c(Sales, s|x,\psi) = \sum_{i=1}^{N} \sum_{s=1}^{S} \mathbb{I}(S_i = s)[\log(\pi_c) + \log(f(Sales_i|x_i,\beta_s))] \tag{20}$$

The EM algorithm repeatedly alternates between the E-step and M step. In the E-step the posterior probabilities p_{is} are calculated, using fixed values of the parameter vector ψ. Given the estimates for p_{is} we then update our estimates for ψ. The process repeats itself until convergence is achieved. Let us next show the derivation for these two steps.

E-step:. Note that $\mathbb{I}(S_i = s)$ in equation (20) is latent and hence cannot be used as input. Instead, we consider the expectation of $\mathbb{I}(S_i = s)$ conditional on $Sales_i$:

$$\begin{aligned} E(\mathbb{I}(S_i = s)|Sales_i) &= P(S_i = s|Sales_i) \\ &= \frac{f(Sales_i, S_i = s|x, \beta_s)}{f(Sales_i|x, \beta_s)} \\ &= \frac{\pi_s f(Sales_i|x, \beta_s)}{\sum_{m=1}^{S} \pi_m f(Sales_i|x, \beta_m)} = p_{is} \end{aligned} \tag{21}$$

Here the result of 21 are the posterior probabilities.

M-step:. After we have computed the E-step, we update the estimates for π_s and β_s by solving first order conditions. We can find these first order conditions by filling the result of (21) into (20) and split the terms, such that we can write (20) into two parts

$$\mathcal{L}_c(\beta, \pi|Sales, s; x) = \sum_{i=1}^{N}\sum_{s=1}^{S} p_{is}\log(\pi_s) + \sum_{i=1}^{N}\sum_{s=1}^{S} p_{is}\log(f(Sales_i|x_i, \beta_s)) \tag{22}$$

Since (22) is the sum of two functions, we can estimate the π- and β-vectors independently from each other. Estimating the parameters in π boils down solving the following equation

$$\hat{\pi}_s = \arg\max_{\pi_s} \sum_{i=1}^{N}\sum_{s=1}^{S} p_{is}\log(\pi_s), \text{ for } s \in \{1, 2, ..., S\} \tag{23}$$

$$\text{subject to: } \pi_s \geq 0 \; s \in \{1, 2, ..., S\} \text{ and } \sum_{s=1}^{S} \pi_s = 1$$

(23) can easily be solved if we write this problem down in a Lagrangian form and then find the first order conditions with respect to this form. Furthermore, since the log-function is concave, we will attain a maximum. By doing so, we obtain that our estimates for π_s are

$$\hat{\pi}_s = \frac{1}{N}\sum_{i=1}^{N} p_{is}, \text{ for } s \in \{1, 2, ..., S\} \tag{24}$$

Note that the result in (24) could be interpreted the average of the conditional segment probabilities over the different products. Given the solution for π_s as defined in (24), we can find estimates for β_s by (22). In order to find estimates for β_s, we need to solve

$$\hat{\beta}_s = \arg\max_{\beta_s}(\sum_{i=1}^{N}\sum_{s=1}^{S} p_{is}\log(f(Sales_i|x_i, \beta_s))), \text{ for } s \in \{1, 2, ..., S\} \tag{25}$$

We can achieve this by solving the following first order condition

$$\sum_{i=1}^{N}\sum_{s=1}^{S} p_{is}\frac{\Delta\log(f(Sales_i|x_i, \beta_s))}{\Delta\beta_s} \overset{s}{=} 0 \tag{26}$$

The complexity of solving the first order condition of (26) depends on the complexity of the specific form of $f(y_i|x_i, \beta_s)$. In this study, $f(y_i|x_i, \beta_s)$ would be the Poisson density, which can be solved using

iterative reweighed least-squares (see Wedel and DeSarbo (1995)).

5.1.3. Specifications λ_{its}

Depending on the model specification, we include different regressors. In general, we decompose x'_{it} into three different parts, the intercept, the study variables (Study) and the controlling variables (Control). Recall that the control variables are depicted in Table 6 with different day dummies for the regular and holiday periods (Black Friday and Lockdown are not used during the regular period). For a given segment s, we denote the intercept by ω_s, the vector of study variables by θ_s, and the vector of control variables by γ_s. Hence we have that

$$\lambda_{its} = \exp(\omega_s + \text{Study}'_{it}\theta_s + \text{Control}'_{it}\gamma_s) \tag{27}$$

In every study part, we include the study variables, as well as the interaction terms of the shop categories with the study variables. Since we have 11 different shop categories, and exclude *DIY* as the baseline, we have in total ten interactions per study variable. For every shop category except the baseline, we create a dummy-variable which we denote by $D(SC_g)_{it}$. The dummy variable equals 1 if product i belongs to shop category g and is 0 otherwise. All-in-all, we distinguish three different model specifications for the study part of the regressor vectors. First, we have the model specification for estimating $\sigma_{9.21}(\text{RP}_p)$ and $\sigma_{9.21}(\text{RP}_d)$

$$\begin{aligned}\text{Study}'_{\sigma it}\theta_s =& \sigma_{9.21}(RP_p)_{it}\theta_{1s} + \sum_{g=1}^{10} D(SC_g)_{it}\sigma_{9.21}(RP_p)_{it}\theta_{(1+g)s} \\ &+ \sigma_{9.21}(RP_d)\theta_{12s} + \sum_{g=1}^{10} D(SC_g)_{it}\sigma_{9.21}(RP_d)_{it}\theta_{(12+g)s}\end{aligned} \tag{28}$$

Here the subscript σ implies that we are dealing with the study variables $\sigma_{9.21}(\text{RP}_p)$ and $\sigma_{9.21}(\text{RP}_d)$. Second, we write the model specification for estimating RC, WTP and UTP

$$\begin{aligned}\text{Study}'_{\text{RWU}it}\theta_s =& RC_{it}\theta_{1s} + \sum_{g=1}^{10} D(SC_g)_{it} RC_{it}\theta_{(1+g)s} + WTP_{it}\theta_{12s} + \sum_{g=1}^{10} D(SC_g)_{it}\, WTP_{it}\theta_{(12+g)s} \\ &+ UTP_{it}\theta_{23s} + \sum_{g=1}^{10} D(SC_g)_{it}\, UTP_{it}\theta_{(23+g)s}\end{aligned} \tag{29}$$

Here the subscript RWU denotes that we are dealing with the study variable RC, WTP and UTP. Lastly, we write the model specification for estimating willingness to pay around Sinterklaas and Christmas

$$\begin{aligned}\text{Study}'_{\text{RWSC}it}\theta =& RC_{it}\theta_1 + \sum_{g=1}^{10} D(SC_g)_{it} RC_{it}\theta_{(1+g)} + WTP_{it}\theta_{12} + \sum_{g=1}^{10} D(SC_g)_{it}\, WTP_{it}\theta_{(12+g)} \\ &+ WTPSC_{it}\theta_{23} + \sum_{g=1}^{10} D(SC_g)_{it}\, WTPSC_{it}\theta_{(23+g)}\end{aligned} \tag{30}$$

Here the subscript RWSC denotes that we are dealing with the variables RC, WTP and WTPSC. We want to note that the time subscripts t are different for the regular- and holiday periods and that

WTPSC in (30) denotes willingness to pay around Sinterklaas and Christmas.

5.2. Limitations Finite Mixture Poisson Models

The framework we propose to estimate the effects of the study variables has a couple of limitations which we want to discuss. First of all, as we assume that the daily sales data follows a Poisson distribution, we also assume that the mean is equal to the variance (equidispersion). However, for our application this is not the case. In fact, we observe that the variance for our outcome variable highly exceeds the mean (overdispersion). In addition, we find relatively many observations with no sales. Poisson regression models have trouble with taking these situations in account and usually tend to underestimate the true number of zero sales (excess zeros). For a more detailed discussion on these two topics, we refer to Appendix C.1 or section 20.2 in Cameron and Trivedi (2005).

Despite the existence of these issues in our model framework, we believe that these two problems partly can be reduced by using a Finite Mixture Model framework, but not completely. In order to explain why, we need to make a distinction between the variability of sales within a product and between products. The Finite Mixture model architecture estimates S different Poisson regression models, all with their own means. All products are allocated to at least one of these segments with non-zero probability. This implies that if the variance of sales and excess zeros depends on the different products and not on observations within a product (within a product we do not have overdispersion and the excess of zeros is less severe) we can account for this by estimating multiple Poisson regression models, all with different values of the mean. For the total model, we then still have that the variance exceeds the mean, but within the mixtures this is less apparent. By increasing the number of segments we can make the model more flexible, allowing for more total variability. This argument is stronger in case we observe cross-sectional data, since then we do not have any variation within a product and only between products. Within this setting we can mention a couple of studies which use a variant of Finite Mixture Poisson Models and have satisfactory results, such that of Park and Lord (2009), Dalrymple et al. (2003), and Bermúdez and Karlis (2012). The study of Park and Lord (2009) forms an example in what way Poisson and NB Finite Mixture models can deal with overdispersion and can have better model fit compared to a NB regression model based on a crash vehicle dataset. in Dalrymple et al. (2003) it is shown that Finite Mixtures can have a similar fit zero-inflated Poisson and hurdle models on a dataset concerning sudden infant death syndrome (SIDS). To mention another study, in Bermúdez and Karlis (2012) the researchers show that a Finite Mixture Model with a bivariate Poisson density is better able to deal with overdispersion than zero-inflated and hurdle-models without finite mixtures.

Within products we still observe levels of overdispersion and in some cases also excess zeros. In order to reduce these issues further, we could alternatively apply a negative binomial setting to deal better with overdispersion, and/or a set-up in which we use a model architecture more flexible to deal with excess zeros, such as hurdle models. For more details on these model architectures, we refer to section 20.2 of Cameron and Trivedi (2005).

5.3. Training Strategy for Finite Mixture Poisson Models

One of the major difficulties in utilising the Finite Mixture Model framework is to determine the number of clusters/segments. We determine the number of clusters based on the following ordering of factors:

1. **Selection Criteria**: For the first factor, we rely on a different number of selection criteria which are commonly used to determine the number of clusters. The idea behind the usage of selection criteria is simple. We select the number of products which minimises the selection criterion under consideration. In Appendix C3.3 we provide an overview of the different selection criteria which occur often in the literature. We can distinguish three types of selection criteria: those based on penalised versions of the log-likelihood, those which include some form entropy, and a combination of both approaches. For approaches based on the penalisation of the log-likelihood the idea is to penalise the log-likelihood by the (increasing) complexity of the models. For criteria which use entropy, the intuition is to compare models based on the amount of cluster separability, which usually is expressed in terms of entropy. As both approaches consider the problem from different angles, we include criteria from both perspectives. Furthermore, we include a selection criterion which combines the two perspectives. To be more specific, we compare the different clusters based on AIC, CAIC, AWE, BIC, CLC, NEC and ICL-BIC.
2. **Cluster Size**: The second factor considers the size of added clusters. The motivation to add this factor is that in case the cluster sizes become too small, the reliability of our results can depend on the sample. In order to have reliable results we do not want to have clusters which are too small. For the cluster sizes, we use a mix of hard and soft requirements. The hardest requirement is that we require every cluster to have at least 100 different products. This is irrespective of the dataset we are using. Additionally, we leave the option to remove a cluster in case it contains less than 1% of the products of a given dataset and the number of different clusters is at least 10.

The proposed selection criteria of the first factor are often used in the literature to determine the number of different segments. In this study we use these selection criteria as a starting point. However, it is not guaranteed that we find any convincing conclusions based on the selection criteria alone, or that the selection criteria are optimal under the same number of segments. Therefore, we want to have a back-up measure to determine the number of different clusters. Consequently, we consider the size of the clusters as a second criterion.

The training regime we apply consists of two phases. First specify models with respectively 5, 10, 15, 20, and 25 different clusters. Based on the results of these cluster levels, we confine our search space to models with cluster sizes which seem most promising in terms of the two factors. The initial range of 5, 10, 15, 20, and 25 clusters is based on an initial training regime we applied to determine the maximum number of clusters we want to use for the first phase. For this, we ran several short runs of the EM-algorithm to determine how the cluster size evolves as we add more clusters. We ran models for respectively, 10, 20, 30, 40, and 50 different clusters. We observed that for models with more than 20 clusters, we mainly added clusters which comprised of less than 1% of all data. What

is more, the EM-algorithm had a tendency to diverge for models with 40 and 50 different clusters, making the training unstable within these ranges. For these two reasons we have decided to let the maximum number of different clusters be in the range of 20 to 30 different clusters.

The results of Finite Mixture models are susceptible of being stuck in local optima, which depend on the starting values. In order to overcome this issue, we run the EM-algorithm 10 times with randomly taken starting values and use the result with the largest log-likelihood.

Once we have decided on the number of different segments, we relabel all segments based on there prior size. Based on the effects and the relabeling of the clusters, we can start interpreting the results.

5.4. Effect Types

After we trained one model specification, we obtain the prior- and probabilities. Given these results, we can determine different effect types. This concept is best explained by means of an example.

Let us consider a model in which we have obtained parameter estimates for $\sigma_{9.21}(\mathrm{RP}_p)$ and $\sigma_{9.21}(\mathrm{RP}_d)$ for a mixture with S segments. This implies that we have $11 \times S$ different parameter estimates for both $\sigma_{9.21}(\mathrm{RP}_p)$ and $\sigma_{9.21}(\mathrm{RP}_d)$, and obtain posterior probabilities p_{is}, for all products i, $i = 1, 2, ..N$. Conditioned on a shop category, let us be interested in determining whether the parameter estimate of $\sigma_{9.21}(\mathrm{RP}_p)$ in one of the segments s is significantly larger than that of $\sigma_{9.21}(\mathrm{RP}_d)$ in the same segment s for a given α-level. In order to make the example easier to follow, let us take the parameter estimates corresponding to shop category *DIY*, θ_{1s} and θ_{12s} of (28). In case we reject the null hypothesis at the corresponding α-level, we have found evidence that the parameter estimate corresponding to θ_{1s} is significantly larger than that of θ_{12s} and abbreviate this result by saying that in cluster s $\sigma_{9.21}(\mathrm{RP}_p)$ is larger (than $\sigma_{9.21}(\mathrm{RP}_d)$). By doing so, we find one possible effect type. If we repeat this process for all S clusters, we therefore determine which clusters have this particular effect type. Similarly, we can apply hypothesis tests to determine in which segments the parameter estimates of θ_{12s} are significantly larger than those of θ_{1s}, or for which segments we fail to reject both null hypotheses, which provides us with two other effect types for the shop category *DIY*.

Once we have labeled the different clusters with the corresponding effect types conditioned on a shop category, we regard the clusters with a similar effect type as the same for a given shop category. The next step is to weight the different effect types for a shop category, which we do by using the posterior probabilities p_{is}.

In order to explain this procedure, let N_g be the number of products for shop category g. Then i_g denotes one of the products of shop category g, where $i_g = 1, 2, ..., N_g$. In addition, let E be the set of all effect types. Then $ET \in E$ implies that ET is one of the possible effect types. We then say that ETS_g is the set of all segments s with the effect type ET for shop category g. Hence, $ETS_g = \{s \in S | s \text{ has effect type } ET \text{ for shop category } g\}$. We define the size of ETS_g as

$$SETS_g = \frac{1}{N_g} \sum_{i_g=1}^{N_g} \sum_{s \in ETS_g} p_{i_g s} \tag{31}$$

For the hypothesis test we make use of the parameter estimates and the variance-covariance matrix

we obtain after estimation of the parameters. Note that for all shop categories except the baseline we include results of the baseline to obtain the values we use to conduct the hypothesis test with. In case we test only for the sign of the parameters we use a simple t-test. For situations in which we are also interested in the magnitudes of the one variable compared to another, we make use of a slightly different form. For explanation purposes, we again consider θ_{1s} and θ_{12s} of (28):

$H_0 : R = \hat{\theta}_{1s} - \hat{\theta}_{12s} = 0$ versus $H_1 : R = \hat{\theta}_{1s} - \hat{\theta}_{12s} > 0$ with test statistic

$$t = \frac{R}{\sqrt{\widehat{\text{VAR}}(R)}} \tag{32}$$

Where $\widehat{\text{VAR}}(R) = \widehat{\text{VAR}}(\hat{\theta}_{1s}) + \widehat{\text{VAR}}(\hat{\theta}_{12s}) - 2\widehat{\text{COV}}(\hat{\theta}_{1s}, \hat{\theta}_{12s})$. We perform multiple hypothesis tests at the same time. As a result, we need to account for the Family-Wise Error Rate (FWER), and False Discovery Rate (FDR). Based on the literature, we know that the holm-procedure of Holm (1979) guarantees FWER, while the method of Benjamini and Hochberg (1995) guarantees FDR. In this study we make use of holm-procedure as this is the more conservative approach.

In the remainder of this subsection, we introduce the different effect types per model specification.

5.4.1. $\sigma_{9.21}(RP_p)$ and $\sigma_{9.21}(RP_d)$

When we study the effect types of $\sigma_{9.21}(\text{RP}_p)$ and $\sigma_{9.21}(\text{RP}_d)$, we can distinguish four possibilities. For the first option, we have that the parameter estimates corresponding to $\sigma_{9.21}(\text{RP}_p)$ are significantly larger than those of $\sigma_{9.21}(\text{RP}_d)$. In this situation we find evidence that sales are more sensitive for changes in $\sigma_{9.21}(\text{RP}_p)$ than for changes in $\sigma_{9.21}(\text{RP}_d)$. If we take the reciprocal of this relationship, we obtain the second effect type. Here we find evidence that sales are more sensitive for changes in $\sigma_{9.21}(\text{RP}_d)$ compared to changes in $\sigma_{9.21}(\text{RP}_p)$. For the third effect type, we cannot find any conclusive evidence in any direction. That is, there is no statistical evidence that sales are more sensitive for changes in $\sigma_{9.21}(\text{RP}_p)$ compared to changes in $\sigma_{9.21}(\text{RP}_d)$, or that sales are more sensitive for changes in $\sigma_{9.21}(\text{RP}_d)$ compared to changes in $\sigma_{9.21}(\text{RP}_p)$. In this case we label the effect type as *inconclusive*.

For the first three effect types, we implicitly assume that the corresponding parameter estimates for $\sigma_{9.21}(\text{RP}_p)$ are non-negative. The reason why we make this assumption is because we assume consumers behave rationally and are aware of the product offers of the market. However, in reality this assumption does not have to hold. Consequently, we might observe situations in which the parameter estimates of $\sigma_{9.21}(\text{RP}_p)$ for some products are significantly negative. If this is the case, we disregard the other possibilities and label the effect type as *unaware*. Based on this study design, we cannot explain why the parameters of $\sigma_{9.21}(\text{RP}_p)$ are negative for these products, but only that these most likely fall outside the assumptions we make about consumers. Possible explanations why consumers are unaware are that (1) consumers are not interested in one particular product and hence do not directly compare the prices and delivery promises of other competitors, (2) consumers are unaware that other offers exist, (3) behave purposefully irrational.

5.4.2. RC, WTP and UTP

When we study the effect types based on the parameters for RC, WTP and UTP, we are mainly interested in the signs of these variables. For starters, we assume that consumers behave rational.

Hence, we expect the parameters for RC to be non-negative. In case we observe significantly negative parameter estimates of RC, we therefore have our first effect type. We label this effect type as *irrational*.

	Sign WTP		
Sign UTP	> 0	$= 0$	< 0
> 0	other effects (positive)	strong UTP	strong UTP
$= 0$	strong WTP	indifferent	weak UTP
< 0	strong WTP	weak WTP	other effects (negative)

Table 7: Different effect types based on the signs of WTP and UTP, conditioned on non-negative parameters of RC

Conditioned on products for which the parameter estimates of RC are non-negative, we can distinguish seven other effect types. We have summarised these effect types in Table 7. Based on this table we can distinguish nine different combinations based on the signs of WTP and UTP (negative, zero and positive). Given these nine different combinations, we have seven different effect types, being *other effect (positive)* (WTP>0 and UTP>0), *strong UTP* (WTP $\leq$ 0, UTP>0), *weak UTP* (WTP<0, UTP=0), *strong WTP* (WTP >0, UTP $\leq$ 0), *weak WTP* (WTP=0, UTP<0), *indifferent* (WTP=0, UTP=0), and *other effect (negative)* (WTP<0, UTP<0). Of these different effect types, five are consistent within the theoretical framework. For the effect types *strong UTP* we find evidence that sales of products increase in case UTP increases and decreases whenever WTP increases, while for *weak UTP*, we only find evidence that sales decrease when WTP increases. In case a product falls into the effect types *strong WTP* or *weak WTP* these relationships are reversed. In case WTP and UTP both are insignificant, we have the effect type *Indifferent*. The effect types related to *other effects* fall outside the scope of our theoretical framework, since the parameter estimates of WTP and UTP share the same sign. For products with these types of effects, consumers might take other purchase decisions into account rather than the trade-off between prices and delivery promises, are unaware of prices and/or delivery promises of other retailers, or simply purchase irrationally. As we cannot tell from our study design which of these effects hold, we aggregate them into the same effect type.

5.4.3. Willingness to Pay around Sinterklaas and Christmas

We can distinguish eight different effect types when we study willingness to pay around Sinterklaas and Christmas. The first effect type is determined by considering the sign corresponding to the parameter estimates of RC. In case these are statistically negative, we have the effect type *irrational*. Otherwise, we determine one of the seven other effect types. These effect types are determined based on the signs and magnitudes of the parameter estimates of WTP and WTPSC. For the first two effects types, the two variables have opposite signs. For the third effect type, the parameter estimates of WTP and WTPSC are both positive, but the parameter estimate of WTP is significantly larger than WTPSC. We call this effect type *WTP amplifier*. This effect type indicates that we find evidence that the sales of a product is more susceptible for changes in WTP outside the weeks prior to Sinterklaas and Christmas compared to situations in which WTPSC is active. For the effect type *WTPSC amplifier*, the roles of WTP and WTPSC are reversed. That is both effect types are positive, but WTPSC

is significantly larger than WTP. For the effect types *WTP dampener* and *WTPSC dampener* both parameter estimates of WTP and WTPSC are negative, but WTP is less negative (*WTP dampener*), or the other way around (*WTPSC dampener*). For the former effect type we find that there is evidence that changes of WTP outside the weeks prior to Sinterklaas and Christmas have a less negative effect on the sales of a product compared to situations in which WTPSC is active, while for the latter we find evidence for the reciprocal. Lastly, the effect type *indifferent* indicates that there is no significant difference between the parameter estimates of WTP and WTPSC. Of the different effect types, we expect that *WTPSC dampener* and *WTPSC amplifier* are least occurring, given the general declining sales patterns in the weeks prior to Sinterklaas and Christmas.

6. Results

In this section we present the results of our different modelling approaches. For the five different model specifications we have used mixtures with respectively 23 ($\sigma_{9.21}(\mathrm{RP}_p)$ and $\sigma_{9.21}(\mathrm{RP}_d)$ regular period), 24 ($\sigma_{9.21}(\mathrm{RP}_p)$ and $\sigma_{9.21}(\mathrm{RP}_d)$ holiday period), 24 (RC, WTP, and UTP regular period), 20 (RC, WTP and UTP holiday period) and 13 (Willingness to pay around Sinterklaas and Christmas) different clusters. For all model specifications, the decisive factor was the size of added clusters which covered less than 100 products for number of clusters higher than the ones we have chosen. For a more detailed discussion on these results we refer to Appendix D. Based on these mixtures, we have presented in Section 6.4 the output tables of parameter estimates with regard to the study variables per shop category, while in Appendix D.1 we also show the parameter estimates of the control variables. In every table the shop category *DIY* is taken as a baseline. In the remainder of this section we show the results of the different effect types conditioned on the different shop categories. In Section 6.1 we use an α-level of 5%, while in Sections 6.2 and 6.3 we use α-levels of 1%. The reason why we use different α-levels has to do with different levels of statistical power for the different study variables. For the variable $\sigma_{9.21}(\mathrm{RP}_d)$, we find relatively weak statistical power, which is why we use higher α-levels. For a detailed discussion on this topic, we refer to Appendix D. All the presented results are based on a combination of the results shown in the tables of Section 6.4, and the posterior sizes conditioned per shop category as shown in Figures D.24, D.35, D.46, D.57 and D.70, included in Appendix D.

6.1. Results $\sigma_{9.21}(RP_p)$ and $\sigma_{9.21}(RP_d)$

In Figures 6 and 7 we present the results of the different effect types for studying $\sigma_{9.21}(\mathrm{RP}_p)$ and $\sigma_{9.21}(\mathrm{RP}_d)$ during the regular and holiday periods. In these figures the proportion of effects conditioned on a shop category correspond to the size of effect types as determined by (31). Based on the different effect types, we show in Appendix D2.3 and Appendix D3.3 how products allocated to the different effect types differ based on popularity (sales), price propositions and delivery promise propositions.

6.1.1. Regular Period

Based on the plot of Figure 6, we have evidence that for a majority of the products for a majority of the shop categories $\sigma_{9.21}(\mathrm{RP}_p)$ is significantly larger than the effect of $\sigma_{9.21}(\mathrm{RP}_d)$ at a 5% α-level.

In fact, we only find three shop categories for which we find evidence in the opposite direction (that is where effect of $\sigma_{9.21}(\mathrm{RP}_d)$ is significantly larger than the effect of $\sigma_{9.21}(\mathrm{RP}_p)$), being *DIY*, *Hardware* and *Sports and Activity*. Of thee three shop categories, only for *Hardware* we observe that a consider proportion is colored in green, providing evidence that $\sigma_{9.21}(\mathrm{RP}_d)$ has significant larger effects than $\sigma_{9.21}(\mathrm{RP}_p)$ for some products in this shop category. What is more, we see that for all shop categories a significant proportion is colored in red. This might indicate that for all shop categories there are products for which consumers are unaware of the relative offer position of the internal retailer compared to that of the market. Lastly, we find that for the shop categories *DIY*, *Drugs and Baby* and *Kitchen and Household* we fail to reject both null hypotheses and hence have products with the effect type *inconclusive*.

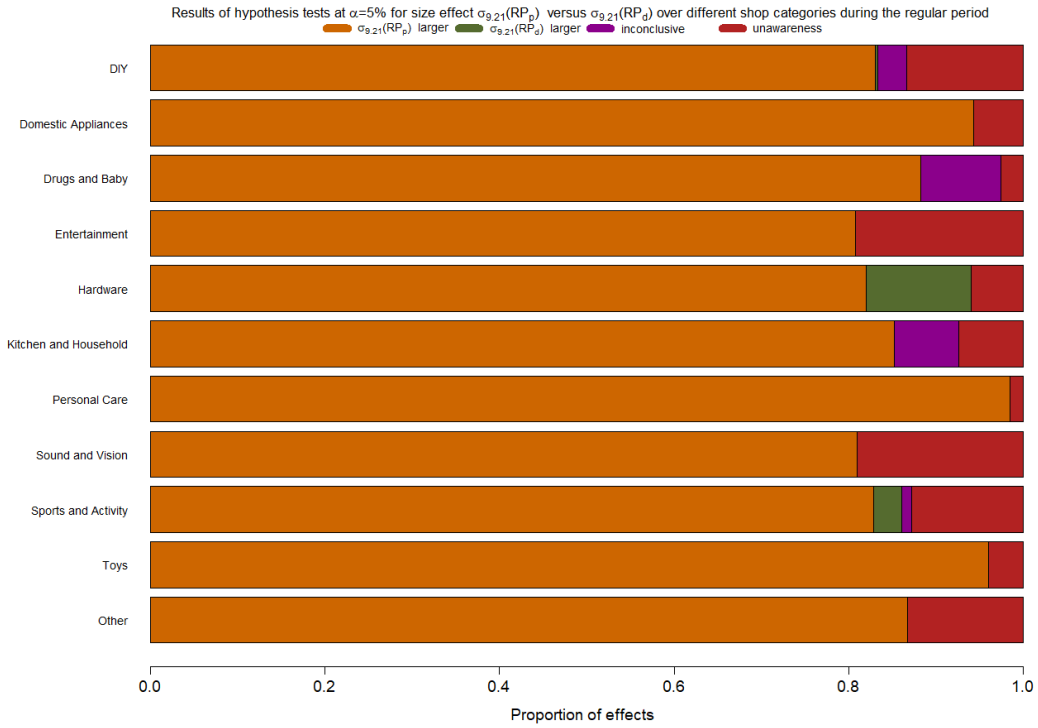

Figure 6: Products per shop category divided over the possible effect types measured during the regular period. Effects are determined based on hypothesis tests with a value for α of 0.05 and the size of every effect type (proportion of effects) conditioned on a shop category is determined by (31)

6.1.2. Holiday Period

By considering Figure 7 we first observe a clash between the effect types $\sigma_{9.21}(RP_p)$ *larger* and *unawareness*. For a couple of shops, we see that $\sigma_{9.21}(RP_p)$ *larger* is the most dominant effect type, while for some others *unawareness* has a more dominant presence. This is a different observation compared to the ones we made for the regular period, in which we concluded that *unawareness* takes much smaller proportions for the different shop categories. These contrasting results might indicate that during the holiday period consumers are less aware of their purchase decisions than in the regular period for relatively more products, or that consumers take other purchase considerations into account

for these products. Continuing the comparison between the results of the regular period and holiday period, we find that the effect type $\sigma_{9.21}(RP_d)$ *larger* is apparent in more shops during the holiday period compared to the regular period. However, this effect type can still considered to be small to moderate compared to the proportions of the effect type $\sigma_{9.21}(RP_p)$ *larger*.

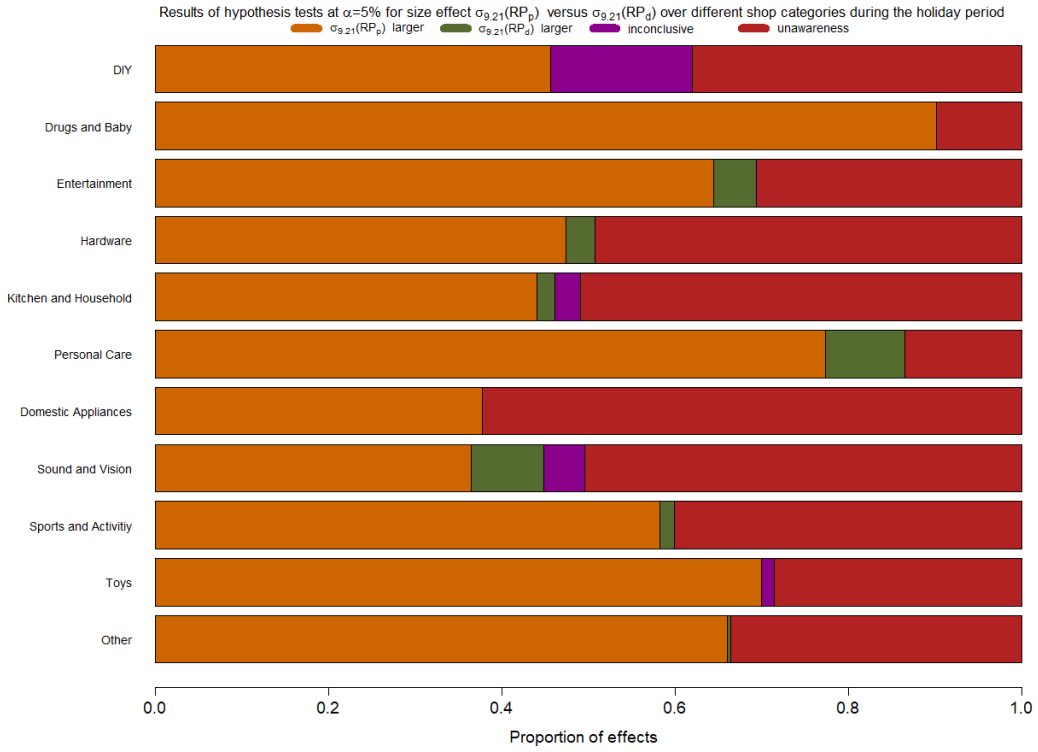

Figure 7: Products per shop category divided over the possible effect types measured during the holiday period. Effects are determined based on hypothesis tests with a value for α of 0.05 and the size of every effect type (proportion of effects) conditioned on a shop category is determined by (31)

6.2. Results RC, WTP and UTP

In Figures 8 and 9 we have depicted mosaic plots (or Marimekko diagrams), for testing the significance of different effect types for the study variables RC, WTP and UTP for respectively the regular and holiday period at an α-level of 1%. The mosaic plots are based on Table 7 and the size of every effect type is based on (31). Here we want to note that for the results as shown in the mosaic plots we first condition on clusters with non-negative parameter estimates of RC. All clusters with significant negative parameter estimates of RC conditioned on a shop category are treated as a separate effect type. Next to the shop category we indicate the proportion of products with significant non-negative parameter estimates of RC. Based on the different effect types, we show in Appendix D4.3 and Appendix D5.3 how products allocated to the different effect types differ based on popularity (sales), price propositions and delivery promise propositions.

6.2.1. Regular Period

In Figure 8 we can find the mosaic plots of the different effect types over all shop categories. The size of every effect type is depicted in every tile of the mosaic plot. The larger the tile, the larger the effect type is within a shop category. Note that the effect types *strong UTP* and *strong WTP* consist of multiple tiles, while the effect types *other effects (positive)* and *other effects (negative)* are given the same color. Regarding the numbers in the tiles, note that the sum of all effects does not always sum up to one, due to rounding. For instance, for the shop category *Toys*, we find that the sum of all tiles equals 0.9, since there are two effect types both take less than 5% of the pie and hence are rounded down to 0. As a last remark, effect types which are absent in a shop category are indicated with dots.

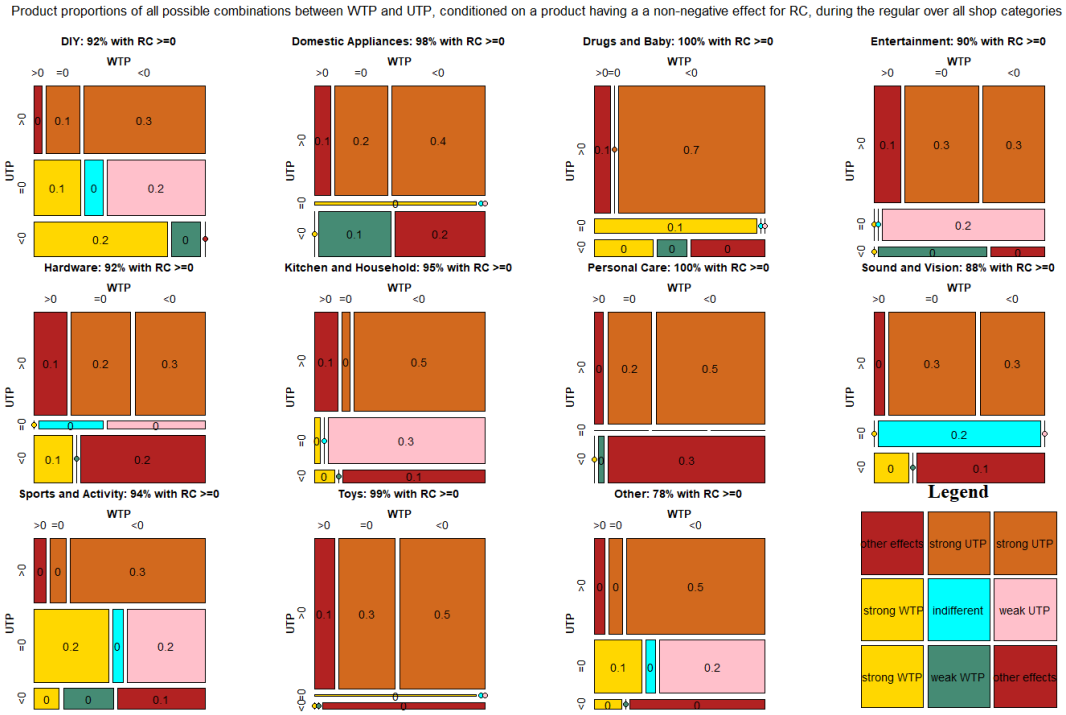

Figure 8: Mosaicplot for different effect type combinations between WTP and UTP. In the mosaicplot, we condition on all products for which the parameter estimate of RC is non-negative. Every plot is labeled with the shop category and the percentage of products for which we observe a non-negative parameter estimate of RC. The size of every effect type conditioned on a shop category is determined by (31)

Let us digest the information of Figure 8 by first considering the additional information next to the shop categories. These percentages show the percentage of products for which the coefficient estimates of RC are statistically non-negative for a level of α of 1%. For instance, for the shop category *DIY* 92% of all products in our dataset have a coefficient estimate of RC which is statistically non-negative. We find that these percentage are above 90% for most shop categories. For the shop category *Sound and Vision*, we obtain a percentage a little under 90%, while for the shop category *Other* the percentage is lowest with 78%.

Moving to the mosaic plots themselves, at a first glance, the orange color seems to be dominating over the other colors. This indicates that the effect type *strong UTP* is most dominant for most shop

categories. By further inspection and including the pink colored tiles into the analysis, we see that this is indeed the case for a majority of the shop categories. Shop categories which deviate from this pattern are *DIY*, *Hardware* and *Sports and Activity*, for different reasons. For the shop categories *DIY* and *Sports and Activity*, we observe presence of almost all different shop effects, indicating a heterogeneity of different effect types. For *Hardware* on the other hand, we find that the *other effects* effect types seems to be reasonably present with approximately 30% of all products falling into this effect type.

With regards to the effect types *strong WTP* and *weak WTP*, the lack of presence of these effect types in most shop categories is worth mentioning. In a majority of the shop categories these effect types account take less than 20% of the pie. The shop categories for which this percentage is above 20% are *DIY*, and *Sports and Activity*. Other smaller observations we can make are the overall lack of presence of the effect types *other effect* and *indifferent*, indicating that for a majority of the products fall directly in the theoretical trade-off structure of this study.

All-in-all, we can draw the following conclusions. First, for most shop categories the parameter estimates of RC are statistically non-negative at an α level of 1%. Conditioned on these effects, we find that the effect types related to UTP are most present for most shops. This provides evidence for the statement that on the aggregate product level, consumers are willing to receive a slower delivery promise in case the product can be bought at a lower price during the regular period. The shop categories *DIY*, and *Sports and Activity* seem to have a moderate proportion of products for which there is willingness to pay more for receiving a faster delivery promise.

6.2.2. Holiday Period

In Figure 9 we have plotted the mosaic plots which contain the different effect types of WTP and UTP conditioned on products having non-negative estimates of RC for the holiday period.

Comparing the results of Figure 9 to those of Figure 8 we can find a couple of interesting differences. First in terms of the percentage of products with non-negative estimates for RC, we see that during the holiday period relatively less products have non-negative estimates compared to the regular period. For the shop category *Domestic Appliances* this seems to be most severe, with the largest drop in terms of percentage points (from 98% to 46%) This can point towards the direction that during the holiday period consumers exhibit other purchase behavior. We can find more evidence for this claim for some specific shop categories if we put our attention to the tiles of the mosaic plots. Here the increase in proportion of the effect type *other effect* (positive and negative) for the shop categories *Drugs and Baby*, *Hardware*, *Kitchen and Household* and *Sound and Vision* is noticeable. As this effect type does not fall directly in the trade-off framework we propose in this study, other purchase considerations might play a role for products for which we estimate this type of effect. Besides this large noticeable difference between the effect types during the regular period and holiday period, we can see that during the holiday period the effect types *strong WTP* and *weak WTP* take larger proportions of the pie for the shop categories *Hardware* and *Sports and Activity*.

With these differences mentioned, let us now look at the similarities. Once we condition on the percentage of products with non-negative parameter estimates for the variable RC, we find that the

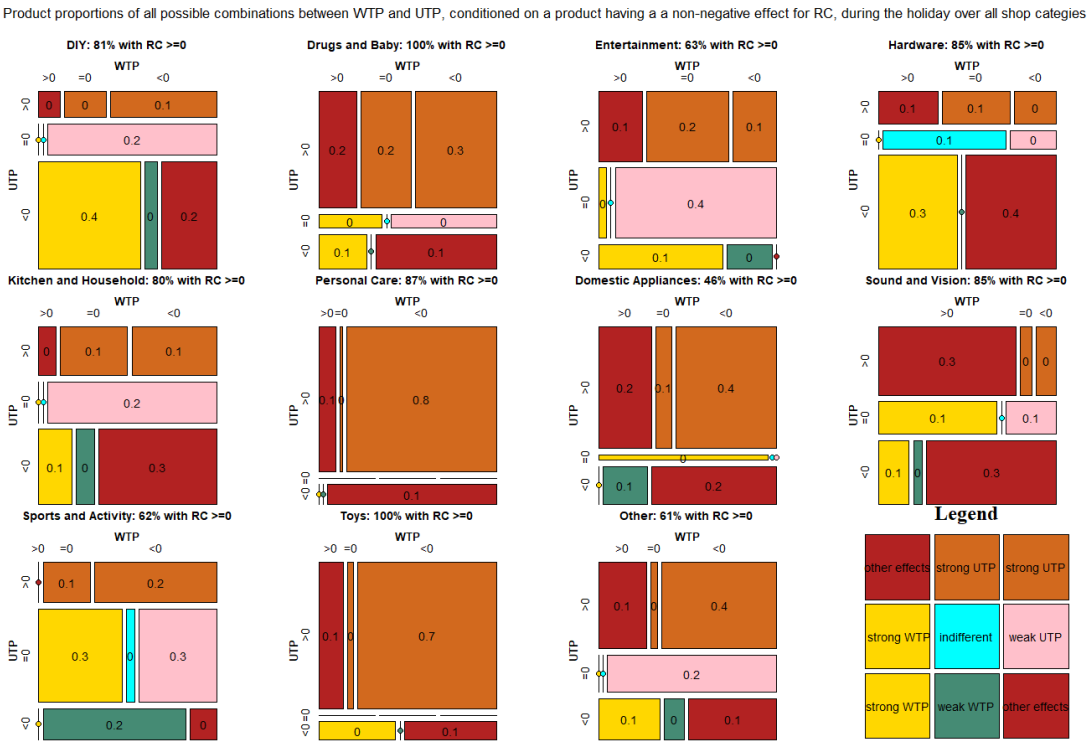

Figure 9: Mosaicplot for different effect type combinations between WTP and UTP. In the mosaicplot, we condition on all products for which the parameter estimate of RC is non-negative. Every plot is labeled with the shop category and the percentage of products for which we observe a non-negative parameter estimate of RC. The size of every effect type conditioned on a shop category is determined by (31)

mosaic plots themselves are similar over the two periods for a majority of the shop categories. To be more specific, for the shop categories *Domestic Appliances*, *Personal Care*, *Toys* and *Other* we observe almost identical mosaic plots in terms of size of the different effect types. For the shop categories *DIY*, *Entertainment* and *Sports and Activity* we observe small shifts from effect types, but these do not lead to other conclusions for the two periods. All things considered, when we compare the results of the holiday period to the regular period, we observe more products which fall outside the theoretical framework we want to study, but for the products which fall in the framework the distribution of the different effect types over the two periods is generally similar.

6.3. Results Willingness to Pay around Sinterklaas and Christmas

In Figure 10 we present the results of the different effect types for estimating willingness to pay around Sinterklaas and Christmas for an α-level of 1%. The effect types are based on the explanation of Section 5.4.3, while the proportion of effects conditioned on a shop category correspond to the size of effect types as determined by (31). Similar to the results of studying the different effect types of RC, WTP and UTP, we condition on the products which have non-negative parameter estimates for the variable RC. In Figure 10, the percentages next to the shop categories indicate the percentage of products for which we observe those non-negative parameter estimates.

Based on this explanation of how to interpret the plot of Figure 10, let us now consider the results shown in this figure. By a large margin, the effect type *indifferent* is the most dominating effect

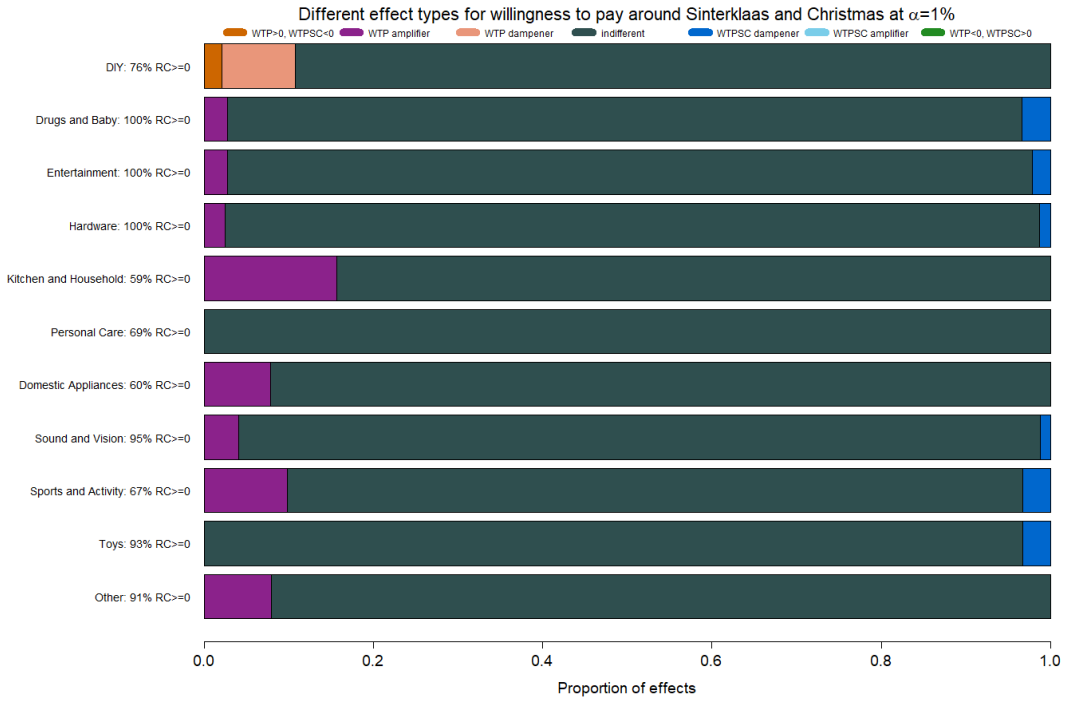

Figure 10: Size of different effect types conditioned on products for which RC has a positive parameter estimate. Values next to the shop category indicates the percentage of products for which RC has a positive parameter estimate. The size of every effect type (proportion of effects) conditioned on a shop category and non-negative parameter estimates of RC is determined by (31)

type in all shop categories, indicating that there are no significant differences between the parameter estimates of WTP and WTPSC for a majority of products of which the parameter estimate of RC is non-negative. The effect type *WTP amplifier* present by means of small to moderate proportion most of the shop categories. This might suggest that for products with non negative parameter estimates of RC and for which the parameter estimate of WTP and WTPSC are both positive, the willingness to pay in a general setting is larger than for the setting in which WTPSC is active. The effect type *WTPSC dampener* takes a small proportion of the pie in the shop categories *Drugs and Baby*, *Entertainment*, *Hardware*, *Sound and Vision*, *Sports and Activity*, and *Toys*, but these proportions are in our opinion too small to base any conclusions on. Lastly, for the shop category *DIY* we find that the effect type *WTP dampener* has a moderate size. This can point towards the direction of the existence of products within the shop category for which in the setting in which WTPSC is active, consumers are less willing to pay more for receiving the product before Sinterklaas and/or Christmas than in a general setting in which WTP is active.

All-in-all, we cannot find any conclusive evidence which suggests that in the week before Sinterklaas and Christmas, the sensitivity of WTPSC is larger than that of WTP. Hence, based on the sample of products we have used in this study, we cannot say that products for which the internal retailer is the only online platform which promises to deliver the product before Sinterklaas or Christmas in at least one day in the week prior to these two holidays, sell relatively more on these days compared to days in which we observe opportunities to measure general willingness to pay. However, these results

do not say that no true effect exists, only that we are not able to find them.

We can think of several reasons why we cannot find any evidence. From the methodological perspective, we were only able to select products for which we observed at least one day in which WTPSC was active. As a consequence, there might exist products which are susceptible to the effects we want to measure, but are not included because we did not observe any day in which WTPSC was active. Therefore, the results should only be regarded with respect to the products we have included in this study. In Appendix B.2 we compare how the chosen sample relates to the actual population, in order to determine to what extent our sample is representative for the population. Based on this explanation, the sample matches the underlying population quite well. However, we rely here on aggregate numbers. Therefore, it might be the case that we miss some products which cannot be captured by the analysis we make in this section. From an observational nature, it might be the case that it is impossible to measure the effects we want to estimate. To be more specific, in case the product offers of the market and the internal retailer are very similar for products which are susceptible for the effects we want to measure, we never observe situations in which we can measure the possible effects, a disadvantage of relying on observational data. As an alternative of the approach we are using, an experimental design could be used which aims to create situations in which we can measure the effects of interest. However, the practical usability of the set-up is questionable in case it is very unlikely that such situations occur substantially in the real world.

6.4. Output Tables Study Variables

Table 8: Estimates for $\sigma_{9.21}(\mathrm{RP}_p)$ and $\sigma_{9.21}(\mathrm{RP}_d)$ over the different shop categories with *DIY* as a baseline during the regular period.

Variables	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7	Cluster 8
$\sigma_{9.21}(\mathrm{RP}_p)$	0.55 (0.05)$_L$	0.37 (0.05)$_L$	1.58 (0.06)$_L$	6.60 (0.36)$_L$	5.09 (0.07)$_L$	5.64 (0.11)$_L$	4.62 (0.13)$_L$	0.28 (0.05)$_L$
$\sigma_{9.21}(\mathrm{RP}_d)$	0.36 (0.03)$_L$	-0.03 (0.03)	-0.22 (0.03)$_L$	-2.44 (0.13)$_L$	-0.17 (0.03)$_L$	0.27 (0.03)$_L$	0.00 (0.06)	0.13 (0.03)$_M$
Domestic Appliances:$\sigma_{9.21}(\mathrm{RP}_p)$	1.80 (0.06)$_L$	-0.07 (0.07)	1.56 (0.07)$_L$	-5.49 (0.37)$_L$	-4.00 (0.08)$_L$	-4.14 (0.11)$_L$	-3.03 (0.13)$_L$	2.43 (0.06)$_L$
Drugs and Baby:$\sigma_{9.21}(\mathrm{RP}_p)$	0.03 (0.06)	3.18 (0.06)$_L$	1.32 (0.06)$_L$	-6.56 (0.36)$_L$	-1.08 (0.08)$_L$	-3.77 (0.11)$_L$	-4.14 (0.13)$_L$	0.50 (0.05)$_L$
Entertainment:$\sigma_{9.21}(\mathrm{RP}_p)$	0.39 (0.07)$_L$	-0.47 (0.07)$_L$	1.66 (0.09)$_L$	-3.06 (0.37)$_L$	-3.67 (0.09)$_L$	-1.94 (0.13)$_L$	-2.72 (0.14)$_L$	1.87 (0.08)$_L$
Hardware:$\sigma_{9.21}(\mathrm{RP}_p)$	2.33 (0.06)$_L$	-0.21 (0.08)	0.03 (0.07)	-3.85 (0.37)$_L$	-4.27 (0.13)$_L$	-4.07 (0.13)$_L$	-3.64 (0.14)$_L$	1.61 (0.06)$_L$
Kitchen and Household:$\sigma_{9.21}(\mathrm{RP}_p)$	0.49 (0.07)$_L$	1.29 (0.07)$_L$	-0.67 (0.07)$_L$	-6.03 (0.37)$_L$	-3.99 (0.08)$_L$	-2.09 (0.11)$_L$	-1.77 (0.13)$_L$	0.40 (0.05)$_L$
other:$\sigma_{9.21}(\mathrm{RP}_p)$	0.76 (0.06)$_L$	0.28 (0.07)$_M$	-1.55 (0.07)$_L$	-7.42 (0.37)$_L$	-3.68 (0.08)$_L$	-3.69 (0.12)$_L$	-8.75 (0.16)$_L$	0.49 (0.06)$_L$
Personal Care:$\sigma_{9.21}(\mathrm{RP}_p)$	3.95 (0.15)$_L$	2.07 (0.06)$_L$	-1.27 (0.06)$_L$	-4.61 (0.37)$_L$	-4.72 (0.07)$_L$	-4.31 (0.11)$_L$	-3.46 (0.13)$_L$	2.28 (0.06)$_L$
Sound and Vision:$\sigma_{9.21}(\mathrm{RP}_p)$	3.38 (0.13)$_L$	1.26 (0.06)$_L$	0.19 (0.09)	-1.41 (0.37)$_S$	-3.98 (0.10)$_L$	-1.87 (0.16)$_L$	-3.40 (0.14)$_L$	2.07 (0.09)$_L$
Sports and Activity:$\sigma_{9.21}(\mathrm{RP}_p)$	-0.23 (0.07)	0.24 (0.07)	4.73 (0.15)$_L$	-4.98 (0.37)$_L$	-7.34 (0.09)$_L$	0.99 (0.14)$_L$	-2.49 (0.14)$_L$	-0.70 (0.07)$_L$
Toys:$\sigma_{9.21}(\mathrm{RP}_p)$	-0.17 (0.06)	3.27 (0.07)$_L$	-1.00 (0.06)$_L$	1.28 (0.37)	-4.81 (0.07)$_L$	-3.45 (0.11)$_L$	-2.28 (0.14)$_L$	2.34 (0.06)$_L$
Domestic Appliances:$\sigma_{9.21}(\mathrm{RP}_d)$	-0.40 (0.03)$_L$	-0.27 (0.04)$_L$	0.25 (0.03)$_L$	2.50 (0.13)$_L$	0.05 (0.04)	0.06 (0.03)	0.62 (0.06)$_L$	-0.08 (0.03)
Drugs and Baby:$\sigma_{9.21}(\mathrm{RP}_d)$	-0.28 (0.03)$_L$	0.10 (0.03)	0.28 (0.03)$_L$	2.45 (0.13)$_L$	-0.20 (0.04)$_L$	-0.18 (0.03)$_L$	0.04 (0.06)	0.10 (0.03)
Entertainment:$\sigma_{9.21}(\mathrm{RP}_d)$	-0.45 (0.04)$_L$	-0.15 (0.04)$_S$	0.46 (0.04)$_L$	2.75 (0.14)$_L$	-0.39 (0.05)$_L$	-0.20 (0.05)$_M$	0.31 (0.06)$_L$	0.20 (0.04)$_L$
Hardware:$\sigma_{9.21}(\mathrm{RP}_d)$	-0.17 (0.03)$_L$	0.42 (0.04)$_L$	0.24 (0.04)$_L$	2.74 (0.13)$_L$	-0.37 (0.05)$_L$	0.61 (0.05)$_L$	0.18 (0.06)	0.32 (0.03)$_L$
Kitchen and Household:$\sigma_{9.21}(\mathrm{RP}_d)$	-0.56 (0.04)$_L$	-0.27 (0.04)$_L$	0.10 (0.04)	2.50 (0.13)$_L$	0.03 (0.04)	-0.21 (0.04)$_L$	0.31 (0.06)$_L$	-0.23 (0.03)$_L$
other:$\sigma_{9.21}(\mathrm{RP}_d)$	-0.58 (0.03)$_L$	-0.11 (0.04)	0.05 (0.04)	2.61 (0.13)$_L$	0.31 (0.04)$_L$	0.05 (0.04)	0.39 (0.07)$_L$	-0.22 (0.03)$_L$
Personal Care:$\sigma_{9.21}(\mathrm{RP}_d)$	3.23 (0.10)$_L$	0.06 (0.03)	0.26 (0.03)$_L$	2.30 (0.13)$_L$	0.12 (0.04)	0.08 (0.03)	0.26 (0.06)$_M$	-0.09 (0.03)
Sound and Vision:$\sigma_{9.21}(\mathrm{RP}_d)$	-0.24 (0.05)$_L$	0.15 (0.03)$_L$	0.33 (0.04)$_L$	2.82 (0.13)$_L$	0.37 (0.06)$_L$	0.34 (0.07)$_L$	0.44 (0.07)$_L$	-0.27 (0.04)$_L$
Sports and Activity:$\sigma_{9.21}(\mathrm{RP}_d)$	-0.47 (0.04)$_L$	0.01 (0.04)	0.66 (0.08)$_L$	2.33 (0.13)$_L$	0.10 (0.05)	-0.93 (0.05)$_L$	0.42 (0.07)$_L$	-0.18 (0.04)$_L$
Toys:$\sigma_{9.21}(\mathrm{RP}_d)$	-0.33 (0.03)$_L$	-0.17 (0.03)$_L$	0.18 (0.03)$_L$	2.11 (0.13)$_L$	0.02 (0.04)	-0.38 (0.03)$_L$	1.03 (0.06)$_L$	-0.05 (0.03)
Variables	Cluster 9	Cluster 10	Cluster 11	Cluster 12	Cluster 13	Cluster 14	Cluster 15	Cluster 16
$\sigma_{9.21}(\mathrm{RP}_p)$	2.08 (0.08)$_L$	3.59 (0.10)$_L$	0.56 (0.18)	4.17 (0.14)$_L$	-0.05 (0.08)	4.19 (0.18)$_L$	0.24 (0.06)$_M$	-0.94 (0.09)$_L$
$\sigma_{9.21}(\mathrm{RP}_d)$	-0.43 (0.04)$_L$	-0.11 (0.04)	1.02 (0.07)$_L$	0.11 (0.05)	0.14 (0.04)$_S$	-0.29 (0.07)$_M$	0.04 (0.03)	0.00 (0.04)
Domestic Appliances:$\sigma_{9.21}(\mathrm{RP}_p)$	2.31 (0.09)$_L$	-0.44 (0.10)$_M$	3.56 (0.18)$_L$	-1.04 (0.14)$_L$	5.01 (0.11)$_L$	-3.06 (0.19)$_L$	2.48 (0.08)$_L$	1.54 (0.09)$_L$
Drugs and Baby:$\sigma_{9.21}(\mathrm{RP}_p)$	-1.58 (0.08)$_L$	0.91 (0.10)$_L$	2.83 (0.18)$_L$	-0.78 (0.14)$_L$	4.21 (0.09)$_L$	-3.48 (0.18)$_L$	1.46 (0.06)$_L$	7.23 (0.10)$_L$
Entertainment:$\sigma_{9.21}(\mathrm{RP}_p)$	-0.41 (0.09)$_L$	0.64 (0.11)$_L$	1.14 (0.19)$_L$	-4.46 (0.16)$_L$	-1.10 (0.14)$_L$	-3.09 (0.20)$_L$	0.43 (0.09)$_L$	3.54 (0.10)$_L$
Hardware:$\sigma_{9.21}(\mathrm{RP}_p)$	4.47 (0.10)$_L$	1.29 (0.11)$_L$	2.35 (0.18)$_L$	-0.81 (0.16)$_L$	-3.46 (0.13)$_L$	-2.37 (0.19)$_L$	4.80 (0.11)$_L$	6.68 (0.12)$_L$
Kitchen and Household:$\sigma_{9.21}(\mathrm{RP}_p)$	-1.98 (0.09)$_L$	-2.70 (0.10)$_L$	2.62 (0.20)$_L$	-2.98 (0.14)$_L$	1.89 (0.09)$_L$	-1.09 (0.21)$_L$	-0.72 (0.08)$_L$	2.54 (0.09)$_L$
other:$\sigma_{9.21}(\mathrm{RP}_p)$	-1.41 (0.08)$_L$	2.17 (0.11)$_L$	1.21 (0.18)$_L$	-5.50 (0.14)$_L$	1.55 (0.09)$_L$	-3.66 (0.19)$_L$	3.25 (0.10)$_L$	6.01 (0.11)$_L$
Personal Care:$\sigma_{9.21}(\mathrm{RP}_p)$	-0.84 (0.08)$_L$	-3.25 (0.10)$_L$	-0.26 (0.18)	-1.53 (0.14)$_L$	3.71 (0.08)$_L$	3.13 (0.20)$_L$	1.91 (0.06)$_L$	0.63 (0.09)$_L$
Sound and Vision:$\sigma_{9.21}(\mathrm{RP}_p)$	-2.36 (0.10)$_L$	-1.15 (0.11)$_L$	1.98 (0.21)$_L$	-4.74 (0.19)$_L$	7.24 (0.29)$_L$	2.52 (0.19)$_L$	3.91 (0.10)$_L$	8.50 (0.32)$_L$
Sports and Activity:$\sigma_{9.21}(\mathrm{RP}_p)$	-0.38 (0.09)$_M$	0.02 (0.11)	2.44 (0.19)$_L$	-2.48 (0.18)$_L$	-0.69 (0.13)$_L$	-4.08 (0.18)$_L$	-1.96 (0.12)$_L$	3.20 (0.09)$_L$
Toys:$\sigma_{9.21}(\mathrm{RP}_p)$	0.12 (0.08)	1.19 (0.10)$_L$	-0.58 (0.18)	-1.88 (0.14)$_L$	2.39 (0.08)$_L$	-3.63 (0.19)$_L$	1.59 (0.06)$_L$	3.35 (0.09)$_L$
Domestic Appliances:$\sigma_{9.21}(\mathrm{RP}_d)$	0.51 (0.05)$_L$	0.35 (0.04)$_L$	-0.89 (0.08)$_L$	0.32 (0.06)$_L$	-0.31 (0.04)$_L$	0.38 (0.07)$_L$	-0.30 (0.04)$_L$	0.09 (0.04)
Drugs and Baby:$\sigma_{9.21}(\mathrm{RP}_d)$	0.57 (0.04)$_L$	0.41 (0.04)$_L$	-0.25 (0.07)$_S$	0.25 (0.06)$_M$	-0.36 (0.04)$_L$	0.29 (0.07)$_M$	0.33 (0.04)$_L$	0.56 (0.05)$_L$
Entertainment:$\sigma_{9.21}(\mathrm{RP}_d)$	0.33 (0.05)$_L$	-0.03 (0.05)	-0.01 (0.08)	0.08 (0.07)	-0.31 (0.07)$_M$	-0.04 (0.08)	-0.11 (0.05)	0.40 (0.05)$_L$
Hardware:$\sigma_{9.21}(\mathrm{RP}_d)$	0.31 (0.05)$_L$	0.29 (0.04)$_L$	-0.67 (0.08)$_L$	1.05 (0.07)$_L$	0.11 (0.05)	0.70 (0.08)$_L$	-0.12 (0.05)	0.36 (0.05)$_L$
Kitchen and Household:$\sigma_{9.21}(\mathrm{RP}_d)$	0.54 (0.05)$_L$	-0.02 (0.05)	-0.98 (0.08)$_L$	-0.15 (0.06)	-0.13 (0.04)	-0.94 (0.08)$_L$	-0.31 (0.04)$_L$	0.43 (0.04)$_L$
other:$\sigma_{9.21}(\mathrm{RP}_d)$	0.80 (0.05)$_L$	-0.03 (0.05)	-1.00 (0.08)$_L$	0.17 (0.06)	0.21 (0.04)$_L$	0.38 (0.07)$_L$	-0.31 (0.05)$_L$	-0.06 (0.05)
Personal Care:$\sigma_{9.21}(\mathrm{RP}_d)$	0.22 (0.04)$_L$	0.01 (0.04)	-0.95 (0.08)$_L$	0.47 (0.06)$_L$	0.12 (0.04)	0.40 (0.09)$_M$	-0.03 (0.04)	0.16 (0.05)
Sound and Vision:$\sigma_{9.21}(\mathrm{RP}_d)$	0.31 (0.05)$_L$	0.44 (0.05)$_L$	-0.68 (0.09)$_L$	-0.30 (0.08)$_S$	-0.24 (0.10)	0.75 (0.07)$_L$	-0.03 (0.05)	1.45 (0.09)$_L$
Sports and Activity:$\sigma_{9.21}(\mathrm{RP}_d)$	0.11 (0.05)	-0.26 (0.05)$_L$	-0.22 (0.08)	-0.99 (0.09)$_L$	-0.44 (0.07)$_L$	0.55 (0.07)$_L$	0.45 (0.09)$_L$	0.32 (0.05)$_L$
Toys:$\sigma_{9.21}(\mathrm{RP}_d)$	0.49 (0.04)$_L$	-0.05 (0.05)	-0.66 (0.08)$_L$	-0.05 (0.06)	0.15 (0.04)$_S$	0.28 (0.07)$_M$	-0.12 (0.04)	0.19 (0.04)$_L$
Variables	Cluster 17	Cluster 18	Cluster 19	Cluster 20	Cluster 21	Cluster 22	Cluster 23	
$\sigma_{9.21}(\mathrm{RP}_p)$	1.76 (0.12)$_L$	0.84 (0.10)$_L$	-0.70 (0.12)$_L$	-1.26 (0.10)$_L$	0.83 (0.07)$_L$	0.03 (0.11)	1.48 (0.42)$_S$	
$\sigma_{9.21}(\mathrm{RP}_d)$	0.28 (0.06)$_L$	1.09 (0.06)$_L$	-0.46 (0.06)$_L$	-0.75 (0.05)$_L$	0.22 (0.04)$_L$	0.49 (0.10)$_L$	-1.51 (0.16)$_L$	
Domestic Appliances:$\sigma_{9.21}(\mathrm{RP}_p)$	-4.58 (0.15)$_L$	-0.18 (0.11)	12.79 (0.25)$_L$	1.58 (0.11)$_L$	1.84 (0.10)$_L$	-1.43 (0.17)$_L$	-6.29 (0.43)$_L$	
Drugs and Baby:$\sigma_{9.21}(\mathrm{RP}_p)$	0.24 (0.13)	1.05 (0.10)$_L$	0.57 (0.12)$_L$	6.83 (0.12)$_L$	-0.78 (0.08)$_L$	3.13 (0.12)$_L$	3.23 (0.43)$_L$	
Entertainment:$\sigma_{9.21}(\mathrm{RP}_p)$	5.32 (0.15)$_L$	0.19 (0.11)	2.90 (0.18)$_L$	1.05 (0.12)$_L$	1.35 (0.11)$_L$	0.45 (4.51)	-0.72 (0.44)	
Hardware:$\sigma_{9.21}(\mathrm{RP}_p)$	2.08 (0.14)$_L$	10.02 (0.11)$_L$	2.00 (0.13)$_L$	1.59 (0.12)$_L$	-1.47 (0.12)$_L$	3.59 (0.18)$_L$	19.31 (0.95)$_L$	
Kitchen and Household:$\sigma_{9.21}(\mathrm{RP}_p)$	2.50 (0.15)$_L$	-2.70 (0.13)$_L$	0.94 (0.14)$_L$	-1.64 (0.12)$_L$	-1.23 (0.13)$_L$	2.39 (0.20)$_L$	1.42 (0.49)	
other:$\sigma_{9.21}(\mathrm{RP}_p)$	-0.66 (0.12)$_L$	-1.10 (0.10)$_L$	5.33 (0.13)$_L$	2.59 (0.11)$_L$	-1.87 (0.10)$_L$	1.21 (0.12)$_L$	-0.61 (0.42)	
Personal Care:$\sigma_{9.21}(\mathrm{RP}_p)$	0.40 (0.13)	0.51 (0.10)$_L$	4.05 (0.12)$_L$	3.19 (0.10)$_L$	1.13 (0.08)$_L$	2.74 (0.12)$_L$	4.04 (0.42)$_L$	
Sound and Vision:$\sigma_{9.21}(\mathrm{RP}_p)$	4.26 (0.18)$_L$	1.82 (0.13)$_L$	1.65 (0.13)$_L$	-0.25 (0.18)	0.49 (0.11)$_M$	0.54 (0.21)	3.91 (0.53)$_L$	
Sports and Activity:$\sigma_{9.21}(\mathrm{RP}_p)$	-0.45 (0.13)	0.32 (0.16)	1.08 (0.12)$_L$	1.39 (0.12)$_L$	4.43 (0.13)$_L$	0.08 (0.12)	0.03 (0.43)	
Toys:$\sigma_{9.21}(\mathrm{RP}_p)$	-0.61 (0.13)$_L$	0.52 (0.10)$_L$	-0.06 (0.12)	8.26 (0.11)$_L$	1.80 (0.08)$_L$	4.44 (0.22)$_L$	-2.04 (0.43)$_L$	
Domestic Appliances:$\sigma_{9.21}(\mathrm{RP}_d)$	0.21 (0.07)	-0.76 (0.06)$_L$	0.37 (0.10)$_S$	0.82 (0.05)$_L$	0.16 (0.05)	-0.27 (0.11)	2.70 (0.16)$_L$	
Drugs and Baby:$\sigma_{9.21}(\mathrm{RP}_d)$	-0.13 (0.06)	-0.78 (0.06)$_L$	0.55 (0.06)$_L$	1.24 (0.06)$_L$	-0.14 (0.05)	-0.42 (0.10)$_M$	1.77 (0.16)$_L$	
Entertainment:$\sigma_{9.21}(\mathrm{RP}_d)$	-0.08 (0.08)	-1.40 (0.06)$_L$	-0.81 (0.09)$_L$	0.74 (0.07)$_L$	-0.11 (0.06)	1.07 (3.13)	0.97 (0.18)$_L$	
Hardware:$\sigma_{9.21}(\mathrm{RP}_d)$	0.25 (0.07)$_S$	-0.27 (0.07)$_S$	0.50 (0.07)$_L$	0.78 (0.06)$_L$	-0.27 (0.06)$_L$	-0.90 (0.13)$_L$	2.17 (0.21)$_L$	
Kitchen and Household:$\sigma_{9.21}(\mathrm{RP}_d)$	-0.45 (0.08)$_L$	-0.47 (0.07)$_L$	0.10 (0.07)	1.81 (0.07)$_L$	-0.60 (0.06)$_L$	-0.89 (0.12)$_L$	1.33 (0.18)$_L$	
other:$\sigma_{9.21}(\mathrm{RP}_d)$	-0.14 (0.06)	-0.89 (0.06)$_L$	0.55 (0.07)$_L$	0.37 (0.05)$_L$	-0.14 (0.05)	-0.68 (0.10)$_L$	1.23 (0.16)$_L$	
Personal Care:$\sigma_{9.21}(\mathrm{RP}_d)$	-0.25 (0.07)$_S$	-0.96 (0.06)$_L$	0.70 (0.06)$_L$	0.71 (0.05)$_L$	-0.26 (0.04)$_L$	-0.31 (0.10)	2.30 (0.16)$_L$	
Sound and Vision:$\sigma_{9.21}(\mathrm{RP}_d)$	-0.30 (0.08)$_S$	-0.47 (0.07)$_L$	0.23 (0.06)$_S$	0.85 (0.10)$_L$	-0.58 (0.06)$_L$	-0.63 (0.12)$_L$	1.39 (0.20)$_L$	
Sports and Activity:$\sigma_{9.21}(\mathrm{RP}_d)$	-0.38 (0.06)$_L$	-0.57 (0.09)$_L$	0.19 (0.06)	0.52 (0.06)$_L$	-0.44 (0.08)$_L$	-0.36 (0.10)$_S$	1.36 (0.16)$_L$	
Toys:$\sigma_{9.21}(\mathrm{RP}_d)$	-0.19 (0.06)	-0.62 (0.06)$_L$	0.49 (0.06)$_L$	0.52 (0.05)$_L$	-0.05 (0.04)	-1.73 (0.12)$_L$	2.80 (0.16)$_L$	

S: p-value $< 5\%$ α-level
M: p-value $< 1\%$ α-level
L: p-value $< 0.1\%$ α-level

Table 9: Coefficient estimates for $\sigma_{9.21}(\mathrm{RP}_p)$ and $\sigma_{9.21}(\mathrm{RP}_d)$ over the different shop categories during the holiday period. Shop category *DIY* is taken as a baseline.

Variable	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7	Cluster 8
$\sigma_{9.21}(\mathrm{RP}_p)$	0.09 (0.07)	-0.08 (0.07)	4.04 (0.17)$_L$	-2.29 (0.13)$_L$	0.06 (0.07)	1.10 (0.06)$_L$	4.39 (0.12)$_L$	0.52 (0.08)$_L$
$\sigma_{9.21}(\mathrm{RP}_d)$	-0.02 (0.04)	-0.25 (0.03)$_L$	-0.52 (0.06)$_L$	-0.01 (0.05)	-0.37 (0.04)$_L$	0.17 (0.03)$_L$	1.88 (0.06)$_L$	0.08 (0.04)
Drugs and Baby:$\sigma_{9.21}(\mathrm{RP}_p)$	0.19 (0.07)	0.72 (0.08)$_L$	-3.51 (0.17)$_L$	3.18 (0.13)$_L$	0.50 (0.08)$_L$	1.43 (0.06)$_L$	-0.95 (0.15)$_L$	2.61 (0.09)$_L$
Entertainment:$\sigma_{9.21}(\mathrm{RP}_p)$	1.09 (0.08)$_L$	1.19 (0.10)$_L$	-3.87 (0.17)$_L$	2.65 (0.13)$_L$	2.02 (0.09)$_L$	-1.15 (0.07)$_L$	-4.57 (0.12)$_L$	1.90 (0.09)$_L$
Hardware:$\sigma_{9.21}(\mathrm{RP}_p)$	-0.45 (0.08)$_L$	3.38 (0.08)$_L$	-4.60 (0.18)$_L$	3.05 (0.14)$_L$	3.31 (0.09)$_L$	-1.59 (0.08)$_L$	-4.59 (0.12)$_L$	-0.70 (0.10)$_L$
Kitchen and Household:$\sigma_{9.21}(\mathrm{RP}_p)$	0.75 (0.10)$_L$	0.39 (0.10)$_S$	-5.29 (0.19)$_L$	2.49 (0.14)$_L$	-2.18 (0.12)$_L$	0.18 (0.07)	-2.09 (0.14)$_L$	-0.83 (0.10)$_L$
other:$\sigma_{9.21}(\mathrm{RP}_p)$	8.16 (0.14)$_L$	0.57 (0.09)$_L$	-3.69 (0.18)$_L$	4.92 (0.13)$_L$	4.17 (0.10)$_L$	-1.48 (0.08)$_L$	-2.23 (0.13)$_L$	-0.67 (0.08)$_L$
Personal Care:$\sigma_{9.21}(\mathrm{RP}_p)$	0.53 (0.07)$_L$	4.12 (0.09)$_L$	-5.31 (0.17)$_L$	5.38 (0.13)$_L$	0.56 (0.08)$_L$	0.23 (0.06)$_S$	-4.40 (0.12)$_L$	-1.83 (0.10)$_L$
Domestic Appliances:$\sigma_{9.21}(\mathrm{RP}_p)$	0.25 (0.09)	-0.39 (0.09)$_M$	-4.18 (0.18)$_L$	2.48 (0.14)$_L$	0.41 (0.08)$_L$	-2.31 (0.07)$_L$	-2.19 (0.12)$_L$	-1.04 (0.09)$_L$
Sound and Vision:$\sigma_{9.21}(\mathrm{RP}_p)$	-0.26 (0.09)	-0.02 (0.10)	3.66 (0.22)$_L$	1.92 (0.16)$_L$	0.93 (0.10)$_L$	-1.86 (0.09)$_L$	-3.79 (0.13)$_L$	1.67 (0.11)$_L$
Sports and Activity:$\sigma_{9.21}(\mathrm{RP}_p)$	-0.71 (0.10)$_L$	0.49 (0.10)$_L$	-3.25 (0.18)$_L$	2.78 (0.13)$_L$	0.36 (0.10)$_S$	1.93 (0.09)$_L$	-4.70 (0.14)$_L$	-2.09 (0.15)$_L$
Toys:$\sigma_{9.21}(\mathrm{RP}_p)$	-0.24 (0.07)	1.20 (0.08)$_L$	-2.88 (0.17)$_L$	5.84 (0.13)$_L$	5.43 (0.08)$_L$	11.34 (0.15)$_L$	-3.64 (0.12)$_L$	3.52 (0.09)$_L$
Drugs and Baby:$\sigma_{9.21}(\mathrm{RP}_d)$	0.08 (0.04)	0.40 (0.04)$_L$	0.63 (0.07)$_L$	-0.09 (0.05)	0.30 (0.04)$_L$	0.68 (0.04)$_L$	-2.10 (0.08)$_L$	0.57 (0.05)$_L$
Entertainment:$\sigma_{9.21}(\mathrm{RP}_d)$	0.33 (0.04)$_L$	-1.01 (0.04)$_L$	0.19 (0.07)	-0.30 (0.06)$_L$	1.09 (0.05)$_L$	0.19 (0.04)$_L$	-1.94 (0.07)$_L$	-0.77 (0.05)$_L$
Hardware:$\sigma_{9.21}(\mathrm{RP}_d)$	0.19 (0.04)$_L$	0.43 (0.04)$_L$	0.81 (0.07)$_L$	-0.90 (0.06)$_L$	0.90 (0.05)$_L$	0.70 (0.04)$_L$	-1.46 (0.07)$_L$	0.37 (0.05)$_L$
Kitchen and Household:$\sigma_{9.21}(\mathrm{RP}_d)$	0.18 (0.05)$_S$	0.42 (0.04)$_L$	0.26 (0.07)$_S$	-0.37 (0.06)$_L$	0.12 (0.05)	0.07 (0.04)	-1.55 (0.08)$_L$	-0.18 (0.05)$_S$
other:$\sigma_{9.21}(\mathrm{RP}_d)$	1.55 (0.07)$_L$	0.00 (0.04)	0.24 (0.07)	0.27 (0.05)$_L$	0.20 (0.05)$_M$	-0.09 (0.04)	-1.98 (0.07)$_L$	-0.40 (0.05)$_L$
Personal Care:$\sigma_{9.21}(\mathrm{RP}_d)$	0.13 (0.04)	-0.93 (0.04)$_L$	-0.06 (0.07)	0.07 (0.05)	0.28 (0.04)$_L$	0.39 (0.04)$_L$	-1.77 (0.07)$_L$	-0.90 (0.05)$_L$
Domestic Appliances:$\sigma_{9.21}(\mathrm{RP}_d)$	0.08 (0.04)	0.02 (0.04)	0.39 (0.07)$_L$	0.07 (0.05)	0.14 (0.04)	0.99 (0.04)$_L$	-2.12 (0.07)$_L$	0.09 (0.04)
Sound and Vision:$\sigma_{9.21}(\mathrm{RP}_d)$	-0.37 (0.05)$_L$	0.31 (0.05)$_L$	0.83 (0.09)$_L$	-0.28 (0.06)$_L$	0.05 (0.05)	0.05 (0.04)	-2.03 (0.07)$_L$	-0.41 (0.05)$_L$
Sports and Activity:$\sigma_{9.21}(\mathrm{RP}_d)$	0.31 (0.05)$_L$	-0.10 (0.05)	0.22 (0.07)	-0.19 (0.05)$_S$	-0.10 (0.05)	-0.46 (0.05)$_L$	-1.80 (0.07)$_L$	-0.46 (0.07)$_L$
Toys:$\sigma_{9.21}(\mathrm{RP}_d)$	-0.03 (0.04)	0.19 (0.04)$_L$	0.51 (0.06)$_L$	-0.20 (0.05)$_M$	0.04 (0.04)	-3.31 (0.06)$_L$	-1.64 (0.07)$_L$	0.72 (0.05)$_L$
Variable	Cluster 9	Cluster 10	Cluster 11	Cluster 12	Cluster 13	Cluster 14	Cluster 15	Cluster 16
$\sigma_{9.21}(\mathrm{RP}_p)$	0.57 (0.07)$_L$	0.23 (0.05)$_L$	-2.41 (0.12)$_L$	-1.35 (0.12)$_L$	1.46 (0.10)$_L$	7.46 (0.13)$_L$	0.25 (0.09)	4.90 (0.11)$_L$
$\sigma_{9.21}(\mathrm{RP}_d)$	0.63 (0.05)$_L$	0.30 (0.03)$_L$	0.85 (0.05)$_L$	0.50 (0.05)$_L$	0.09 (0.05)	0.98 (0.06)$_L$	-0.04 (0.04)	-0.04 (0.05)
Drugs and Baby:$\sigma_{9.21}(\mathrm{RP}_p)$	2.41 (0.08)$_L$	3.19 (0.08)$_L$	3.05 (0.13)$_L$	1.27 (0.12)$_L$	0.47 (0.12)$_S$	-2.63 (0.15)$_L$	2.70 (0.10)$_L$	-0.60 (0.14)$_M$
Entertainment:$\sigma_{9.21}(\mathrm{RP}_p)$	1.17 (0.07)$_L$	-0.34 (0.08)$_M$	2.99 (0.13)$_L$	-1.23 (0.17)$_L$	3.20 (0.12)$_L$	-7.05 (0.14)$_L$	4.93 (0.11)$_L$	-0.10 (0.13)
Hardware:$\sigma_{9.21}(\mathrm{RP}_p)$	2.76 (0.09)$_L$	0.80 (0.08)$_L$	3.20 (0.13)$_L$	3.01 (0.13)$_L$	5.14 (0.11)$_L$	-7.04 (0.14)$_L$	0.29 (0.10)	4.00 (0.17)$_L$
Kitchen and Household:$\sigma_{9.21}(\mathrm{RP}_p)$	-0.12 (0.11)	-0.38 (0.07)$_L$	2.35 (0.13)$_L$	2.88 (0.14)$_L$	1.49 (0.12)$_L$	-8.84 (0.18)$_L$	0.04 (0.10)	-2.91 (0.16)$_L$
other:$\sigma_{9.21}(\mathrm{RP}_p)$	1.37 (0.08)$_L$	1.70 (0.08)$_L$	2.47 (0.13)$_L$	2.46 (0.13)$_L$	2.55 (0.14)$_L$	-2.44 (0.15)$_L$	-0.52 (0.11)$_L$	-5.09 (0.14)$_L$
Personal Care:$\sigma_{9.21}(\mathrm{RP}_p)$	3.57 (0.09)$_L$	0.67 (0.06)$_L$	9.05 (0.13)$_L$	2.77 (0.12)$_L$	-0.57 (0.10)$_L$	-4.88 (0.14)$_L$	5.91 (0.10)$_L$	-4.38 (0.12)$_L$
Domestic Appliances:$\sigma_{9.21}(\mathrm{RP}_p)$	3.61 (0.09)$_L$	-0.87 (0.08)$_L$	2.24 (0.13)$_L$	2.31 (0.13)$_L$	-3.26 (0.12)$_L$	-4.99 (0.14)$_L$	1.66 (0.10)$_L$	-2.45 (0.14)$_L$
Sound and Vision:$\sigma_{9.21}(\mathrm{RP}_p)$	-0.96 (0.08)$_L$	-2.21 (0.12)$_L$	2.52 (0.14)$_L$	2.52 (0.13)$_L$	2.84 (0.15)$_L$	-3.15 (0.15)$_L$	-0.22 (0.12)	-1.27 (0.13)$_L$
Sports and Activity:$\sigma_{9.21}(\mathrm{RP}_p)$	1.87 (0.14)$_L$	0.77 (0.10)$_L$	-0.28 (0.20)	-0.33 (0.18)	-0.05 (0.14)	-5.91 (0.16)$_L$	3.98 (0.20)$_L$	-2.70 (0.19)$_L$
Toys:$\sigma_{9.21}(\mathrm{RP}_p)$	1.44 (0.07)$_L$	4.73 (0.07)$_L$	2.15 (0.13)$_L$	2.89 (0.12)$_L$	-1.07 (0.11)$_L$	-7.53 (0.13)$_L$	-1.64 (0.10)$_L$	-1.86 (0.11)$_L$
Drugs and Baby:$\sigma_{9.21}(\mathrm{RP}_d)$	-0.53 (0.06)$_L$	0.28 (0.05)$_L$	-0.65 (0.06)$_L$	-0.46 (0.06)$_L$	-0.18 (0.06)	-0.55 (0.07)$_L$	0.32 (0.05)$_L$	0.24 (0.07)
Entertainment:$\sigma_{9.21}(\mathrm{RP}_d)$	-0.52 (0.05)$_L$	-0.79 (0.05)$_L$	-0.67 (0.06)$_L$	-0.78 (0.10)$_L$	-0.82 (0.06)$_L$	-0.24 (0.06)$_M$	-0.21 (0.06)	0.61 (0.07)$_L$
Hardware:$\sigma_{9.21}(\mathrm{RP}_d)$	-0.02 (0.06)	-0.03 (0.04)	-0.19 (0.06)	-0.66 (0.06)$_L$	-0.33 (0.05)$_L$	-0.29 (0.06)$_L$	0.19 (0.05)$_S$	0.21 (0.08)
Kitchen and Household:$\sigma_{9.21}(\mathrm{RP}_d)$	-1.13 (0.07)$_L$	-0.11 (0.04)	-0.45 (0.06)$_L$	-0.85 (0.06)$_L$	0.62 (0.06)$_L$	-0.92 (0.08)$_L$	0.48 (0.05)$_L$	0.74 (0.09)$_L$
other:$\sigma_{9.21}(\mathrm{RP}_d)$	-0.42 (0.06)$_L$	1.08 (0.05)$_L$	-0.92 (0.06)$_L$	-0.54 (0.06)$_L$	-1.09 (0.06)$_L$	-0.82 (0.07)$_L$	0.14 (0.05)	1.21 (0.08)$_L$
Personal Care:$\sigma_{9.21}(\mathrm{RP}_d)$	-0.85 (0.06)$_L$	-0.08 (0.04)	-1.98 (0.06)$_L$	-1.02 (0.06)$_L$	0.09 (0.05)	-0.76 (0.06)$_L$	-1.02 (0.05)$_L$	0.45 (0.06)$_L$
Domestic Appliances:$\sigma_{9.21}(\mathrm{RP}_d)$	-0.62 (0.06)$_L$	0.07 (0.04)	-0.85 (0.06)$_L$	-0.30 (0.06)$_L$	-0.15 (0.05)	-0.63 (0.06)$_L$	0.11 (0.05)	1.29 (0.07)$_L$
Sound and Vision:$\sigma_{9.21}(\mathrm{RP}_d)$	-0.49 (0.06)$_L$	0.12 (0.06)	-0.17 (0.07)	-0.47 (0.06)$_L$	0.60 (0.08)$_L$	-0.67 (0.06)$_L$	0.98 (0.06)$_L$	1.19 (0.07)$_L$
Sports and Activity:$\sigma_{9.21}(\mathrm{RP}_d)$	-1.38 (0.07)$_L$	-0.15 (0.05)	0.08 (0.09)	-0.85 (0.07)$_L$	0.70 (0.07)$_L$	-0.60 (0.07)$_L$	-0.08 (0.09)	-0.34 (0.09)$_S$
Toys:$\sigma_{9.21}(\mathrm{RP}_d)$	-0.66 (0.06)$_L$	-0.20 (0.04)$_L$	-1.40 (0.06)$_L$	-0.24 (0.06)$_M$	0.25 (0.05)$_L$	-0.48 (0.06)$_L$	0.05 (0.05)	0.69 (0.05)$_L$
Variable	Cluster 17	Cluster 18	Cluster 19	Cluster 20	Cluster 21	Cluster 22	Cluster 23	Cluster 24
$\sigma_{9.21}(\mathrm{RP}_p)$	3.02 (0.24)$_L$	0.97 (0.06)$_L$	-0.04 (0.11)	-0.52 (0.13)$_M$	1.67 (0.14)$_L$	0.57 (0.06)$_L$	3.12 (0.16)$_L$	6.29 (0.25)$_L$
$\sigma_{9.21}(\mathrm{RP}_d)$	0.16 (0.13)	0.30 (0.03)$_L$	0.78 (0.05)$_L$	-0.57 (0.06)$_L$	-1.01 (0.06)$_L$	0.09 (0.03)	1.12 (0.10)$_L$	1.13 (0.13)$_L$
Drugs and Baby:$\sigma_{9.21}(\mathrm{RP}_p)$	-1.39 (0.24)$_L$	0.97 (0.20)$_L$	0.03 (0.12)	-0.43 (0.15)	3.69 (0.15)$_L$	1.71 (0.06)$_L$	-2.20 (0.17)$_L$	-4.77 (0.26)$_L$
Entertainment:$\sigma_{9.21}(\mathrm{RP}_p)$	-1.86 (0.24)$_L$	1.37 (0.08)$_L$	6.75 (0.14)$_L$	-1.08 (0.15)$_L$	-1.27 (0.14)$_L$	3.83 (0.08)$_L$	-2.37 (0.17)$_L$	0.13 (0.26)
Hardware:$\sigma_{9.21}(\mathrm{RP}_p)$	-4.75 (0.25)$_L$	-1.73 (0.09)$_L$	2.65 (0.15)$_L$	16.11 (0.18)$_L$	0.97 (0.15)$_L$	-3.55 (0.09)$_L$	5.41 (0.19)$_L$	-1.09 (0.27)$_M$
Kitchen and Household:$\sigma_{9.21}(\mathrm{RP}_p)$	-0.06 (0.25)	-1.78 (0.11)$_L$	-1.97 (0.15)$_L$	-1.29 (0.19)$_L$	2.11 (0.22)$_L$	-5.60 (0.19)$_L$	-3.95 (0.16)$_L$	-0.06 (0.30)
other:$\sigma_{9.21}(\mathrm{RP}_p)$	-1.02 (0.24)$_M$	-2.39 (0.09)$_L$	0.31 (0.11)	1.03 (0.14)$_L$	-2.14 (0.15)$_L$	-5.54 (0.17)$_L$	-0.59 (0.18)	-6.48 (0.27)$_L$
Personal Care:$\sigma_{9.21}(\mathrm{RP}_p)$	-1.16 (0.24)$_L$	2.30 (0.07)$_L$	0.34 (0.12)	4.47 (0.19)$_L$	-2.29 (0.14)$_L$	-1.94 (0.07)$_L$	5.13 (0.19)$_L$	-1.22 (0.27)$_L$
Domestic Appliances:$\sigma_{9.21}(\mathrm{RP}_p)$	3.10 (0.24)$_L$	8.68 (0.12)$_L$	4.77 (0.12)$_L$	1.34 (0.14)$_L$	-0.73 (0.14)$_L$	6.55 (0.09)$_L$	2.02 (0.19)$_L$	-6.61 (0.28)$_L$
Sound and Vision:$\sigma_{9.21}(\mathrm{RP}_p)$	0.34 (0.26)	0.58 (0.06)$_L$	0.93 (0.12)$_L$	0.67 (0.16)$_M$	-1.55 (0.14)$_L$	0.34 (0.11)	-0.67 (0.18)$_S$	-5.18 (0.28)$_L$
Sports and Activity:$\sigma_{9.21}(\mathrm{RP}_p)$	-1.44 (0.24)$_L$	-0.94 (0.16)$_L$	-1.48 (0.27)$_L$	-2.31 (0.24)$_L$	3.28 (0.21)$_L$	1.92 (0.17)$_L$	-3.22 (0.21)$_L$	-6.42 (0.29)$_L$
Toys:$\sigma_{9.21}(\mathrm{RP}_p)$	-1.18 (0.24)$_L$	0.84 (0.08)$_L$	1.81 (0.11)$_L$	2.98 (0.13)$_L$	-1.50 (0.14)$_L$	-0.13 (0.06)	-1.71 (0.16)$_L$	-3.60 (0.25)$_L$
Drugs and Baby:$\sigma_{9.21}(\mathrm{RP}_d)$	0.29 (0.13)	-2.65 (0.08)$_L$	-0.21 (0.06)	0.91 (0.08)$_L$	0.76 (0.06)$_L$	0.62 (0.04)$_L$	-1.07 (0.10)$_L$	-0.62 (0.14)$_M$
Entertainment:$\sigma_{9.21}(\mathrm{RP}_d)$	0.11 (0.13)	0.65 (0.05)$_L$	0.01 (0.06)	0.54 (0.07)$_L$	1.31 (0.06)$_L$	0.01 (0.05)	-0.17 (0.10)	-0.45 (0.14)
Hardware:$\sigma_{9.21}(\mathrm{RP}_d)$	-0.66 (0.13)$_L$	0.27 (0.04)$_L$	-2.05 (0.07)$_L$	2.78 (0.07)$_L$	0.96 (0.06)$_L$	-0.49 (0.05)$_L$	0.13 (0.11)	-0.41 (0.14)
Kitchen and Household:$\sigma_{9.21}(\mathrm{RP}_d)$	-0.16 (0.13)	0.74 (0.06)$_L$	0.26 (0.07)$_S$	0.15 (0.09)	0.82 (0.09)$_L$	1.32 (0.11)$_L$	-0.21 (0.10)	-1.40 (0.15)$_L$
other:$\sigma_{9.21}(\mathrm{RP}_d)$	-0.21 (0.13)	0.11 (0.04)	0.07 (0.06)	0.16 (0.07)	1.40 (0.07)$_L$	-0.29 (0.07)$_M$	0.48 (0.11)$_M$	-1.61 (0.14)$_L$
Personal Care:$\sigma_{9.21}(\mathrm{RP}_d)$	-0.02 (0.13)	0.20 (0.03)$_L$	-0.02 (0.06)	-0.13 (0.08)	0.60 (0.06)$_L$	-0.44 (0.05)$_L$	-1.94 (0.10)$_L$	-0.38 (0.14)
Domestic Appliances:$\sigma_{9.21}(\mathrm{RP}_d)$	-0.48 (0.13)$_S$	0.44 (0.06)$_L$	0.24 (0.06)$_M$	0.27 (0.06)$_L$	0.76 (0.06)$_L$	0.52 (0.05)$_L$	0.75 (0.12)$_L$	0.41 (0.15)
Sound and Vision:$\sigma_{9.21}(\mathrm{RP}_d)$	-0.26 (0.14)	0.43 (0.03)$_L$	0.40 (0.07)$_L$	0.85 (0.08)$_L$	0.90 (0.06)$_L$	-0.08 (0.06)	-0.55 (0.11)$_L$	-0.43 (0.18)
Sports and Activity:$\sigma_{9.21}(\mathrm{RP}_d)$	0.05 (0.13)	0.24 (0.07)	-3.22 (0.12)$_L$	0.22 (0.09)	-0.21 (0.09)	0.59 (0.09)$_L$	0.48 (0.13)$_S$	-1.22 (0.15)$_L$
Toys:$\sigma_{9.21}(\mathrm{RP}_d)$	-0.01 (0.13)	1.30 (0.05)$_L$	0.37 (0.06)$_L$	0.66 (0.06)$_L$	1.19 (0.06)$_L$	0.02 (0.03)	-0.40 (0.10)$_M$	-0.81 (0.13)$_L$

S: p-value $< 5\%$ α-level
M: p-value $< 1\%$ α-level
L: p-value $< 0.1\%$ α-level

Table 10: Estimates for RC, WTP and UTP over the different shop categories with *DIY* as a baseline for the regular period.

Variables	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7	Cluster 8
UTP	-0.33 (0.05)$_L$	0.05 (0.04)	0.52 (0.07)$_L$	0.59 (0.06)$_L$	0.43 (0.05)$_L$	0.28 (0.05)$_L$	0.02 (0.05)	-0.28 (0.07)$_S$
RC	0.16 (0.04)$_S$	0.33 (0.03)$_L$	0.96 (0.05)$_L$	0.39 (0.04)$_L$	0.58 (0.03)$_L$	0.49 (0.04)$_L$	0.04 (0.04)	0.85 (0.04)$_L$
WTP	0.57 (0.06)$_L$	-1.21 (0.18)$_L$	2.03 (0.14)$_L$	-0.77 (0.09)$_L$	0.19 (0.09)	-0.52 (0.09)$_L$	-0.34 (0.06)$_L$	0.02 (0.09)
Domestic Appliances:UTP	0.54 (0.05)$_L$	0.06 (0.05)	-0.65 (0.07)$_L$	0.58 (0.08)$_L$	0.80 (0.07)$_L$	0.02 (0.05)	0.18 (0.05)	0.38 (0.07)$_L$
Drugs and Baby:UTP	0.75 (0.06)$_L$	1.34 (0.06)$_L$	-0.62 (0.07)$_L$	-0.56 (0.06)$_L$	-0.24 (0.05)$_L$	-0.33 (0.05)$_L$	0.07 (0.05)	0.70 (0.07)$_L$
Entertainment:UTP	0.53 (0.07)$_L$	0.27 (0.15)	0.46 (0.08)$_L$	-0.47 (0.06)$_L$	0.38 (0.06)$_L$	-0.03 (0.08)	-0.22 (0.08)	0.20 (0.08)
Hardware:UTP	1.90 (0.07)$_L$	0.30 (0.07)$_M$	-0.29 (0.08)	-2.15 (0.08)$_L$	-0.57 (0.06)$_L$	0.29 (0.05)$_L$	0.39 (0.06)$_L$	0.61 (0.08)$_L$
Kitchen and Household:UTP	0.36 (0.06)$_L$	0.20 (0.05)$_S$	-0.35 (0.08)$_M$	-0.50 (0.06)$_L$	-0.26 (0.05)$_L$	-0.05 (0.06)	0.46 (0.07)$_L$	0.20 (0.07)
other:UTP	0.32 (0.06)$_L$	-0.37 (0.06)$_L$	-0.46 (0.07)$_L$	-0.58 (0.06)$_L$	-0.26 (0.06)$_M$	0.15 (0.05)	-0.62 (0.11)$_L$	-0.29 (0.09)
Personal Care:UTP	1.09 (0.06)$_L$	0.07 (0.05)	-0.65 (0.07)$_L$	-0.54 (0.06)$_L$	-0.15 (0.05)	-0.19 (0.05)$_S$	0.15 (0.05)	0.12 (0.07)
Sound and Vision:UTP	-0.08 (0.10)	-0.35 (0.07)$_L$	-0.32 (0.08)$_S$	-0.12 (0.07)	-0.28 (0.07)$_S$	-0.03 (0.06)	1.19 (0.10)$_L$	-0.01 (0.09)
Sports and Activity:UTP	-0.04 (0.08)	0.12 (0.07)	-0.40 (0.08)$_L$	-0.59 (0.07)$_L$	-0.48 (0.06)$_L$	-0.56 (0.09)$_L$	0.42 (0.06)$_L$	0.13 (0.07)
Toys:UTP	0.43 (0.05)$_L$	0.35 (0.05)$_L$	-0.08 (0.08)	-0.76 (0.06)$_L$	-0.23 (0.05)$_M$	-0.23 (0.06)$_S$	0.32 (0.05)$_L$	0.71 (0.07)$_L$
Domestic Appliances:RC	0.89 (0.04)$_L$	0.19 (0.04)$_L$	-0.83 (0.06)$_L$	0.99 (0.06)$_L$	1.15 (0.06)$_L$	-0.30 (0.05)$_L$	0.74 (0.04)$_L$	-0.19 (0.05)$_S$
Drugs and Baby:RC	0.95 (0.04)$_L$	1.93 (0.04)$_L$	-0.67 (0.05)$_L$	-0.19 (0.04)$_L$	-0.11 (0.04)	-0.33 (0.05)$_L$	0.31 (0.04)$_L$	0.72 (0.04)$_L$
Entertainment:RC	0.99 (0.05)$_L$	-0.80 (0.08)$_L$	0.81 (0.07)$_L$	-0.24 (0.05)$_L$	-0.36 (0.05)$_L$	-0.68 (0.06)$_L$	-0.07 (0.06)	-0.50 (0.05)$_L$
Hardware:RC	2.32 (0.06)$_L$	2.11 (0.06)$_L$	-0.10 (0.06)	-0.21 (0.06)	-0.51 (0.04)$_L$	0.70 (0.05)$_L$	0.97 (0.05)$_L$	0.33 (0.05)$_L$
Kitchen and Household:RC	0.04 (0.04)	0.05 (0.04)	-0.71 (0.06)$_L$	-0.23 (0.05)$_M$	-0.33 (0.04)$_L$	-0.37 (0.05)$_L$	1.28 (0.05)$_L$	-0.42 (0.05)$_L$
other:RC	0.07 (0.04)	-0.55 (0.04)$_L$	-0.45 (0.06)$_L$	-0.16 (0.04)$_S$	-0.22 (0.04)$_L$	-0.19 (0.05)$_S$	-0.01 (0.07)	-0.95 (0.05)$_L$
Personal Care:RC	1.54 (0.04)$_L$	0.12 (0.03)$_S$	-0.83 (0.05)$_L$	-0.05 (0.04)	0.19 (0.04)$_L$	-0.18 (0.05)	0.68 (0.04)$_L$	-0.12 (0.05)
Sound and Vision:RC	-0.44 (0.07)$_L$	-0.85 (0.06)$_L$	-0.07 (0.06)	0.28 (0.06)$_L$	-0.22 (0.05)$_M$	-0.18 (0.06)	2.51 (0.08)$_L$	0.14 (0.07)
Sports and Activity:RC	0.56 (0.05)$_L$	-0.27 (0.05)$_L$	-0.79 (0.06)$_L$	-0.52 (0.05)$_L$	-0.34 (0.04)$_L$	-1.19 (0.06)$_L$	0.05 (0.05)	-0.59 (0.05)$_L$
Toys:RC	0.18 (0.04)$_M$	0.13 (0.03)$_M$	0.34 (0.06)$_L$	-0.33 (0.04)$_L$	-0.17 (0.04)$_M$	-0.45 (0.05)$_L$	0.58 (0.04)$_L$	-0.11 (0.05)
Domestic Appliances:WTP	0.11 (0.07)	1.25 (0.19)$_L$	-2.38 (0.15)$_L$	1.13 (0.16)$_L$	-0.02 (0.18)	-0.03 (0.12)	0.32 (0.09)	-0.24 (0.09)
Drugs and Baby:WTP	-0.71 (0.08)$_L$	2.37 (0.20)$_L$	-1.79 (0.14)$_L$	0.83 (0.09)$_L$	-0.68 (0.10)$_L$	0.47 (0.10)$_L$	0.19 (0.07)	-0.47 (0.09)$_L$
Entertainment:WTP	-0.51 (0.14)	-360.92 (479.52)	-1.28 (0.21)$_L$	0.12 (0.11)	-0.12 (0.10)	0.29 (0.12)	-0.23 (0.17)	-1.13 (0.13)$_L$
Hardware:WTP	1.03 (0.14)$_L$	1.17 (0.27)$_M$	-2.09 (0.16)$_L$	0.45 (0.14)	-0.85 (0.11)$_L$	-0.08 (0.12)	0.18 (0.12)	-0.36 (0.12)
Kitchen and Household:WTP	-0.97 (0.10)$_L$	0.40 (0.19)	-2.58 (0.15)$_L$	0.29 (0.11)	-0.21 (0.11)	-0.37 (0.12)	1.64 (0.12)$_L$	-0.21 (0.10)
other:WTP	-0.88 (0.08)$_L$	2.02 (0.19)$_L$	-2.20 (0.15)$_L$	1.19 (0.10)$_L$	-1.11 (0.10)$_L$	0.30 (0.10)	3.73 (0.12)$_L$	0.55 (0.09)$_L$
Personal Care:WTP	-0.69 (0.10)$_L$	1.05 (0.19)$_L$	-2.44 (0.14)$_L$	0.80 (0.10)$_L$	-1.64 (0.11)$_L$	0.07 (0.10)	-0.04 (0.08)	0.03 (0.10)
Sound and Vision:WTP	-0.07 (0.16)	0.35 (0.23)	-3.15 (0.17)$_L$	0.10 (0.17)	-0.50 (0.16)	0.21 (0.13)	2.53 (0.26)$_L$	-0.89 (0.17)$_L$
Sports and Activity:WTP	1.06 (0.11)$_L$	1.75 (0.20)$_L$	-1.63 (0.15)$_L$	-1.91 (0.15)$_L$	-0.47 (0.10)$_L$	-1.44 (0.22)$_L$	-2.23 (0.13)$_L$	-0.01 (0.10)
Toys:WTP	-0.60 (0.07)$_L$	1.13 (0.19)$_L$	-2.01 (0.16)$_L$	0.34 (0.10)	-0.77 (0.10)$_L$	3.42 (0.12)$_L$	-0.03 (0.08)	-0.52 (0.10)$_L$

Variables	Cluster 9	Cluster 10	Cluster 11	Cluster 12	Cluster 13	Cluster 14	Cluster 15	Cluster 16
UTP	0.98 (0.13)$_L$	0.85 (0.08)$_L$	-4.48 (1.15)$_S$	2.47 (0.11)$_L$	0.50 (0.07)$_L$	-0.09 (0.06)	-0.60 (0.12)$_L$	-0.05 (0.05)
RC	0.90 (0.10)$_L$	0.73 (0.06)$_L$	-4.21 (0.26)$_L$	1.46 (0.09)$_L$	0.60 (0.05)$_L$	0.70 (0.04)$_L$	-0.79 (0.08)$_L$	0.11 (0.04)
WTP	-0.46 (0.22)	-1.34 (0.19)$_L$	-7.99 (0.78)$_L$	-1.52 (0.28)$_L$	-0.13 (0.12)	0.47 (0.11)$_M$	-0.84 (0.15)$_L$	0.60 (0.09)$_L$
Domestic Appliances:UTP	-0.87 (0.14)$_L$	-0.78 (0.08)$_L$	5.02 (1.15)$_M$	0.71 (0.28)	0.01 (0.08)	-0.27 (0.06)$_M$	0.77 (0.12)$_L$	0.28 (0.06)$_L$
Drugs and Baby:UTP	-0.55 (0.13)$_M$	-0.58 (0.08)$_L$	4.53 (1.15)$_S$	-2.36 (0.12)$_L$	-0.45 (0.07)$_L$	0.34 (0.07)$_L$	1.76 (0.12)$_L$	-0.07 (0.06)
Entertainment:UTP	-0.93 (0.14)$_L$	-0.35 (0.11)	4.56 (1.15)$_S$	-2.20 (0.12)$_L$	-0.12 (0.10)	0.31 (0.08)$_S$	1.34 (0.13)$_L$	-0.02 (0.07)
Hardware:UTP	-0.66 (0.13)$_L$	-0.49 (0.08)$_L$	3.74 (1.15)	-2.53 (0.12)$_L$	-0.79 (0.08)$_L$	-0.20 (0.08)	0.69 (0.13)$_L$	0.16 (0.06)
Kitchen and Household:UTP	-1.02 (0.14)$_L$	-0.52 (0.08)$_L$	4.75 (1.15)$_S$	-2.49 (0.13)$_L$	0.01 (0.09)	-0.26 (0.07)$_S$	0.66 (0.12)$_L$	0.68 (0.07)$_L$
other:UTP	-0.47 (0.13)	-0.73 (0.09)$_L$	4.77 (1.15)$_M$	-2.28 (0.13)$_L$	0.06 (0.11)	0.12 (0.08)	0.72 (0.12)$_L$	0.44 (0.07)$_L$
Personal Care:UTP	-0.72 (0.13)$_L$	-0.58 (0.08)$_L$	4.45 (1.15)$_S$	-1.66 (0.12)$_L$	-0.41 (0.07)$_L$	0.36 (0.06)$_L$	1.32 (0.12)$_L$	0.30 (0.06)$_L$
Sound and Vision:UTP	-1.19 (0.13)$_L$	0.01 (0.10)	4.74 (1.15)$_S$	-2.06 (0.14)$_L$	-0.24 (0.12)	0.59 (0.18)	0.82 (0.12)$_L$	-0.39 (0.09)$_M$
Sports and Activity:UTP	-0.77 (0.13)$_L$	-0.77 (0.09)$_L$	4.45 (1.15)$_S$	-2.40 (0.12)$_L$	0.69 (0.11)$_L$	1.30 (0.08)$_L$	0.57 (0.12)$_L$	2.44 (0.11)$_L$
Toys:UTP	-0.53 (0.13)$_S$	-0.68 (0.09)$_L$	4.81 (1.15)$_M$	-2.38 (0.12)$_L$	0.03 (0.08)	0.83 (0.06)$_L$	0.08 (0.12)	0.22 (0.06)
Domestic Appliances:RC	-0.51 (0.10)$_L$	-0.62 (0.06)$_L$	5.31 (0.26)$_L$	4.98 (0.18)$_L$	0.36 (0.06)$_L$	-0.25 (0.05)$_L$	1.22 (0.09)$_L$	0.49 (0.05)$_L$
Drugs and Baby:RC	-0.31 (0.10)	-0.35 (0.06)$_L$	4.97 (0.26)$_L$	-0.89 (0.09)$_L$	0.21 (0.06)	0.90 (0.05)$_L$	2.23 (0.09)$_L$	0.00 (0.05)
Entertainment:RC	-0.87 (0.11)$_L$	0.08 (0.09)	4.75 (0.27)$_L$	-1.28 (0.10)$_L$	0.41 (0.08)$_L$	0.70 (0.06)$_L$	2.26 (0.09)$_L$	0.30 (0.05)$_L$
Hardware:RC	-0.77 (0.10)$_L$	0.03 (0.06)	4.06 (0.27)$_L$	-0.66 (0.09)$_L$	-0.11 (0.06)	-0.24 (0.06)$_S$	1.39 (0.09)$_L$	0.49 (0.05)$_L$
Kitchen and Household:RC	-0.69 (0.10)$_L$	0.08 (0.06)	5.00 (0.27)$_L$	0.17 (0.10)	-0.45 (0.06)$_L$	-0.50 (0.05)$_L$	1.07 (0.09)$_L$	0.52 (0.06)$_L$
other:RC	-1.08 (0.10)$_L$	-0.19 (0.06)	5.06 (0.26)$_L$	0.04 (0.10)	2.39 (0.07)$_L$	0.13 (0.05)	1.63 (0.09)$_L$	0.74 (0.05)$_L$
Personal Care:RC	-0.56 (0.10)$_L$	-0.05 (0.06)	4.42 (0.26)$_L$	-0.06 (0.09)	-0.31 (0.06)$_L$	0.26 (0.05)$_L$	2.84 (0.08)$_L$	0.59 (0.04)$_L$
Sound and Vision:RC	-1.62 (0.10)$_L$	0.03 (0.08)	4.72 (0.27)$_L$	0.44 (0.11)$_S$	-0.82 (0.11)$_L$	1.07 (0.12)$_L$	1.46 (0.08)$_L$	0.79 (0.07)$_L$
Sports and Activity:RC	-0.76 (0.10)$_L$	-0.71 (0.06)$_L$	4.24 (0.27)$_L$	-0.86 (0.10)$_L$	1.14 (0.08)$_L$	1.87 (0.06)$_L$	1.19 (0.08)$_L$	2.58 (0.10)$_L$
Toys:RC	-0.71 (0.10)$_L$	-0.51 (0.06)$_L$	5.11 (0.26)$_L$	-0.78 (0.09)$_L$	0.64 (0.06)$_L$	1.34 (0.04)$_L$	0.77 (0.08)$_L$	0.17 (0.04)$_M$
Domestic Appliances:WTP	0.45 (0.23)	0.92 (0.20)$_M$	7.81 (0.78)$_L$	5.68 (0.36)$_L$	0.24 (0.14)	-0.58 (0.12)$_L$	1.18 (0.17)$_L$	-0.93 (0.11)$_L$
Drugs and Baby:WTP	-0.21 (0.22)	1.17 (0.19)$_L$	7.54 (0.78)$_L$	0.94 (0.29)	-0.49 (0.12)$_S$	-0.19 (0.13)	-2.03 (0.22)$_L$	-0.58 (0.09)$_L$
Entertainment:WTP	-1.37 (0.28)$_L$	1.36 (0.25)$_L$	8.28 (0.79)$_L$	1.53 (0.30)$_L$	0.99 (0.20)$_L$	-0.47 (0.17)	2.11 (0.19)$_L$	-4.49 (0.16)$_L$
Hardware:WTP	0.04 (0.23)	-0.02 (0.20)	7.33 (0.79)$_L$	0.16 (0.29)	-0.06 (0.14)	-0.13 (0.17)	0.94 (0.17)$_L$	-0.61 (0.10)$_L$
Kitchen and Household:WTP	2.22 (0.22)$_L$	2.09 (0.20)$_L$	9.90 (0.79)$_L$	-0.25 (0.36)	-0.01 (0.14)	-1.77 (0.17)$_L$	0.41 (0.16)	-1.52 (0.15)$_L$
other:WTP	0.24 (0.22)	0.93 (0.20)$_M$	8.37 (0.78)$_L$	1.53 (0.29)$_L$	1.89 (0.17)$_L$	-0.43 (0.13)	-1.81 (0.19)$_L$	-0.54 (0.10)$_L$
Personal Care:WTP	0.40 (0.22)	1.32 (0.19)$_L$	7.65 (0.78)$_L$	0.92 (0.29)	-0.07 (0.12)	0.18 (0.13)	0.58 (0.16)	-1.28 (0.09)$_L$
Sound and Vision:WTP	0.14 (0.25)	1.16 (0.23)$_L$	7.09 (0.79)$_L$	1.82 (0.33)$_L$	-3.83 (0.34)$_L$	0.95 (0.28)	-0.05 (0.16)	-0.24 (0.16)
Sports and Activity:WTP	0.04 (0.22)	1.05 (0.20)$_L$	7.96 (0.79)$_L$	1.89 (0.29)$_L$	-0.81 (0.20)$_S$	1.01 (0.18)$_L$	0.40 (0.15)	-0.32 (0.30)
Toys:WTP	-0.22 (0.22)	1.23 (0.20)$_L$	7.04 (0.78)$_L$	1.16 (0.29)$_S$	0.39 (0.13)	0.32 (0.13)	-0.82 (0.16)$_L$	-1.56 (0.10)$_L$

Variables	Cluster 17	Cluster 18	Cluster 19	Cluster 20	Cluster 21	Cluster 22	Cluster 23	Cluster 24
UTP	0.16 (0.07)	-0.04 (0.08)	0.01 (0.07)	1.58 (0.28)$_L$	-0.06 (0.05)	0.51 (0.22)	-0.75 (0.12)$_L$	-0.96 (0.08)$_L$
RC	0.27 (0.04)$_L$	0.19 (0.06)	0.56 (0.05)$_L$	2.15 (0.26)$_L$	-0.13 (0.05)	0.29 (0.14)	-0.37 (0.07)$_L$	-0.49 (0.06)$_L$
WTP	-0.84 (0.11)$_L$	0.14 (0.14)	0.69 (0.09)$_L$	1.80 (0.59)	1.03 (0.12)$_L$	-12.37 (2.10)$_L$	0.05 (0.19)	0.10 (0.12)
Domestic Appliances:UTP	-0.42 (0.08)$_L$	-0.65 (0.10)$_L$	0.35 (0.08)$_M$	-1.59 (0.28)$_L$	-0.10 (0.06)	-0.72 (0.22)	0.02 (0.14)	1.91 (0.11)$_L$
Drugs and Baby:UTP	0.85 (0.08)$_L$	0.73 (0.08)$_L$	-0.07 (0.08)	-1.50 (0.28)$_L$	0.45 (0.05)$_L$	0.21 (0.22)	0.44 (0.13)	3.75 (0.11)$_L$
Entertainment:UTP	0.19 (0.09)	0.34 (0.09)$_S$	0.53 (0.07)$_L$	-1.22 (0.29)$_M$	-0.26 (0.09)	-0.04 (0.23)	0.81 (0.17)$_L$	0.66 (0.11)$_L$
Hardware:UTP	-0.26 (0.09)	-0.16 (0.11)	0.11 (0.09)	-0.78 (0.29)	0.42 (0.08)$_L$	-0.10 (0.24)	1.40 (0.16)$_L$	1.33 (0.12)$_L$
Kitchen and Household:UTP	0.01 (0.09)	0.35 (0.11)	-0.56 (0.11)$_L$	-1.47 (0.28)$_L$	0.01 (0.07)	-1.07 (0.24)$_M$	0.59 (0.37)	0.24 (0.13)
other:UTP	-0.23 (0.08)	-0.08 (0.10)	0.08 (0.08)	-2.66 (0.29)$_L$	0.31 (0.07)$_M$	-0.14 (0.22)	1.12 (0.13)$_L$	0.90 (0.11)$_L$
Personal Care:UTP	1.34 (0.10)$_L$	-0.14 (0.09)	0.48 (0.07)$_L$	-2.05 (0.28)$_L$	0.27 (0.05)$_L$	0.50 (0.22)	1.60 (0.13)$_L$	0.44 (0.09)$_L$
Sound and Vision:UTP	-0.16 (0.09)	0.92 (0.18)$_L$	0.89 (0.20)$_M$	-1.49 (0.32)$_M$	-0.29 (0.09)	0.27 (0.22)	1.48 (0.17)$_L$	0.93 (0.14)$_L$
Sports and Activity:UTP	0.13 (0.09)	-0.65 (0.10)$_L$	-0.04 (0.15)	-2.07 (0.35)$_L$	-0.19 (0.09)	-0.27 (0.22)	0.57 (0.14)$_S$	0.07 (0.16)
Toys:UTP	0.17 (0.08)	0.42 (0.08)$_L$	0.33 (0.07)$_L$	-1.07 (0.28)$_S$	0.13 (0.05)	-0.64 (0.22)	6.85 (0.25)$_L$	1.44 (0.09)$_L$
Domestic Appliances:RC	-0.41 (0.05)$_L$	-2.22 (0.11)$_L$	0.80 (0.06)$_L$	-1.86 (0.26)$_L$	0.81 (0.06)$_L$	-0.45 (0.14)	0.36 (0.08)$_M$	1.07 (0.09)$_L$
Drugs and Baby:RC	1.07 (0.05)$_L$	1.53 (0.06)$_L$	-0.14 (0.05)	-2.11 (0.26)$_L$	1.56 (0.06)$_L$	0.84 (0.14)$_L$	0.43 (0.08)$_L$	5.45 (0.08)$_L$
Entertainment:RC	0.05 (0.05)	0.13 (0.07)	0.89 (0.06)$_L$	-1.18 (0.26)$_M$	1.61 (0.08)$_L$	-0.58 (0.15)$_S$	-0.20 (0.14)	0.35 (0.07)$_L$
Hardware:RC	0.49 (0.05)$_L$	0.34 (0.11)	-0.28 (0.07)$_S$	-2.11 (0.27)$_L$	2.34 (0.08)$_L$	0.31 (0.16)	1.96 (0.12)$_L$	1.32 (0.09)$_L$
Kitchen and Household:RC	-0.22 (0.05)$_M$	0.33 (0.07)$_L$	-0.68 (0.06)$_L$	-1.80 (0.26)$_L$	0.00 (0.07)	-0.45 (0.31)	0.59 (0.18)	0.88 (0.07)$_L$
other:RC	-0.38 (0.04)$_L$	-0.13 (0.08)	-0.58 (0.06)$_L$	-2.08 (0.26)$_L$	0.66 (0.06)$_L$	0.31 (0.14)	0.80 (0.07)$_L$	1.19 (0.07)$_L$
Personal Care:RC	4.91 (0.07)$_L$	0.31 (0.07)$_M$	0.74 (0.05)$_L$	-2.06 (0.26)$_L$	1.69 (0.06)$_L$	0.85 (0.14)$_L$	1.81 (0.08)$_L$	0.72 (0.06)$_L$
Sound and Vision:RC	-0.06 (0.06)	1.95 (0.15)$_L$	0.66 (0.19)	-2.75 (0.30)$_L$	0.25 (0.07)	0.82 (0.14)$_L$	2.03 (0.18)$_L$	1.34 (0.10)$_L$
Sports and Activity:RC	0.93 (0.06)$_L$	-1.74 (0.09)$_L$	0.36 (0.08)$_M$	-2.04 (0.27)$_L$	0.56 (0.08)$_L$	-0.03 (0.14)	0.31 (0.08)$_S$	-0.38 (0.10)$_S$
Toys:RC	0.11 (0.05)	0.51 (0.06)$_L$	0.47 (0.05)$_L$	-1.27 (0.26)$_L$	0.99 (0.05)$_L$	-1.01 (0.14)$_L$	5.22 (0.13)$_L$	1.32 (0.06)$_L$
Domestic Appliances:WTP	0.01 (0.12)	-10.26 (1.35)$_L$	-0.48 (0.13)	-1.09 (0.59)	-1.69 (0.14)$_L$	11.67 (2.11)$_L$	-1.06 (0.27)$_S$	-0.32 (0.23)
Drugs and Baby:WTP	-0.03 (0.14)	-0.81 (0.15)$_L$	-0.27 (0.11)	-1.92 (0.59)	-2.01 (0.13)$_L$	10.83 (2.10)$_L$	-2.53 (0.25)$_L$	3.47 (0.17)$_L$
Entertainment:WTP	-0.47 (0.19)	-0.55 (0.15)	-0.32 (0.12)	-2.03 (0.61)	-0.61 (0.21)	10.44 (2.11)$_L$	-950.13 (121.29)$_L$	-0.60 (0.16)$_S$
Hardware:WTP	0.26 (0.15)	-2.59 (0.37)$_L$	0.14 (0.26)	0.09 (0.60)	-1.44 (0.23)$_L$	12.13 (2.11)$_L$	-0.12 (0.28)	-1.53 (0.31)$_L$
Kitchen and Household:WTP	-0.89 (0.19)$_L$	-0.84 (0.14)$_L$	-1.32 (0.14)$_L$	-2.64 (0.59)$_M$	-0.01 (0.15)	8.46 (2.22)$_S$	1.00 (0.43)	0.74 (0.15)$_L$
other:WTP	0.87 (0.12)$_L$	2.07 (0.17)$_L$	-0.35 (0.12)	-2.68 (0.59)$_M$	-1.33 (0.14)$_L$	11.61 (2.10)$_L$	-0.97 (0.20)$_L$	0.14 (0.15)
Personal Care:WTP	5.58 (0.21)$_L$	-1.52 (0.17)$_L$	-1.02 (0.11)$_L$	-3.50 (0.59)$_L$	-0.58 (0.13)$_M$	11.92 (2.10)$_L$	-0.87 (0.22)$_S$	-1.35 (0.15)$_L$
Sound and Vision:WTP	0.94 (0.14)$_L$	-0.50 (0.51)	-6.02 (0.73)$_L$	-5.86 (0.73)$_L$	-3.24 (0.28)$_L$	12.47 (2.10)$_L$	0.55 (1.27)	1.50 (0.86)
Sports and Activity:WTP	-0.45 (0.16)	-4.08 (0.37)$_L$	-0.79 (0.23)	-5.10 (0.68)$_L$	-0.85 (0.15)$_L$	11.49 (2.10)$_L$	-0.74 (0.21)	-0.31 (0.34)
Toys:WTP	0.70 (0.13)$_L$	-0.31 (0.14)	-1.02 (0.10)$_L$	-2.53 (0.59)$_M$	-0.10 (0.12)	11.19 (2.10)$_L$	3.97 (0.35)$_L$	-0.20 (0.13)

S: p-value $< 5\%$ α-level
M: p-value $< 1\%$ α-level
L: p-value $< 0.1\%$ α-level

Table 11: Coefficient estimates for RC, WTP and UTP over the different shop categories during the holiday period. Shop category *DIY* is taken as a baseline.

Variables	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7	Cluster 8	Cluster 9	Cluster 10
WTP	0.42 (0.08)$_L$	-0.20 (0.07)	0.37 (0.07)$_L$	-0.55 (0.08)$_L$	0.12 (0.14)	-0.54 (0.09)$_L$	-0.10 (0.07)	-1.26 (0.11)$_L$	-0.33 (0.07)$_L$	-1.89 (0.22)$_L$
UTP	-0.41 (0.07)$_L$	0.04 (0.06)	-0.18 (0.06)	-0.50 (0.06)$_L$	0.42 (0.09)$_L$	0.16 (0.05)	-0.21 (0.04)$_L$	-0.21 (0.06)	-0.26 (0.07)$_S$	-1.91 (0.24)$_L$
RC	0.21 (0.04)$_L$	-0.04 (0.03)	0.34 (0.03)$_L$	0.07 (0.03)	0.97 (0.06)$_L$	-0.25 (0.04)$_L$	0.32 (0.02)$_L$	0.38 (0.03)$_L$	0.06 (0.04)	-0.16 (0.07)
Drugs and Baby:WTP	1.37 (0.13)$_L$	0.57 (0.09)$_L$	-0.59 (0.09)$_L$	0.51 (0.10)$_L$	-1.06 (0.15)$_L$	0.28 (0.10)	-0.32 (0.08)$_S$	1.42 (0.12)$_L$	0.45 (0.09)$_L$	0.76 (0.23)
Entertainment:WTP	-1.05 (0.10)$_L$	0.14 (0.08)	-0.64 (0.07)$_L$	0.31 (0.09)	0.59 (0.15)$_S$	-0.95 (0.16)$_L$	-0.14 (0.11)	2.38 (0.13)$_L$	0.60 (0.08)$_L$	1.46 (0.22)$_L$
Hardware:WTP	-0.57 (0.09)$_L$	1.04 (0.09)$_L$	-0.56 (0.09)$_L$	0.49 (0.09)$_L$	0.30 (0.15)	0.99 (0.10)$_L$	-0.43 (0.11)$_S$	1.16 (0.12)$_L$	0.24 (0.11)	0.19 (0.26)
Kitchen and Household:WTP	2.65 (0.23)$_L$	0.83 (0.11)$_L$	-0.53 (0.08)$_L$	1.00 (0.09)$_L$	-0.72 (0.16)$_M$	0.59 (0.10)$_L$	0.24 (0.10)	1.97 (0.11)$_L$	0.62 (0.11)$_L$	1.46 (0.24)$_L$
other:WTP	-0.95 (0.09)$_L$	-0.36 (0.09)$_S$	-0.97 (0.08)$_L$	-0.10 (0.10)	-0.04 (0.15)	1.02 (0.12)$_L$	0.12 (0.08)	0.62 (0.13)$_L$	0.55 (0.23)	2.50 (0.32)$_L$
Personal Care:WTP	-1.21 (0.09)$_L$	-0.11 (0.08)	-0.91 (0.08)$_L$	0.14 (0.09)	-0.90 (0.15)$_L$	-0.58 (0.11)$_L$	0.05 (0.23)	0.81 (0.12)$_L$	-0.32 (0.10)	4.15 (0.22)$_L$
Domestic Appliances:WTP	-0.98 (0.10)$_L$	0.36 (0.09)$_S$	-0.48 (0.08)$_L$	-0.17 (0.09)	2.71 (0.17)$_L$	-0.01 (0.10)	-0.44 (0.07)$_L$	2.19 (0.12)$_L$	0.51 (0.09)$_L$	0.24 (0.23)
Sound and Vision:WTP	-0.79 (0.10)$_L$	-0.62 (0.11)$_L$	-0.14 (0.09)	0.24 (0.16)	1.05 (0.15)$_L$	0.72 (0.11)$_L$	-0.87 (0.11)$_L$	1.82 (0.14)$_L$	-0.39 (0.10)$_S$	2.09 (0.24)$_L$
Sports and Activity:WTP	-0.75 (0.12)$_L$	0.05 (0.11)	-1.51 (0.11)$_L$	-0.04 (0.11)	0.30 (0.17)	0.45 (0.11)$_M$	-5.76 (0.46)$_L$	1.48 (0.24)$_L$	-0.70 (0.11)$_L$	2.03 (0.23)$_L$
Toys:WTP	-0.54 (0.09)$_L$	-0.15 (0.07)	-2.27 (0.09)$_L$	0.47 (0.10)$_L$	0.98 (0.15)$_L$	0.98 (0.10)$_L$	-1.23 (0.07)$_L$	1.04 (0.11)$_L$	-0.17 (0.08)	1.58 (0.22)$_L$
Drugs and Baby:UTP	2.96 (0.10)$_L$	-0.06 (0.06)	0.58 (0.07)$_L$	0.63 (0.07)$_L$	-0.09 (0.09)	-0.29 (0.06)$_L$	0.39 (0.05)$_L$	0.30 (0.07)$_M$	0.42 (0.08)$_L$	1.99 (0.24)$_L$
Entertainment:UTP	0.90 (0.07)$_L$	0.24 (0.06)$_S$	0.23 (0.07)	0.46 (0.07)$_L$	-1.25 (0.10)$_L$	1.11 (0.07)$_L$	0.35 (0.05)$_L$	0.55 (0.08)$_L$	0.27 (0.07)$_S$	2.15 (0.24)$_L$
Hardware:UTP	0.15 (0.08)	-0.97 (0.08)$_L$	-0.93 (0.08)$_L$	0.55 (0.07)$_L$	-0.55 (0.09)$_L$	-0.41 (0.07)$_L$	-0.14 (0.09)	0.30 (0.08)$_S$	0.41 (0.08)$_L$	2.75 (0.24)$_L$
Kitchen and Household:UTP	3.59 (0.18)$_L$	-0.47 (0.08)$_L$	-0.04 (0.07)	0.02 (0.07)	-0.49 (0.09)$_L$	-0.06 (0.06)	0.09 (0.07)	-0.27 (0.07)$_S$	-0.99 (0.13)$_L$	2.50 (0.24)$_L$
other:UTP	-0.27 (0.08)	0.08 (0.06)	-0.05 (0.06)	0.38 (0.07)$_L$	-0.56 (0.09)$_L$	0.19 (0.07)	-1.20 (0.07)$_L$	0.44 (0.07)$_L$	4.20 (0.12)$_L$	2.40 (0.25)$_L$
Personal Care:UTP	0.71 (0.07)$_L$	-0.44 (0.06)$_L$	0.25 (0.06)$_M$	1.03 (0.06)$_L$	-0.38 (0.09)$_M$	3.41 (0.06)$_L$	3.40 (0.06)$_L$	0.45 (0.07)$_L$	1.24 (0.08)$_L$	3.26 (0.24)$_L$
Domestic Appliances:UTP	0.50 (0.07)$_L$	-0.11 (0.07)	-0.24 (0.07)	0.24 (0.07)	-0.49 (0.13)$_S$	0.47 (0.06)$_L$	-0.51 (0.05)$_L$	0.72 (0.08)$_L$	0.68 (0.08)$_L$	0.68 (0.24)
Sound and Vision:UTP	-0.26 (0.09)	-0.08 (0.07)	0.10 (0.07)	1.32 (0.12)$_L$	0.78 (0.10)$_L$	0.24 (0.07)	0.13 (0.05)	-0.07 (0.11)	0.38 (0.07)$_L$	2.97 (0.25)$_L$
Sports and Activity:UTP	0.10 (0.09)	-1.46 (0.10)$_L$	0.34 (0.08)$_M$	0.57 (0.08)$_L$	-0.39 (0.10)$_S$	-0.18 (0.07)	0.22 (0.08)	1.95 (0.12)$_L$	0.58 (0.09)$_L$	2.13 (0.24)$_L$
Toys:UTP	0.55 (0.07)$_L$	0.11 (0.06)	0.10 (0.06)	0.87 (0.07)$_L$	-0.18 (0.09)	-0.50 (0.06)$_L$	-0.07 (0.04)	0.35 (0.06)$_L$	0.42 (0.07)$_L$	2.20 (0.24)$_L$
Drugs and Baby:RC	2.22 (0.06)$_L$	0.65 (0.04)$_L$	1.08 (0.04)$_L$	0.13 (0.04)	0.22 (0.06)$_S$	0.52 (0.04)$_L$	-0.12 (0.03)$_S$	0.23 (0.04)$_L$	0.29 (0.04)$_L$	0.97 (0.07)$_L$
Entertainment:RC	-0.07 (0.05)	0.09 (0.04)	-0.31 (0.04)$_L$	-0.14 (0.04)	-1.01 (0.06)$_L$	2.54 (0.05)$_L$	0.94 (0.04)$_L$	1.27 (0.05)$_L$	0.54 (0.04)$_L$	0.05 (0.07)
Hardware:RC	-0.08 (0.05)	0.40 (0.04)$_L$	-0.10 (0.04)	0.32 (0.04)$_L$	-0.73 (0.06)$_L$	0.43 (0.05)$_L$	1.36 (0.05)$_L$	0.30 (0.04)$_L$	-0.47 (0.06)$_L$	1.40 (0.08)$_L$
Kitchen and Household:RC	2.66 (0.11)$_L$	-0.12 (0.05)	-0.17 (0.04)$_M$	0.37 (0.04)$_L$	-0.69 (0.06)$_L$	0.78 (0.04)$_L$	-0.35 (0.04)$_L$	-0.07 (0.04)	-0.61 (0.06)$_L$	0.30 (0.08)$_S$
other:RC	0.03 (0.05)	0.43 (0.04)$_L$	-0.61 (0.04)$_L$	-0.30 (0.04)$_L$	-1.53 (0.06)$_L$	1.86 (0.05)$_L$	-0.52 (0.03)$_L$	-0.38 (0.04)$_L$	0.32 (0.11)	3.46 (0.09)$_L$
Personal Care:RC	0.83 (0.04)$_L$	0.02 (0.04)	0.32 (0.04)$_L$	0.64 (0.03)$_L$	-0.74 (0.06)$_L$	-0.18 (0.05)	0.34 (0.06)$_L$	0.58 (0.04)$_L$	0.27 (0.05)$_L$	0.84 (0.08)$_L$
Domestic Appliances:RC	-0.05 (0.05)	-0.21 (0.04)$_L$	-0.51 (0.04)$_L$	-0.31 (0.04)$_L$	1.29 (0.08)$_L$	0.55 (0.04)$_L$	-1.37 (0.03)$_L$	1.08 (0.04)$_L$	0.03 (0.05)	-1.03 (0.07)$_L$
Sound and Vision:RC	-0.10 (0.05)	-0.25 (0.05)$_L$	-0.03 (0.04)	1.36 (0.06)$_L$	0.67 (0.07)$_L$	0.31 (0.05)$_L$	-0.52 (0.04)$_L$	0.17 (0.06)	-0.35 (0.04)$_L$	1.20 (0.08)$_L$
Sports and Activity:RC	-0.44 (0.05)$_L$	-0.09 (0.05)	-0.16 (0.04)$_S$	0.31 (0.04)$_L$	-0.97 (0.07)$_L$	0.69 (0.04)$_L$	-0.09 (0.05)	0.65 (0.09)$_L$	0.37 (0.06)$_L$	0.68 (0.08)$_L$
Toys:RC	0.11 (0.04)	0.26 (0.03)$_L$	-0.24 (0.04)$_L$	1.82 (0.04)$_L$	0.75 (0.06)$_L$	0.22 (0.04)$_L$	-0.33 (0.03)$_L$	0.19 (0.03)$_L$	0.33 (0.04)$_L$	0.77 (0.07)$_L$

Variables	Cluster 11	Cluster 12	Cluster 13	Cluster 14	Cluster 15	Cluster 16	Cluster 17	Cluster 18	Cluster 19	Cluster 20
WTP	1.20 (0.08)$_L$	-0.47 (0.07)$_L$	-0.61 (0.20)	-0.53 (0.09)$_L$	-0.89 (0.22)$_S$	-3.36 (0.32)$_L$	-1.50 (0.15)$_L$	-1.58 (0.24)$_L$	-2.42 (0.27)$_L$	0.34 (0.13)
UTP	-0.09 (0.08)	-0.04 (0.04)	1.73 (0.12)$_L$	0.07 (0.06)	0.83 (0.09)$_L$	-1.16 (0.15)$_L$	-1.98 (0.13)$_L$	0.64 (0.19)	0.23 (0.06)$_S$	0.74 (0.06)$_L$
RC	-0.44 (0.04)$_L$	0.44 (0.02)$_L$	2.91 (0.10)$_L$	0.31 (0.04)$_L$	0.54 (0.09)$_L$	0.52 (0.08)$_L$	-1.06 (0.06)$_L$	1.83 (0.09)$_L$	0.00 (0.04)	0.24 (0.07)
Drugs and Baby:WTP	-1.83 (0.09)$_L$	0.60 (0.08)$_L$	-2.72 (0.28)$_L$	0.18 (0.11)	2.90 (0.26)$_L$	-6.77 (2.77)	-0.57 (0.20)	2.45 (0.26)$_L$	2.31 (0.27)$_L$	-0.84 (0.14)$_L$
Entertainment:WTP	-1.34 (0.10)$_L$	0.96 (0.11)$_L$	1.33 (0.21)$_L$	0.56 (0.11)$_L$	-0.14 (0.24)	2.34 (0.33)$_L$	2.35 (0.16)$_L$	0.44 (0.26)	2.41 (0.27)$_L$	-0.34 (0.14)
Hardware:WTP	-5.18 (0.14)$_L$	-0.85 (0.11)$_L$	1.17 (0.21)$_L$	0.31 (0.09)	3.78 (0.27)$_L$	3.52 (0.33)$_L$	2.31 (0.16)$_L$	0.21 (0.30)	0.90 (0.27)	-0.48 (0.15)
Kitchen and Household:WTP	-0.27 (0.12)	-0.48 (0.12)$_S$	-0.22 (0.29)	0.15 (0.12)	1.62 (0.26)$_L$	1.46 (0.36)$_M$	1.71 (0.19)$_L$	5.62 (0.29)$_L$	2.48 (0.27)$_L$	-0.69 (0.17)$_M$
other:WTP	-1.70 (0.09)$_L$	1.02 (0.08)$_L$	1.06 (0.23)$_L$	0.11 (0.11)	0.07 (0.25)	2.38 (0.34)$_L$	1.50 (0.15)$_L$	2.25 (0.25)$_L$	2.22 (0.27)$_L$	0.77 (0.16)$_L$
Personal Care:WTP	-6.63 (1.15)$_L$	0.36 (0.09)$_S$	-0.01 (0.21)	-0.12 (0.10)	0.22 (0.22)	4.02 (0.33)$_L$	1.15 (0.16)$_L$	2.04 (0.28)$_L$	1.07 (0.27)$_S$	-1.74 (0.16)$_L$
Domestic Appliances:WTP	-1.48 (0.10)$_L$	0.63 (0.08)$_L$	0.42 (0.23)	-0.68 (0.10)$_L$	0.65 (0.27)	2.87 (0.33)$_L$	1.53 (0.15)$_L$	2.23 (0.26)$_L$	2.50 (0.27)$_L$	0.17 (0.14)
Sound and Vision:WTP	0.00 (0.11)	-0.03 (0.08)	-0.34 (0.24)	0.63 (0.11)$_L$	0.96 (0.28)	3.01 (0.33)$_L$	2.41 (0.16)$_L$	0.91 (0.28)	3.05 (0.30)$_L$	-0.68 (0.20)
Sports and Activity:WTP	-1.58 (0.11)$_L$	-0.69 (0.13)$_L$	1.50 (0.25)$_L$	-1.36 (0.19)$_L$	0.75 (0.24)	1.58 (0.45)	1.70 (0.19)$_L$	-0.27 (0.30)	2.59 (0.29)$_L$	-2.18 (0.29)$_L$
Toys:WTP	-0.75 (0.09)$_L$	0.44 (0.08)$_L$	1.07 (0.21)$_L$	-0.71 (0.10)$_L$	0.78 (0.22)	3.43 (0.33)$_L$	0.46 (0.16)	1.70 (0.25)$_L$	1.78 (0.28)$_L$	-0.56 (0.14)$_S$
Drugs and Baby:UTP	0.33 (0.08)$_M$	-0.15 (0.05)	-1.32 (0.13)$_L$	0.18 (0.07)	0.93 (0.13)$_L$	1.93 (0.26)$_L$	1.62 (0.14)$_L$	-1.14 (0.20)$_L$	-0.29 (0.07)$_M$	-0.71 (0.07)$_L$
Entertainment:UTP	0.60 (0.09)$_L$	-0.87 (0.07)$_L$	-2.29 (0.12)$_L$	-0.10 (0.08)	-0.59 (0.10)$_L$	1.50 (0.15)$_L$	2.57 (0.14)$_L$	-1.03 (0.19)$_L$	-0.49 (0.07)$_L$	-0.96 (0.06)$_L$
Hardware:UTP	-1.81 (0.11)$_L$	0.85 (0.06)$_L$	-1.90 (0.13)$_L$	-0.08 (0.06)	1.32 (0.13)$_L$	1.67 (0.16)$_L$	2.58 (0.14)$_L$	-2.49 (0.22)$_L$	-0.70 (0.07)$_L$	-0.66 (0.08)$_L$
Kitchen and Household:UTP	-0.52 (0.11)$_L$	0.07 (0.06)	-2.51 (0.18)$_L$	0.12 (0.08)	-0.24 (0.13)	0.13 (0.18)	2.81 (0.16)$_L$	-2.34 (0.26)$_L$	0.17 (0.07)	-1.00 (0.08)$_L$
other:UTP	0.09 (0.08)	0.25 (0.05)$_L$	-2.10 (0.14)$_L$	-0.13 (0.07)	-0.60 (0.10)$_L$	1.29 (0.15)$_L$	1.90 (0.13)$_L$	0.09 (0.20)	0.05 (0.07)	-0.08 (0.08)
Personal Care:UTP	1.64 (0.08)$_L$	0.14 (0.05)	-1.59 (0.12)$_L$	-0.68 (0.07)$_L$	-1.35 (0.09)$_L$	1.29 (0.16)$_L$	-0.10 (0.15)	1.34 (0.19)$_L$	-1.01 (0.07)$_L$	-0.01 (0.07)
Domestic Appliances:UTP	0.28 (0.08)	0.31 (0.05)$_L$	-0.89 (0.13)$_L$	-0.26 (0.07)$_S$	-1.41 (0.15)$_L$	0.80 (0.16)$_L$	1.91 (0.13)$_L$	0.56 (0.19)	-1.23 (0.08)$_L$	-0.19 (0.07)
Sound and Vision:UTP	0.41 (0.09)$_M$	-0.16 (0.05)	-4.54 (0.29)$_L$	-0.17 (0.07)	-0.22 (0.12)	1.91 (0.15)$_L$	1.47 (0.16)$_L$	-0.76 (0.20)$_S$	0.92 (0.09)$_L$	-2.48 (0.17)$_L$
Sports and Activity:UTP	0.34 (0.09)$_S$	0.27 (0.06)$_M$	-1.94 (0.15)$_L$	-1.48 (0.12)$_L$	-0.80 (0.11)$_L$	-0.61 (0.22)	1.44 (0.16)$_L$	-0.79 (0.20)$_S$	-0.77 (0.10)$_L$	-0.23 (0.08)
Toys:UTP	0.86 (0.08)$_L$	0.44 (0.04)$_L$	-1.43 (0.12)$_L$	0.56 (0.06)$_L$	-0.49 (0.09)$_L$	2.58 (0.15)$_L$	1.63 (0.14)$_L$	-0.33 (0.19)	2.25 (0.07)$_L$	-0.10 (0.06)
Drugs and Baby:RC	1.84 (0.05)$_L$	-0.34 (0.03)$_L$	-2.09 (0.10)$_L$	0.94 (0.05)$_L$	1.29 (0.13)$_L$	-3.66 (0.23)$_L$	1.52 (0.06)$_L$	-1.88 (0.10)$_L$	0.20 (0.05)$_S$	0.92 (0.07)$_L$
Entertainment:RC	2.15 (0.05)$_L$	-0.23 (0.04)$_L$	-2.44 (0.10)$_L$	-0.45 (0.05)$_L$	-0.61 (0.10)$_L$	-0.37 (0.09)$_M$	2.74 (0.07)$_L$	-2.39 (0.10)$_L$	0.36 (0.05)$_L$	0.34 (0.07)$_L$
Hardware:RC	-1.04 (0.06)$_L$	-0.02 (0.04)	-2.23 (0.10)$_L$	0.01 (0.04)	3.01 (0.12)$_L$	1.07 (0.09)$_L$	2.77 (0.06)$_L$	-3.51 (0.11)$_L$	0.40 (0.05)$_L$	0.96 (0.07)$_L$
Kitchen and Household:RC	0.37 (0.06)$_L$	-0.34 (0.04)$_L$	-1.99 (0.13)$_L$	0.59 (0.05)$_L$	-0.37 (0.11)	-1.89 (0.10)$_L$	0.32 (0.09)	-2.14 (0.12)$_L$	0.49 (0.05)$_L$	-0.75 (0.08)$_L$
other:RC	0.97 (0.05)$_L$	-0.01 (0.03)	-1.60 (0.11)$_L$	-0.20 (0.04)$_L$	-0.66 (0.10)$_L$	0.09 (0.09)	1.86 (0.06)$_L$	-1.51 (0.11)$_L$	0.97 (0.05)$_L$	1.28 (0.08)$_L$
Personal Care:RC	2.85 (0.05)$_L$	0.54 (0.03)$_L$	-2.70 (0.10)$_L$	-0.90 (0.04)$_L$	-1.35 (0.09)$_L$	0.79 (0.09)$_L$	0.69 (0.06)$_L$	-0.82 (0.10)$_L$	-0.82 (0.05)$_L$	1.23 (0.07)$_L$
Domestic Appliances:RC	0.87 (0.05)$_L$	0.19 (0.03)$_L$	-2.10 (0.10)$_L$	-0.15 (0.04)$_S$	1.57 (0.12)$_L$	0.81 (0.09)$_L$	2.44 (0.06)$_L$	1.08 (0.10)$_L$	-0.51 (0.05)$_L$	0.88 (0.07)$_L$
Sound and Vision:RC	0.43 (0.06)$_L$	-0.49 (0.03)$_L$	-4.20 (0.11)$_L$	0.00 (0.04)	0.19 (0.12)	1.36 (0.08)$_L$	2.76 (0.07)$_L$	-1.27 (0.11)$_L$	2.51 (0.08)$_L$	-0.20 (0.09)
Sports and Activity:RC	0.67 (0.06)$_L$	-0.95 (0.04)$_L$	-2.30 (0.11)$_L$	-1.50 (0.06)$_L$	-0.68 (0.10)$_L$	-0.25 (0.10)	1.92 (0.08)$_L$	-1.83 (0.11)$_L$	0.06 (0.06)	-0.78 (0.10)$_L$
Toys:RC	2.02 (0.05)$_L$	0.90 (0.03)$_L$	-1.98 (0.10)$_L$	1.18 (0.04)$_L$	0.23 (0.09)	1.36 (0.08)$_L$	1.12 (0.06)$_L$	-1.24 (0.09)$_L$	-0.47 (0.06)$_L$	0.89 (0.07)$_L$

S: p-value $< 5\%$ α-level
M: p-value $< 1\%$ α-level
L: p-value $< 0.1\%$ α-level

Table 12: Coefficient estimates for RC, WTP and WTPSC for modeling effect willingness to pay around Sinterklaas and Christmas. Shop category *DIY* is taken as a baseline.

Variables	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7
RC	0.21 (0.03)$_L$	-0.67 (0.06)$_L$	1.38 (0.08)$_L$	0.15 (0.05)	0.68 (0.06)$_L$	0.25 (0.06)$_M$	0.14 (0.05)
WTP	-0.32 (0.10)	-1.82 (0.13)$_L$	0.06 (0.18)	0.42 (0.10)$_M$	0.06 (0.13)	0.64 (0.10)$_L$	-0.95 (0.13)$_L$
WTPSC	-1.76 (0.34)$_L$	-1.52 (0.27)$_L$	-0.30 (0.40)	-0.69 (0.38)	-2.38 (0.36)$_L$	-0.21 (0.25)	0.09 (0.30)
Drugs and Baby:RC	0.38 (0.04)$_L$	0.91 (0.07)$_L$	0.65 (0.10)$_L$	0.50 (0.06)$_L$	0.74 (0.10)$_L$	-0.04 (0.07)	0.47 (0.06)$_L$
Entertainment:RC	0.29 (0.04)$_L$	2.29 (0.14)$_L$	-1.08 (0.08)$_L$	0.68 (0.08)$_L$	-0.71 (0.06)$_L$	0.74 (0.08)$_L$	0.39 (0.09)$_M$
Hardware:RC	1.84 (0.05)$_L$	1.33 (0.08)$_L$	-1.25 (0.08)$_L$	-0.06 (0.06)	-0.78 (0.08)$_L$	-0.22 (0.07)	1.13 (0.06)$_L$
Kitchen and Household:RC	-0.53 (0.05)$_L$	-0.36 (0.07)$_L$	-0.85 (0.09)$_L$	-0.51 (0.09)$_L$	0.58 (0.21)	-0.24 (0.07)	-0.20 (0.06)
other:RC	-0.01 (0.05)	1.13 (0.07)$_L$	-0.98 (0.08)$_L$	-0.23 (0.06)$_S$	0.14 (0.10)	-0.05 (0.08)	-0.88 (0.07)$_L$
Personal Care:RC	-0.34 (0.04)$_L$	0.80 (0.07)$_L$	-1.57 (0.09)$_L$	-0.56 (0.07)$_L$	-0.22 (0.07)	0.22 (0.07)	1.49 (0.07)$_L$
Domestic Appliances:RC	-0.02 (0.04)	0.28 (0.07)$_S$	-0.31 (0.09)	0.12 (0.05)	0.47 (0.08)$_L$	-0.02 (0.07)	-0.25 (0.06)$_M$
Sound and Vision:RC	0.40 (0.04)$_L$	0.65 (0.07)$_L$	-1.20 (0.09)$_L$	0.09 (0.07)	-0.89 (0.07)$_L$	-0.20 (0.08)	0.54 (0.06)$_L$
Sports and Activity:RC	0.14 (0.07)	-0.05 (0.10)	-0.98 (0.12)$_L$	-0.84 (0.08)$_L$	-0.71 (0.09)$_L$	0.62 (0.10)$_L$	1.42 (0.11)$_L$
Toys:RC	1.24 (0.04)$_L$	0.95 (0.06)$_L$	-0.67 (0.08)$_L$	-0.42 (0.06)$_L$	-0.49 (0.06)$_L$	0.09 (0.07)	0.14 (0.06)
Drugs and Baby:WTP	0.26 (0.11)	1.73 (0.15)$_L$	0.45 (0.20)	-0.36 (0.11)	-2.95 (0.61)$_L$	-0.96 (0.12)$_L$	-0.22 (0.14)
Entertainment:WTP	0.52 (0.11)$_L$	2.65 (0.29)$_L$	0.15 (0.18)	-1.28 (0.14)$_L$	-0.02 (0.13)	-0.85 (0.14)$_L$	0.31 (0.20)
Hardware:WTP	-0.90 (0.14)$_L$	2.60 (0.16)$_L$	0.27 (0.19)	-0.78 (0.12)$_L$	0.42 (0.15)	-0.81 (0.12)$_L$	1.52 (0.15)$_L$
Kitchen and Household:WTP	-0.35 (0.14)	1.26 (0.14)$_L$	-0.69 (0.20)	2.50 (0.16)$_L$	-4.80 (0.58)$_L$	-0.60 (0.12)$_L$	0.60 (0.14)$_M$
other:WTP	0.25 (0.13)	1.95 (0.16)$_L$	0.19 (0.18)	-0.60 (0.12)$_L$	1.99 (0.23)$_L$	-0.76 (0.15)$_L$	0.08 (0.15)
Personal Care:WTP	0.22 (0.11)	1.07 (0.16)$_L$	-1.00 (0.21)$_L$	-2.96 (0.17)$_L$	-1.05 (0.16)$_L$	-0.83 (0.12)$_L$	0.64 (0.18)
Domestic Appliances:WTP	0.00 (0.11)	2.19 (0.15)$_L$	0.51 (0.19)	-0.58 (0.10)$_L$	-0.44 (0.17)	-1.22 (0.11)$_L$	1.85 (0.14)$_L$
Sound and Vision:WTP	0.21 (0.12)	1.27 (0.16)$_L$	-0.50 (0.20)	-0.38 (0.13)	-0.62 (0.15)$_M$	-0.44 (0.13)	-0.42 (0.16)
Sports and Activity:WTP	-0.39 (0.14)	2.96 (0.17)$_L$	0.09 (0.26)	-1.35 (0.17)$_L$	-0.38 (0.19)	-0.31 (0.14)	-1.39 (0.24)$_L$
Toys:WTP	0.05 (0.12)	1.77 (0.14)$_L$	-0.35 (0.18)	-0.71 (0.11)$_L$	-0.62 (0.13)$_L$	-2.21 (0.11)$_L$	0.57 (0.14)$_M$
Drugs and Baby:WTPSC	1.67 (0.36)$_L$	1.60 (0.32)$_L$	0.74 (0.47)	0.81 (0.40)	-9.66 (7.95)	-0.54 (0.28)	-1.12 (0.33)
Entertainment:WTPSC	2.18 (0.35)$_L$	-625.16 (104.26)$_L$	-0.46 (0.42)	-0.05 (0.43)	2.34 (0.36)$_L$	0.63 (0.30)	-2.37 (0.56)$_M$
Hardware:WTPSC	1.58 (0.37)$_M$	1.64 (0.31)$_L$	0.10 (0.42)	0.49 (0.40)	2.59 (0.38)$_L$	0.02 (0.27)	0.23 (0.32)
Kitchen and Household:WTPSC	1.28 (0.41)	0.79 (0.29)	0.16 (0.45)	-0.01 (0.51)	-0.57 (645256349.60)	-0.70 (0.31)	-0.05 (0.33)
other:WTPSC	1.85 (0.38)$_L$	1.94 (0.33)$_L$	0.55 (0.42)	0.06 (0.42)	4.96 (0.49)$_L$	-0.45 (0.34)	-1.63 (0.40)$_M$
Personal Care:WTPSC	1.90 (0.37)$_L$	0.30 (0.47)	0.24 (0.51)	0.15 (0.55)	1.87 (0.46)$_S$	0.28 (0.35)	-0.77 (0.49)
Domestic Appliances:WTPSC	1.23 (0.35)	1.11 (0.31)	0.81 (0.43)	-0.16 (0.39)	1.30 (0.42)	0.37 (0.26)	0.83 (0.32)
Sound and Vision:WTPSC	1.43 (0.35)$_M$	1.15 (0.31)$_S$	0.15 (0.44)	0.84 (0.42)	2.63 (0.39)$_L$	-0.34 (0.30)	-1.64 (0.39)$_M$
Sports and Activity:WTPSC	0.42 (0.53)	1.24 (0.50)	-0.32 (0.78)	-0.80 (0.52)	0.63 (0.63)	0.29 (0.31)	-2.22 (0.55)$_S$
Toys:WTPSC	1.67 (0.35)$_L$	1.13 (0.28)$_S$	-0.21 (0.42)	0.95 (0.39)	1.64 (0.36)$_M$	-0.83 (0.26)	-0.60 (0.33)

Variables	Cluster 8	Cluster 9	Cluster 10	Cluster 11	Cluster 12	Cluster 13
RC	0.29 (0.11)	0.36 (0.05)$_L$	-0.28 (0.13)	-0.40 (0.07)$_L$	0.10 (0.10)	0.66 (0.09)$_L$
WTP	-1.59 (0.23)$_L$	-0.31 (0.08)$_S$	1.43 (0.19)$_L$	0.96 (0.16)$_L$	-0.20 (0.17)	0.61 (0.15)$_S$
WTPSC	-0.58 (0.59)	-0.47 (0.19)	2.48 (0.32)$_L$	-0.82 (0.53)	0.24 (0.28)	0.74 (0.30)
Drugs and Baby:RC	1.12 (0.12)$_L$	-0.17 (0.06)	1.60 (0.14)$_L$	1.67 (0.08)$_L$	0.70 (0.10)$_L$	0.73 (0.11)$_L$
Entertainment:RC	-0.17 (0.12)	-0.37 (0.06)$_L$	7.27 (0.19)$_L$	1.21 (0.08)$_L$	0.44 (0.10)$_M$	-0.55 (0.10)$_L$
Hardware:RC	-0.30 (0.12)	0.21 (0.06)	2.34 (0.15)$_L$	0.25 (0.09)	-0.01 (0.11)	3.37 (0.14)$_L$
Kitchen and Household:RC	0.03 (0.13)	0.03 (0.07)	1.14 (0.15)$_L$	1.51 (0.09)$_L$	2.97 (0.20)$_L$	-1.19 (0.16)$_L$
other:RC	-1.59 (0.14)$_L$	2.23 (0.12)$_L$	0.97 (0.14)$_L$	1.52 (0.11)$_L$	1.71 (0.11)$_L$	-0.40 (0.11)
Personal Care:RC	1.67 (0.13)$_L$	0.74 (0.08)$_L$	1.13 (0.14)$_L$	0.76 (0.08)$_L$	0.27 (0.10)	0.41 (0.15)
Domestic Appliances:RC	-0.61 (0.13)$_L$	-0.12 (0.07)	3.72 (0.14)$_L$	3.32 (0.08)$_L$	-1.22 (0.11)$_L$	0.47 (0.14)
Sound and Vision:RC	-0.81 (0.13)$_L$	1.26 (0.09)$_L$	1.25 (0.15)$_L$	0.49 (0.09)$_L$	0.18 (0.13)	-0.92 (0.16)$_L$
Sports and Activity:RC	-0.57 (0.17)	-0.57 (0.07)$_L$	2.24 (0.20)$_L$	1.16 (0.12)$_L$	0.13 (0.15)	-2.04 (0.15)$_L$
Toys:RC	0.25 (0.12)	1.14 (0.05)$_L$	1.00 (0.14)$_L$	1.64 (0.07)$_L$	-0.86 (0.10)$_L$	0.38 (0.09)$_M$
Drugs and Baby:WTP	-0.14 (0.24)	0.58 (0.10)$_L$	-2.51 (0.21)$_L$	-2.08 (0.17)$_L$	-0.03 (0.18)	2.09 (0.20)$_L$
Entertainment:WTP	0.46 (0.25)	0.01 (0.09)	3.48 (0.29)$_L$	-0.09 (0.16)	-0.88 (0.17)$_L$	-1.48 (0.18)$_L$
Hardware:WTP	1.15 (0.24)$_L$	0.75 (0.10)$_L$	-1.25 (0.22)$_L$	-3.12 (0.37)$_L$	-0.01 (0.19)	3.51 (0.24)$_L$
Kitchen and Household:WTP	3.00 (0.25)$_L$	0.80 (0.11)$_L$	0.76 (0.23)	-0.80 (0.19)$_M$	2.24 (0.47)$_L$	0.16 (0.26)
other:WTP	0.09 (0.27)	4.39 (0.26)$_L$	-1.20 (0.20)$_L$	-0.46 (0.24)	3.66 (0.20)$_L$	-1.22 (0.21)$_L$
Personal Care:WTP	2.25 (0.25)$_L$	0.26 (0.16)	-1.72 (0.20)$_L$	-1.77 (0.18)$_L$	0.71 (0.18)$_S$	-1.11 (0.34)
Domestic Appliances:WTP	1.80 (0.24)$_L$	0.15 (0.12)	0.62 (0.21)	0.87 (0.17)$_L$	0.02 (0.19)	-0.43 (0.23)
Sound and Vision:WTP	1.02 (0.26)$_S$	-0.16 (0.17)	-1.36 (0.22)$_L$	-0.83 (0.19)$_M$	2.89 (0.20)$_L$	0.61 (0.28)
Sports and Activity:WTP	2.51 (0.31)$_L$	-0.51 (0.12)$_M$	0.72 (0.39)	-0.40 (0.22)	-0.75 (0.28)	-1.87 (0.28)$_L$
Toys:WTP	1.20 (0.23)$_L$	0.14 (0.09)	-1.08 (0.20)$_L$	-1.06 (0.16)$_L$	-0.37 (0.18)	0.13 (0.16)
Drugs and Baby:WTPSC	0.11 (0.60)	0.61 (0.23)	-3.74 (0.39)$_L$	-0.03 (0.54)	0.17 (0.31)	0.71 (0.47)
Entertainment:WTPSC	-1.07 (0.65)	-0.02 (0.21)	-0.13 (0.72)	1.15 (0.53)	-1.21 (0.28)$_M$	-1.52 (0.39)$_S$
Hardware:WTPSC	-0.11 (0.61)	0.82 (0.20)$_M$	-2.18 (0.36)$_L$	-1.18 (0.63)	-0.08 (0.32)	3.27 (0.40)$_L$
Kitchen and Household:WTPSC	0.88 (0.66)	0.65 (0.35)	-1.39 (0.40)	1.59 (0.55)	3.25 (0.67)$_L$	0.73 (0.66)
other:WTPSC	-7.56 (2.51)	1.64 (0.86)	-2.41 (0.39)$_L$	0.85 (0.65)	3.71 (0.32)$_L$	-1.43 (0.53)
Personal Care:WTPSC	0.34 (0.78)	0.26 (0.38)	-3.13 (0.36)$_L$	-0.10 (0.57)	0.31 (0.35)	1.23 (0.97)
Domestic Appliances:WTPSC	1.10 (0.61)	-0.26 (0.25)	-0.04 (0.36)	3.17 (0.53)$_L$	0.20 (0.37)	-0.75 (0.44)
Sound and Vision:WTPSC	-0.50 (0.64)	0.09 (0.33)	-2.39 (0.39)$_L$	0.66 (0.56)	1.91 (0.41)$_L$	2.15 (0.51)$_M$
Sports and Activity:WTPSC	0.45 (0.81)	-0.46 (0.35)	3.12 (0.53)$_L$	1.56 (0.62)	-1.93 (0.89)	-0.42 (0.61)
Toys:WTPSC	-0.06 (0.59)	0.50 (0.20)	-3.14 (0.35)$_L$	0.37 (0.53)	-0.38 (0.32)	0.38 (0.31)

S: p-value $< 5\%$ α-level
M: p-value $< 1\%$ α-level
L: p-value $< 0.1\%$ α-level

7. Conclusions, Implications and Outlook on Further Research

In this paper we have developed a novel framework which makes it possible to compare the offer proposition of online retailers based on prices and delivery promises to that of the market. In addition, utilising the definitions of the sigmoid relative price position and sigmoid relative delivery promise position we have created two variables which are comparable on the same scale. As an extension to the sigmoid relative price position and the sigmoid relative delivery promise position, we have created variables which capture different offer proposition possibilities by means of Rational Choice (RC), Willingness to Pay (WTP) and Unwillingness to Pay (UTP).

Using this theoretical framework, we have researched three types of questions. We have studied how sales of consumer products are affected by changes in the sigmoid relative price position and the sigmoid relative delivery promise position (1), for which type of products changes in the sigmoid relative price position has an larger effect of sales (2), and for which type of products the sales are more affected by changes in the sigmoid relative delivery promise position (3). By following products spread over 11 different shop categories during the periods May 2021 to October 2021 (regular period) and the 2021 holiday period, and using a Finite Mixture Poisson Model architecture, we have made the following observations. First, We have found that for almost all products changes in the sigmoid relative price position have a larger effect on sales than changes in the sigmoid relative delivery promise position. This holds true for all shop categories, during both the regular and holiday period. However, contrasted to the regular period, we have observed that during the holiday period for the shop categories *Entertainment*, *Kitchen and Household*, *Sound and Vision* and *Sports and Activity* there is a relative increase in the number of products which are more susceptible for changes in the sigmoid relative delivery promise position compared to changes in the sigmoid relative price position. What is more, we have found that a large proportion of products in all shop categories has significant negative coefficient estimates for the sigmoid relative price position, which is increasing during the holiday period. This might indicate that (1) consumers are not interested in one particular product and hence do not directly compare the prices and delivery promises of other competitors, (2) consumers are unaware that other offers exist, (3) behave purposefully irrational. Based on our study design, we are not able to detect which of these possibilities (or other possibilities would these exist) holds true.

For the second main research question, we have studie how the sales of consumer products are affected by changes in RC, WTP and UTP during the regular and holiday period. Again, we have considered 11 different shop categories and estimated the effects utilising a Finite Mixture Poisson Model architecture. In this part of the paper the signs of the parameter estimates corresponding to RC, WTP and UTP were of main interest. We have found that during the regular period the parameter estimates of RC are non-negative for practically all products considered in this study. Conditioned on products with non-negative parameter estimates for RC, we have observed that during the regular and holiday periods, the effect types *strong UTP* and *weak UTP* together are most occurring for a majority of products in a majority of product categories. This provides evidence that in case a product is more competitive in terms of price, but less competitive in terms of delivery promise, on aggregate consumers are still willing to buy these products. However, in case the offer of an product is less competitive in terms of price, but more competitive in terms of the delivery promise, consumers

are on aggregate less willing purchase the product. For the shop categories *DIY*, *Drugs and Baby*, *Hardware*, and *Sports and Activity* we have observed a small proportion of products for which the reverse might be true. During the holiday period, we find relatively more products with significant negative parameter estimates of RC, possibly indicating that during this period for relatively more products consumers are less aware of prices and/or delivery promises of other retailers, or simply purchase irrationally. However, using our study design, we cannot explain the exact reason behind this deviation.

To provide the second main research question with more context. we have studied to what extent sales of consumer products are increasing in case we observe that in the week prior to Sinterklaas and/or Christmas the product only one retailer promises to delivery the product before one of these two holidays (a situation which we abbreviated as WTPSC). As a study design we have compared the parameter estimates of WTP to WTPSC. Here WTP indicates general willingness to pay more for receiving a faster delivery promise in a general setting, while WTPSC conditions on the specific scenario as described in the previous sentence. We were not able to find conclusive evidence that in case WTPSC is active sales are more or less affected compared to situations in which only WTP is active.

Based on the results of this study, we believe that the implications for the internal retailer are the following. First, the internal retailer should keep their pricing strategy as it currently is. That is, it needs to keep monitoring price positions and be aware of products for which the price position is lacking. For the internal retailer the main question was whether such an extensive monitoring scheme also should be applied for delivery promises. Based on the results of this study, we do not see a direct need to implement this monitoring scheme as changes in the relative delivery promise position only have small effects on product sales for most products, and are of much less importance than changes in the relative price position. This is complemented by the fact that the internal retailer currently has one of the best delivery promises in the market for a large majority of the products considered in this study for most days of the week, which implies that there is little room to improve compared to the market delivery promises. Therefore, our advise to the internal retailer with regards to delivery promises would be to try to retain their current position and possibly improve their delivery promises for Saturday, as this is the weekday with the worst delivery promises compared to the market. With respect to the observed changes in consumer behaviour of the holiday period compared to the regular period, we advise to study these differences more closely as we cannot explain within on our study design the large difference of the level of rational behaviour between these two periods.

We believe that our current study design possibly can be improved in case a Finite Mixture Poisson Model with Fixed Effects is used. For this, we refer to the paper of Deb and Trivedi (2013). In addition, a negative binomial specification can be used to deal with overdispersion within products. Alternatively, an approach can be taken from the individual consumers perspective. Here the idea is to look at the decisions customers make by means of revealed choices, and then use a Discrete Choice Decision Model to estimate effects for different consumers. Compared to this study design, the emphasis here is more to distinguish different purchase behaviour rather than categorising different effect types for different products.

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Appendices

Appendix A. Data Imputation

In this section, we elaborate upon our method to impute missing competitor data for the variable delivery promise. We explain the data imputation for data of the period May 2021 to October 2021. This section will be divided as follows. First we provide an overview of the amount of data which is currently missing, show how we categorise the available and missing data into different groups, and provide a motivation for how we want to impute the missing data. Based on this motivation, we explain more concretely how we impute the data for the different groups of missing data.

Appendix A.1. Overview of Different Types of Missing Data

For the competitor data, we first need to convert the delivery promise strings into a delivery promise (in days). The difficulty of converting this information depends from string to string. We define the following levels of complexity:

- **Direct Usable Strings**: These strings contain direct information about the delivery promise. Additionally, we know that the source of this string is the competitor's website.
- **Imputable Strings**: Strings of this type cannot directly be used to obtain the delivery promise for different reasons. In some instances we simply lack any information about a delivery promise, while in others we cannot state with certainty that the information in the string reflects the actual delivery promise of the competitor. However, we should be able to recover the delivery promise by making use of the part of the strings for which we have usable strings (or by adding some usable data ourselves).
- **Not Imputable Strings**: This part of the data does not contain any information about the delivery promise. Additionally, it is not possible to recover the delivery promise by making use of additional sources of information.

Based on these three levels of complexity, let us elaborate on the second level (imputable strings) in more detail. For imputing the this part of the data, we categorise the method of imputation into two distinct groups. These groups are based on the type of competitor we are dealing with. First we have the webshop-type. This type is characterised by competitors which do not allow third parties to sell on their platform. Furthermore, these types of competitors only have one delivery promise, or a small fixed ranges of different delivery promises. Therefore, we should be able to recover the missing data of these competitors in case we know these fixed delivery promises.

Secondly, we define a group of competitors which do allow third parties (partners) to sell on their platform. Additionally, each partner has its own (fixed) range of delivery promises. Consequently, is much difficult to impute the missing data for these competitors based on fixed delivery promises. Instead, we need to impute missing data per partner, assuming that we have a sufficient amount of information to do so.

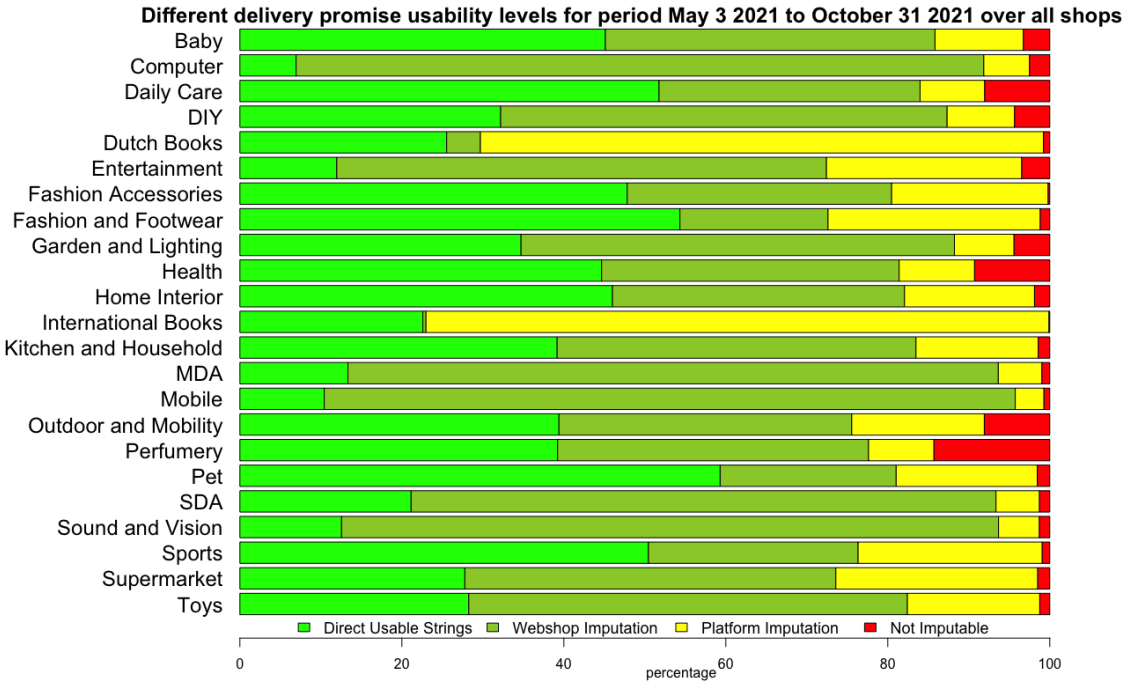

Figure A.11: The different string types for the variable delivery promise of the competitor data before imputation.

In Figure A.11. we plot the the distribution of the different levels of complexity over the different shops. What should become clear by considering this figure is that most data cannot be used in its current state for almost all shops (Digital Reading being the exception). On the positive end, we see that most of the strings which are currently not usable could possibly be recovered in case we impute the data. Therefore, let us next elaborate on our method to recover the missing data. For this, we first explain what aspects need to be taken into account before we start imputing any data.

Appendix A.2. Explanation of Missing Data

Whenever we want to impute missing data, we first need to determine in what way our data is missing. Generally, we can distinguish between three situations. First, we have Missing Completely at Random (MCAR), second Missing at Random (MAR), and lastly Missing Not at Random (MNAR). For MCAR we assume that probability of the data being missing follows the same probability distribution as the part of the non-missing data. Consequently, we cannot tell the reason why the data is missing, implying that we cannot recover the missing values from the data. In case we assume MAR holds on the other hand, we say that we can recover the missing data by variables in our data, or from a more probabilistic point of view that the probability of being missing is the same only within groups defined by the observed data Acock (2005). MNAR deviates from these two assumptions in the sense that it we know the reason why the data is missing, but we cannot infer it. Additionally, the reason why the data is missing both depends on the observed data and the unobserved data.

Given these types of missing data, we believe that we the MAR assumption for the delivery promise is a plausible one to make for the reason that delivery promises tend to be rather consistent within competitors. For this we make the distinction between the product level and competitor level:

1. **Within Products**: In case we do know the delivery promise for a particular product on a particular day (or a couple of days) which is (are) chosen at random, but not for a day very close to this day, we believe that we can infer the delivery promise at the missing day with high probability by making use of the delivery promise of the day for which we have information, accounting for external factors. These external factors include among others the postal service (PostNL, DHL, DPD, etc.), stock amounts and holidays.

2. **Within Competitors (or partners on a platform)**: In case we do know the delivery promise for a random proportion of the products of a competitor, but not for some others, we believe that we can infer with high probability the delivery promise which is close to the actual delivery promise by making use of the delivery promises of the products which are similar to that of the product with missing data. For competitors with only one delivery promise this becomes trivial. For competitors with multiple delivery promises, we can can apply different approaches.

. Based on these levels, we therefore can apply different imputation techniques appropriate for each level. These can range from quite simple methods such as manually corrections to the data or applying mean/median imputation to more complex methods such as Multiple Imputation by Chained Equatons (MICE) Schafer (1997), Van Buuren (2018) and Generative Adverserial Imputation Networks (GAIN) Yoon et al. (2018).

Although the more complex methods might be preferred in terms of imputation accuracy, we believe these methods do not provide any significant additional merit compared to a semi-manual imputation approach. For starters, these methods are much more time consuming to set-up before being usable. In addition, some of these methods rely on the right configuration of hyperparameters, which adds an additional layer of complexity. Furthermore, the running time for training these algorithms can be quite slow in case we have large amounts of data (which we do).

Assuming that we take these considerations for granted, we also have a problem with the current usability of the data. Most likely, we would first need to manually impute some of the missing data before we can use the more complex imputation methods. By doing it is very likely that we introduce some small biases in our data. Consequently, this bias will also be included while imputing the data. As a result, in case the imputation methods are well trained, the accuracy is based on slightly biased inputs.

In order to prevent all these (possible) problems, we therefore implement a semi-manual imputation scheme which is specifically designed to suit the structure of our data, and is based on the explanation of the two types in which we can impute data. Before we explain this scheme, we first want to put emphasis on the different trade offs we need to take into account when imputing the data.

Appendix A.3. Tradeoff for Imputing Data

The goal to impute missing data is to increase the size of usable information. More specifically, by imputing data of the delivery promise we are able include more competitor data into our model, and hence obtain a broader view of the amount of competition within products. Although it is impossible to track all competitors for all products in practice, we would ideally want to recover all the missing data which we have observed in order to approximate the total competition for a product as good as possible. However, as the imputation of data does not necessarily imply that we recover the actual delivery promise, the creation of (small) biases in our data is inevitable. These biases do not have to be problematic as long as we ensure that the imputation does not lead any systematic over/under estimates of the actual delivery promise. Unfortunately, there is no prophecy which states where small biases end and systematic biases start. Consequently, we need to determine by ourselves what we consider to be small biases and what not.

Therefore, before we start imputing data we need to determine what biases are acceptable and which ones might become problematic. In order to understand this, we need to ask ourselves what the consequences of the systematic biases are. In case we systematically overestimate the delivery promise of competitors, the relative delivery promise position of the internal retailer is generally too positive. As a result, whenever the relative delivery promise position of the internal retailer weakens (the internal retailer promises to deliver on a later time compared to the competition) in reality, our data might not fully reflect this changes. Would this weakened position correspond to a decrease in sales, our model would lack the ability to estimate this effect, leading to a damping effect of our estimates. Conversely, would we have an improvement in the relative delivery position of the internal retailer, we might overestimate the actual effect by our bias. A similar reasoning applies in case we systematically overestimate the delivery promise of competitors, in which we overestimate negative effects and dampen positive effects.

Besides the impact of creating a systematical bias, another remark relates to the absolute magnitude of the bias relative to the true delivery promise. In order to illustrate this, imagine two products A and B both in different markets. Here product A is in a market of fast delivery, which is why the actual delivery promise is 1 day. Product B is in a market in which delivery generally takes much longer, and consequently has an actual delivery promise of 10 days. Now let say that we impute a delivery promise for product A of 3 days, while we impute 12 days for product B. Despite the fact that both products have a bias of 2 (the bias in absolute magnitude is the same), the effect of the bias is most likely different between these two products for two reasons. First, product A has a much lower actual promise, which is why a deviation of 2 days already has a much larger impact. Secondly, the delivery promise of product A is in a market for which fast delivery promises (as in one day delivery) are much more likely, which is why bias of 2 days is much more severe compared to a market in which most other competitors also are quite slow (10 days or more).

To conclude above explanation, we need to determine for which products which bounds of biases are acceptable. For this we permit slightly higher biases for markets which have higher delivery promises than for markets which have much faster delivery promises. Based on this remark, let us next explain in more detail our imputation scheme for the competitors of the webshop type and

platform type respectively.

Appendix A.4. Recovering Missing Data of Individual Webshops

For recovering the missing data of the individual webshops we make us of a combination of approaches. The choice on we make depends on the size of the competitor. We define size as the combination of the number relevant products of the competitor (the products which are also available on platform of the e-commerce company) and relevance level of the company. The relevance level is internally determined, and separates the smaller competitors (in terms of reputation, estimated sales) from the bigger ones.

For the most relevant competitors we have manually checked all the delivery promises per competitor (including ultimate order time). Additionally, we have checked the transporter type (PostNL, DHL, UPS, etc.). We use the latter information to determine the delivery promise on special days (mostly national holidays). In case the competitor only has one delivery promise explicitly mentioned, we use this delivery promise for all strings. For the competitors with a fixed range of delivery promises, we make use of external data to correctly map the promises. For this we use price competitor sites (Tweakers, Kieskeurig, etc.) which provide information about the delivery promise. However, these promises are most often not defined in terms of the exact number of days, but rather in a bracket of days, which leads to a bias of the actual delivery promise. Fortunately, the bias is consistent for every competitor we have manually checked. For this reason, we can correct for the bias by mapping the wrong promise of the price competitor site to the actual promise on the website of the competitor. By applying this approach for the most relevant competitors (117 in total) we are able to impute approximately 73% of the missing data of the Webshop Imputation-type over the period May 2021 - October 2021.

For the remaining part of the data, we only impute the part of the data for which we believe we have sufficient evidence that we do not make any mistakes which may lead to significant bias in our variables. In order to to so, we again rely on information of the price competitor sites. However, in this case we check to what extent the delivery promise of the competitor deviates from the competitors which we have manually checked. In case this deviation is relatively low, we include the promise. Otherwise, we disregard the data of the competitor. The reason why we believe that this procedure is justified is as follows. The competitors which remain after manually checking are relatively small webshops in terms of reputation and size (webshops which are only based in one town for example). As a result, it is unlikely that these webshops contribute much to the total amount of sales for particular products, and hence would have a huge impact in terms of our model. Still, we consider removing the information of these competitors as a waste for the situations in which the delivery promises are within the bounds of the manually checked competitors, and consequently would not lead to any systematic biases.

In Table A.13. we have shown the maximum corrections for different delivery promises. Note that these promise are in working days, since (smaller) webshops usually provide a delivery promise in working days. The motivation for these corrections is as follows. For products with a delivery promise of one (working) day, we do not allow any differences, since we assume that for these products one

Delivery Promise (in working days)	Maximum Difference Below Promise	Maximum Difference Above Promise
1	*	0
2	0	1
3	1	1
4	1	1
5	1	2
6	1	3
7	2	3
8	2	*
9	3	*
10	4	*

Table A.13: Allowed deviations below and above the delivery promise for different delivery promises (in working days)

day delivery can already have a large impact. For the same reason, we do not allow delivery promises of two days an downward correction of one working day. For the other delivery promises, allow more and more bias the higher the delivery promise becomes. Note that we upper denote the maximum difference for 8, 9 and 10 days by a star $*$, since we upper bound the delivery promise at 10 working days.

Appendix A.5. Recovering Missing Data of Online Platforms

For imputing the missing data of online platforms, we consider each partner on the platform as a separate entity. For the delivery promises of products conditioned on a specific partner, we make a distinction between products which have delivery promises missing for a fraction of all the days and products for which the delivery promise is unknown for all days. In the former situation, we make use of the delivery promise of the product in other days to impute the missing data (55% of all products of partner platforms in the period May 2021 - October 2021). In the latter, we utilise products for which we have information about the delivery promise and are likely to have a similar delivery promise as for the products of which we lack any information of the delivery promise. Let us next explain both approaches in a little more detail.

Appendix A.5.1. Imputing Products with Fraction of Missing Data

For products which miss data for a fraction of the days, we consider the information of the days for which we have information about the delivery promise as a point of reference. In general, we can distinguish two types of products: products with one delivery promise, and ones with multiple. Products with only one delivery promise we can trivially impute by using the only delivery promise, whereas for the products with multiple delivery promises we need to use a slightly more complex method.

Simple Imputation. In order to asses how many of these products we can easily impute, we have plotted the standard errors of different delivery promises given one particular product (which again condition on a partner) for the period May 2021 - October 2021 in Figure A.12. The left plot shows the histograms, whereas the right plot shows the cumulative plot. Based on this plot, we see for instance that more than 95% of all products have a standard error of lower than one day (in fact 60% of all products have a standard error of zero). In addition, 99% of all products have a standard error of at most 2, and 99.6% of products a standard error of at most 3.

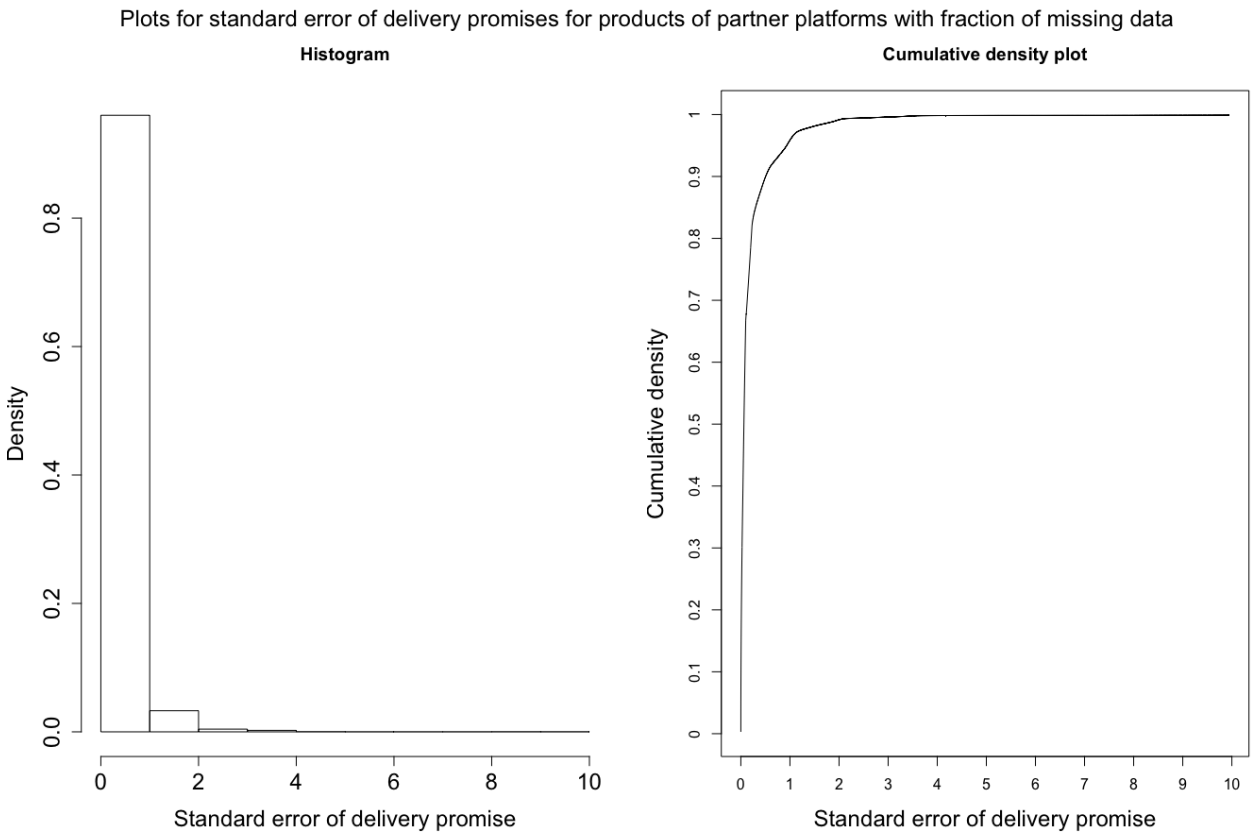

Figure A.12: Histogram and cumulative density plot of standard errors of different delivery promises given one particular product conditioned on a partner for the period May 2021 - October 2021

What these numbers show is that we can impute 60% of this part trivially, while for the remaining 40% we need to use a little more complex method. Furthermore, we disregard imputing products with a variability exceeding three days, since almost all products are covered by setting the bound of the standard error on three days.

Product Selection for More Complex Imputation. For imputing the products which have a standard error of the delivery promise bigger than zero and smaller than three, it is important to understand how reliable our imputations are. For this we believe that the the variation of the delivery promises, as well as the proportion (and number of observations) of missing information are important. The former indicates how difficult the imputation becomes for a product (and to what extent we could create systematic biases), whereas higher proportions of available information lead to more trustable imputation. These two factors furthermore depend on the baseline delivery promise of the product, which we estimate using the average. For example, we are more careful for imputing products with a relative low baseline (say an average delivery promise of 1 day), compared to products with a (relative) high baseline (five days or more). Based on these three pieces of information, we want to obtain thresholds of the minimum proportion of available information of product, conditioned on the variation of delivery promises within a product and the baseline delivery promise of this product. Let us explain how we create these thresholds.

Let D_{ps} denote all delivery promises which we know for some product p conditioned on a partner s. Given D_{ps}, $D_{\hat{\mu}_{p_s}}$ corresponds to the estimate for the baseline of the delivery promise D_{ps} and $D_{\hat{\sigma}_{p_s}}$ to the estimate of the variance of the delivery promises of D_{ps}. Then we define $z_{D_{ps}}$ as the ratio of $D_{\hat{\mu}_{p_s}}$ to $D_{\hat{\sigma}_{p_s}}$, that is:

$$z_{D_{ps}} = \frac{D_{\hat{\mu}_{p_s}}}{D_{\hat{\sigma}_{p_s}}} \tag{A.1}$$

Note that $z_{D_{ps}}$ is assumed to be non-negative, since $D_{\hat{\mu}_{p_s}} \geq 1$ and $D_{\hat{\sigma}_{p_s}} > 0$. We assume that $z_{D_{ps}}$ is a realization of the random variable $Z_{D_{ps}}$ which follows a standard normal distribution, implying is $Z_{D_{ps}} \sim \mathcal{N}(0, 1)$. We denote the CDF (Cumulative Density Function) as $\Phi(z_{D_{ps}})$. Let us call $P_{z_{D_{ps}}}$ the proportion of the border of the amount of missing data for a product, given a value of $z_{D_{ps}}$, which we calculate using the following formula:

$$P_{z_{D_{ps}}} = 2\Phi(z_{D_{ps}}) - 1 \tag{A.2}$$

Which corresponds to the The Half-Standard-Normal Distribution. The intuition behind Formula A.2 is that the higher $z_{D_{ps}}$ becomes, the more data we allow to be missing. The value of $z_{D_{ps}}$ is determined by the amount of dispersion between $D_{\hat{\mu}_{p_s}}$ and $D_{\hat{\sigma}_{p_s}}$. The more $D_{\hat{\mu}_{p_s}}$ exceeds $D_{\hat{\sigma}_{p_s}}$, the lower $z_{D_{ps}}$ becomes and consequently, the higher we allow $P_{z_{D_{ps}}}$ to become. From a practical point of view, this would correspond to products with relatively high baselines for the delivery promises, or for products with relatively low variation in the delivery promise compared to the baseline. On the other hand, the more $D_{\hat{\sigma}_{p_s}}$ starts dominating over $D_{\hat{\mu}_{p_s}}$, the lower $z_{D_{ps}}$ becomes and the lower we allow $P_{z_{D_{ps}}}$ to be. This corresponds to products with low baselines and large variation in the delivery promise. Intuitively, this makes sense since for these products we want to be more careful before imputing.

Using $P_{z_{D_{ps}}}$, we decide whether to impute the missing data for product p of partner s if $P_{z_{D_{ps}}}$ exceeds the proportion of missing data we observe for product p of partner s. For this, let us denote P_{Dps} as the proportion of missing data of the delivery promises for product p of partner s. We base our decision rule, which we denote by I_{ps}, as follows:

$$I_{ps} = \begin{cases} 1 \text{ if } P_{z_{Dps}} \geq P_{Dps} \\ 0 \text{ otherwise} \end{cases} \tag{A.3}$$

Where a 1 indicates that we apply the imputation method, and 0 implies that we do not. In total 99% of all products in this category satisfy the condition of Formula A.3. We move the remaining 1 % of the products whose value is 0 to the next stage in which we impute based on product group levels. In case these products satisfy the conditions we impose in that stage, we impute the missing data. Otherwise, we disregard these observations from our dataset.

System to Impute. Those products who are selected using the decision rule of Formula A.3, we use the information of the available days to impute the data of the missing days. In order to explain how we do this, let us consider a toy example by means of Table A.14. Here we consider a product of

some arbitrary partner of which we have data for the month May. In this table, we see a distinction of the delivery promise depending on the weekday (weekend) and whether the day is an holiday. Furthermore, we see that the delivery promise seems to be structurally different after May 19. Also, we observe missing delivery promise information for a proportion of the days (being May 3, May 9, May 10, May 13, May 19, May 22, May 28 and May 29). We impute the information of the missing days by making use of the days around this date, conditioned on weekends and holidays. To take May 3 as an example, we use weekdays (excluding weekends) which are no holiday around this value to obtain an imputed value for May 3.

Date	Delivery Promise (in days)	Weekend	Holiday
2021-05-01	2	Yes	No
2021-05-02	2	Yes	No
2021-05-03	* **1**	No	No
2021-05-04	1	No	No
2021-05-05	2	No	Yes
2021-05-06	1	No	No
2021-05-07	1	No	No
2021-05-08	2	Yes	No
2021-05-09	* **2**	Yes	No
2021-05-10	* **1**	No	No
2021-05-11	1	No	No
2021-05-12	1	No	No
2021-05-13	* **1**	No	Yes
2021-05-14	1	No	No
2021-05-15	2	Yes	No
2021-05-16	2	Yes	No
2021-05-17	2	No	No
2021-05-18	1	No	No
2021-05-19	* **3**	No	No
2021-05-20	3	No	No
2021-05-21	3	No	No
2021-05-22	* **4**	Yes	Yes
2021-05-23	4	Yes	Yes
2021-05-24	4	No	Yes
2021-05-25	3	No	No
2021-05-27	3	No	No
2021-05-28	* **3**	No	No
2021-05-29	* **3**	No	No
2021-05-30	4	Yes	No
2021-05-31	4	Yes	No

Table A.14: Example of delivery promises for a product with a proportion of days the delivery promise.
* indicates missing information
Bold indicates imputed value

In our decision to impute data, we should make decisions related to the way in which we want to utilise the time structure of the data, and in what way we make use of the available information:

1. **Aspects Related to the Time Structure**: The second aspect relates which datapoints with available information to include for imputation. Here the time structure of the data plays an important role. We distinguish three parts:

   (a) **Preference for Time Horizon**: To include datapoints of a particular product, we can use three approaches. First we could only look at days before the missing day as source of information. Alternatively, we could consider only days after the day of missing information. Lastly, we can combine both days the past and future by considering the days which

are closest to the day for which we do not have any information.

We prefer to choose the third approach in case applicable, since we have no prior information on which of the first two methods should result in more reliable results. However, in some instances the only choice is to only consider the past or future, since we do not have any information about the past or future. For example, May 3 of Table A.14 is the first weekday which we use, but is a missing day. Or take May 29 of Table A.14, which is the last day for which we have information.

(b) **Timeframe of Imputation** The timeframe plays an important role in the imputation in the sense that the closer the days we use are to the day(s) of which we miss information, the more likely it is that the information is more reliable. This is amplified by the amount of volatility of the delivery promise for a product (given a partner) in a period of interest. In the example of Table A.14. we have delivery promises ranging from one day to four days without conditioning on type (weekday/weekend/holiday). If we only consider the weekdays, we find a variability of the delivery promise of two days, which we can dissect into two subperiods with a tipping point around May 20. Therefore, if we would consider weekdays after May 20 for imputation for May 10, the usage of this information is not very reliable for imputing the missing date correctly.

Given that we have disregarded products with relative high amounts of variability, we use a timeframe of five days, which corresponds in the best case to one week in for weekdays, and three weeks for days in the weekend. We include holidays as part of the weekend. We select the five days which are closest to the day of missing information.

(c) **Time Gaps of Imputation** Another important aspect relates to the number of days between the missing day of which we have information missing and next (or previous) day of available information. In the example of Table A.14 we have only small gaps of one day. In reaility however, these gaps might be much larger. The larger the gaps, the less likely it is that the imputation is still reliable. Therefore in case we have large gaps (say of a couple of weeks), the question is whether imputation is justified. For this the amount of variability and the number of datapoints with available information of the delivery promise of a given product for a period of time are important.

Although this factor can have a theoretical impact on the imputation quality, we rely on the assumptions that we can use the five days closest to the missing day for our imputation. The reason why we believe that this assumption is justified is that we already have filtered out products which we believe fall in this category. Furthermore, our time frame of at most three months makes it not very likely to have very large gaps given that a product needs to have observations in at least 50% of the time.

2. **Choice of Summary Statistic (Median)**: Given variability of the delivery promises and the chosen timeframe, a third aspect relates to the way we utilise data. For this we can make use of different summary statistics, such as the mean, a weighted average, mode, or median. As our goal is to prevent systematic biases, our preference goes to the median. For starters, the median

is more outlier robust than the mean (or weighted average). This is preference is strengthened by the fact that the number of datapoints we would calculate the mean (or weighted average) from is rather small, which makes the mean volatile. Additionally, the delivery promise is an ordinal variable, which we can account for using the median. The mode, although more outlier robust than the mean, is not able to take this information into account.

Based on these remarks, we obtain the imputed values for our toy example by means of the numbers in bold. For example, the imputation value for May 19 is calculated by using the five weekdays which are closest to May 3 (May 14, May 18, May 20, May 21, May 25), computing the median of these five days (3), and replacing the missing value by this median value.

Appendix A.5.2. Imputing Products with Only Missing Data: Mode Imputation

For imputing products with only missing data, we make use of the delivery promise of products for which we have information available. For this, we first aggregate the information of these products by the median. Given these aggregated values, we need to determine which products with available information about the delivery promise can be used for the imputation. We start by conditioning on the partners, that is for imputing the delivery promise of products of some partner, we only use the products with a known delivery promise of this partner. However, since partners can sell very different products, we deem this conditioning not sufficient. Therefore, we condition on a product group level in addition. In total we can make use of three product group levels, being shop, product group, and chunk (similar to those of Table 5). Note that the higher we move in the product group level hierarchy (for example from chunk to product group), the more diluted our information (possibly) becomes. Consequently, we start imputing using the lowest product group level and only move to higher levels in case the lower level is not reliably usable, due to not exceeding the minimum amount of required observations, denoted as R_N.

Based on this set-up, we impute the proportion of the missing data conditioned on partner and product group level by the most likely delivery promise conditioned on these two traits. For this, we optimize a zero-one loss function, for which the mode is the optimal estimator. Therefore, we impute this part of the missing data by the mode, so called mode imputation. However, imputing all products with missing information by one value inevitably creates (systematic) biases in case we do not account for the shape of the distribution. Therefore, we only decide to impute in case the shape of the distribution is such that the imputation using the mode creates systematic biases with very low probability. By applying mode imputation with restrictions on the minimum required number of observations for a product group level and shape of the distribution, we are able to impute approximately 30% of missing data of this type. Let us explain next this approach in more detail.

Mathematical Definition Decision Rule. We only intend to impute products using the mode in case the probability of creating systematic biases is very low. For this we use a two-step approach, in which we first determine the mode of our empirical distribution of the delivery promises conditioned on partner and product group level, and consequently calculate whether the imputation creates an error which is expected to cause systematic bias. In order to determine the latter, we calculate the cost

of the imputation. We do this by multiplying the empirical proportion of every delivery promise by a manual set marginal cost, such that we create a weighted cost (or expected cost) for the imputation. We compare this cost to a threshold, which we set manually. In case the expected cost is below the threshold, we impute, and not otherwise.

To define this in a mathematical way, let D_{sg} be the set of delivery promises of partner s in product group level g. Furthermore, let $\hat{\pi}_{sg_j}$ corresponds to the empirical proportion of delivery promise $j \in D_{sg}$, and $C_{j|i}$ corresponds to the cost of the imputation for products whose delivery promise equals that of the value of j, given that we have imputed i, for $i \in D_{sg}$. Then we define the expected cost of imputation for partner s in product group level g as follows:

$$C_{I_{sg}} = \sum_{j \in D_{sg}} \hat{\pi}_{sg_j} * C_{j|i} \tag{A.4}$$

Where we should note that $\sum_{j \in D_{sg}} \hat{\pi}_{sg_j} = 1$. Given $C_{I_{sg}}$ as defined in Equation A.4, we then decide to impute all products of partner s in product level g by its mode if $C_{I_{sg}}$ does not exceed the threshold T. All-in-all, we can summarise the imputation by means of the following formula:

$$M_{I_{sg}} = \begin{cases} Mo_{sg} \text{ if } C_{I_{sg}} \leq T \\ NULL \text{ otherwise} \end{cases} \tag{A.5}$$

Where Mo_{sg} corresponds to the mode of the median delivery promises for products with known delivery promises conditioned on partner s and product group level g.

Determining $C_{j|i}$. We set $C_{j|i}$ according to the minimum proportion we require $\hat{\pi}_{sg_j}$ to differ from $\hat{\pi}_{sg_i}$, assuming that these two delivery promises are the only ones that exist for partner s in product level g. Then we set the cost exactly such that if $\hat{\pi}_{sg_j}$ equals this requirement, we obtain the threshold T. For this let $R_{\pi_{j|}i}$ be this required proportion conditioned on imputing delivery promise i. Note here that we disregard the subscripts s, and g, stating that we do not require this proportion to differ between partners and/or product group levels. In order to derive the cost for $C_{j|i}$ based on this explanation, we can make use of Equation A.4, by restricting that $C_{I_{sg}} = T$, and setting $C_{j|i} = 0$ if $i = j$. Then solving for $C_{j|i}$ yields that

$$C_{j|i} = \begin{cases} \frac{T}{R_{\pi_j|i}} \text{ if } R_{\pi_j|i} > 0 \\ 0 \quad \text{otherwise} \end{cases} \tag{A.6}$$

The intuition behind the choice for $C_{j|i}$ is that if i and j are the only two delivery promises, we impute as long as $\hat{\pi}_{sg_j} \leq R_{\pi_j|i}$. In case we have also other delivery promises, we require $\hat{\pi}_{sg_j} < R_{\pi_j|i}$ for all $j \neq i$, such that we can satisfy the condition set in Equation A.5. The choices for $R_{\pi_j|i}$ are shown in Table A.15.

Minimum Sample Size before Imputation (250 Observations). In order to reliably use the imputation method as provided in Equation A.5, we need to assume that the empirical distribution of the missing data is sufficiently close that that of the observed empirical distribution. For this assumption to hold

Imputed (i)/Actual (j)	1	2	3	4	5	6	7	8	9	10
1	0	$\frac{1}{5}$	$\frac{1}{10}$	$\frac{1}{10}$	$\frac{1}{20}$	$\frac{1}{25}$	$\frac{1}{50}$	$\frac{1}{75}$	$\frac{1}{100}$	$\frac{1}{100}$
2	$\frac{1}{5}$	0	$\frac{1}{4}$	$\frac{1}{5}$	$\frac{1}{10}$	$\frac{1}{20}$	$\frac{1}{25}$	$\frac{1}{50}$	$\frac{1}{75}$	$\frac{1}{100}$
3	$\frac{1}{10}$	$\frac{1}{4}$	0	$\frac{1}{3}$	$\frac{1}{4}$	$\frac{1}{5}$	$\frac{1}{10}$	$\frac{1}{20}$	$\frac{1}{25}$	$\frac{1}{50}$
4	$\frac{1}{10}$	$\frac{1}{5}$	$\frac{1}{3}$	0	$\frac{1}{3}$	$\frac{1}{4}$	$\frac{1}{5}$	$\frac{1}{10}$	$\frac{1}{20}$	$\frac{1}{25}$
5	$\frac{1}{20}$	$\frac{1}{10}$	$\frac{1}{4}$	$\frac{1}{3}$	0	$\frac{1}{3}$	$\frac{1}{3}$	$\frac{1}{4}$	$\frac{1}{4}$	$\frac{1}{5}$
6	$\frac{1}{25}$	$\frac{1}{20}$	$\frac{1}{5}$	$\frac{1}{4}$	$\frac{1}{3}$	0	$\frac{1}{2}$	$\frac{1}{3}$	$\frac{1}{4}$	$\frac{1}{5}$
7	$\frac{1}{50}$	$\frac{1}{25}$	$\frac{1}{10}$	$\frac{1}{5}$	$\frac{1}{3}$	$\frac{1}{2}$	0	$\frac{1}{2}$	$\frac{1}{2}$	$\frac{1}{3}$
8	$\frac{1}{75}$	$\frac{1}{50}$	$\frac{1}{20}$	$\frac{1}{10}$	$\frac{1}{4}$	$\frac{1}{3}$	$\frac{1}{2}$	0	$\frac{1}{2}$	$\frac{1}{2}$
9	$\frac{1}{100}$	$\frac{1}{75}$	$\frac{1}{25}$	$\frac{1}{20}$	$\frac{1}{4}$	$\frac{1}{4}$	$\frac{1}{2}$	$\frac{1}{2}$	0	$\frac{1}{2}$
10	$\frac{1}{100}$	$\frac{1}{100}$	$\frac{1}{50}$	$\frac{1}{25}$	$\frac{1}{5}$	$\frac{1}{5}$	$\frac{1}{3}$	$\frac{1}{2}$	$\frac{1}{2}$	0

Table A.15: Values for $R_{\pi_j|i}$. Note that in case the mode is in between one of the two values, we take the average over the values of $R_{\pi_j|i}$

two factors are important. First, the data generating process of the delivery promises of the missing data needs to be the same as that for the data we observe, which we assume that holds. Second, the shape of the observed empirical distribution closely resembles that of the underlying distribution (the distribution from which the observed empirical distribution is generated). We can define the amount of closeness (or similarity) between these two distribution by means of the Kullback–Leibler Divergence Kullback and Leibler (1951) (KL-Divergence), which is defined as follows. Let P be the reference distribution, and Q the observed empirical distribution which are both defined over the same probability space $\mathcal{X}$. Then we write the KL-Divergence between Q and P as:

$$D_{KL}(Q||P) = \sum_{x \in \mathcal{X}} Q(x) \log \left(\frac{Q(X)}{P(X)} \right) \tag{A.7}$$

Based on the KL-Divergence of Equation A.7, we want to obtain a sample size R_N, such that we find a level of similarity between Q and P which we deem acceptable. However, as P can have many different shapes, we first want to investigate what the effect of the shape of P is on the KL-Divergence, and consequently R_N. For this purpose, let us consider four different toy distributions, all with different shapes. These are plotted in Figure A.13. First we have the uniform distribution, which does not have any mode (or as many modes as different classes). Second, we have distribution with one mode, and for which the differences in proportion from class to class is incremented by equal steps (stepwise upward). Third, we have a distribution with two modes, and symmetrical shape (symmetric). Lastly, we have a distribution with one mode, and by which the proportions from class to class decrease in an exponential fashion (exponentially downward).

We have selected these four examples to represent different amounts of probability mass per class. For example, for the uniform distribution all outcomes are equally likely, whereas for the exponentially decreasing distribution one outcome has very high probability, and all others less and less. We believe that these four distributions represent edge cases for the different distributions. This implies that the actual distributions we observe fall somewhere in between these distributions, if we account for the different orderings of the places probability mass (for example placing the mode at 1 in stead of 10 for the stepwise upward shape), the inclusion or exclusion of different classes, and (slight) adjustments

in probability mass for the different outcomes.

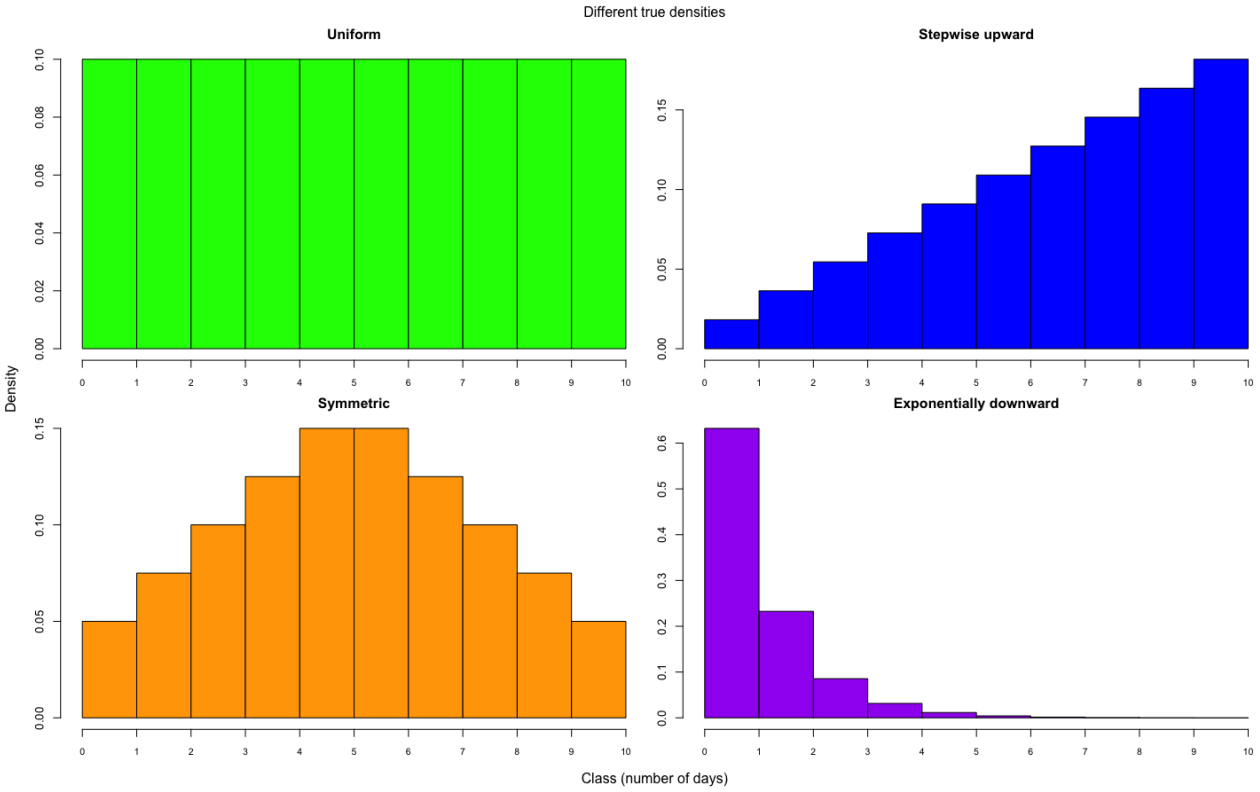

Figure A.13: Four toy distributions with different shapes.

Based on the baseline distributions of Figure A.13, we want to determine how well generated distributions resemble one of the underlying baseline distributions, and what the impact of the sample size is on this resemblance. For this, we have generated 1000 times distributions for sample sizes in the range of 1 to 500 per underlying distributions (hence giving 2.000.000 simulations in total), and calculated the average KL-Divergence over these 1000 simulations per amount of observations. We have applied this approach for distributions in the range of 2 different outcomes classes (minimum amount of classes in our context) up to 10 different outcome classes (maximum amount of classes in our context). The results are plotted in Figure A.14.

Given the plots of Figure A.14, we see that the uniform, stepwise upward, and symmetric distributions have a similar shape between KL-Divergence and number of observations in all plots (neglecting the difference in the part with very few observations). The exponentially downward distribution deviates from the other distributions in the sense that the KL-Divergence is lower for the smaller amounts of observations. Generally we observe that the more classes we add, the more observations are required to achieve a fixed level of KL-Divergence. For example, if we take a KL-Divergence of 0.01, we find that for 2 classes, we are below threshold for all distributions if we have more than 50 observations, whereas we need more than 450 observations to achieve the same result in case we have 10 classes. Note that for the uniform, stepwise upward and symmetric distributions, the required amount of observations are close to each other for all classes, while the exponentially downward distribution

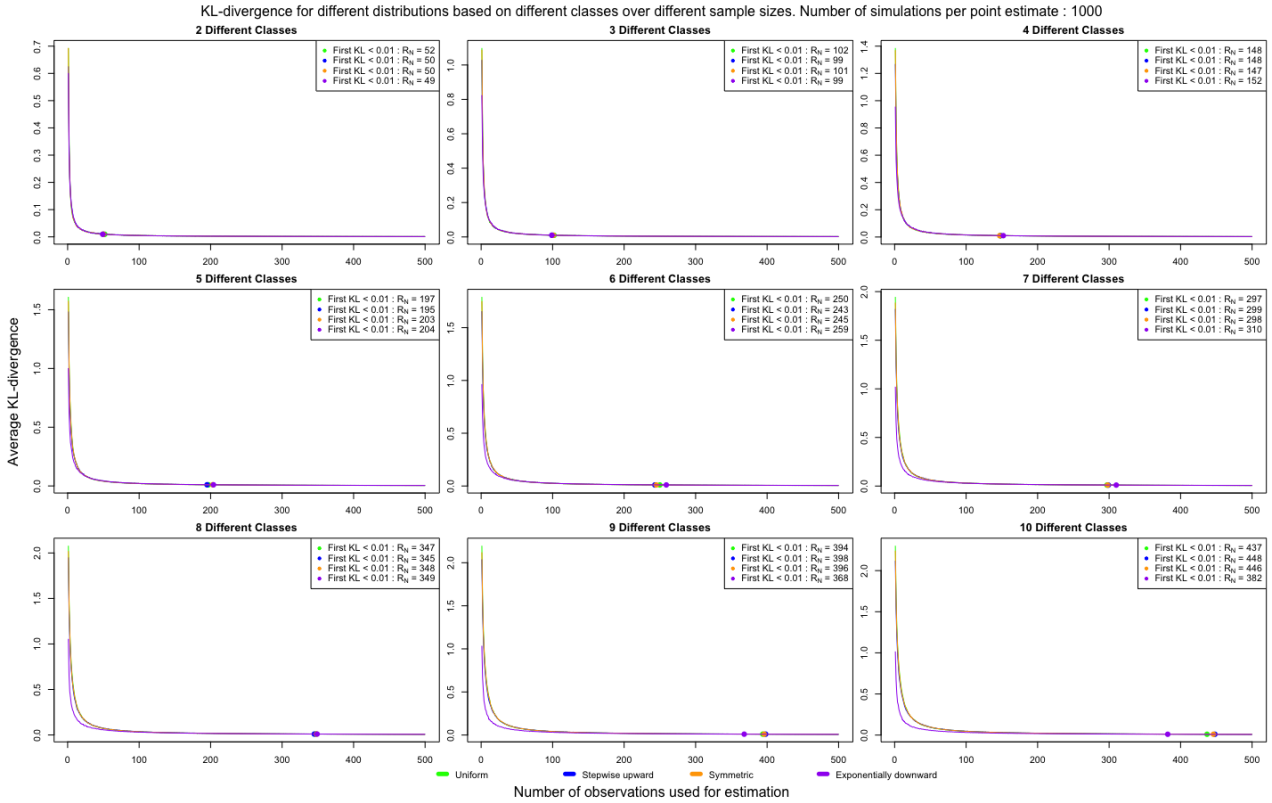

Figure A.14: Average KL-Divergences for different amounts of observations. Plots are based on 500 simulations per number of observation per underlying baseline distribution. Points indicate number of observations between KL-Divergence threshold of 0.025

requires less observations than these distributions for the last two classes. This is not surprising, since for the distribution with a exponential downward shape, every newly added classes receives much less probability mass.

Based on the plots of Figure A.14, we take a KL-Divergence value of 0.01 as our threshold value. We can motivate this choice by considering the plots in Figure A.15. Here we have plotted the average KL-Divergence against the average maximum absolute error (AMAE) between the generated densities and underlying distributions of Figure A.13. Every point estimate is based on the same simulations as those for the plots in Figure A.14. We define maximum absolute error as the maximum absolute difference between the probability mass of every generated distribution and the corresponding true distribution. For example, for the uniform distribution with 3 classes, the true probability masses are $\frac{1}{3}$ for all classes. In case we have generated data given this underlying distribution and obtained estimates of $\frac{3}{12}$, $\frac{2}{12}$ and $\frac{7}{12}$, the maximum absolute error equals $\max(|\frac{2}{12} - \frac{1}{3}|, |\frac{3}{12} - \frac{1}{3}|, |\frac{7}{12} - \frac{1}{3}|) = |\frac{7}{12} - \frac{1}{3}| = \frac{1}{4}$.

Based on these plots we see that for our KL-Divergence threshold of 0.01, we find values of AMAE in the range of up 0.027 with a standard error of 0.013 (for 10 classes) up to 0.05 with a standard error of 0.037 (for 2 classes). We consider these values as acceptable.

If we condition on a KL-Divergence threshold value of 0.01, we can use the plots in Figure A.14

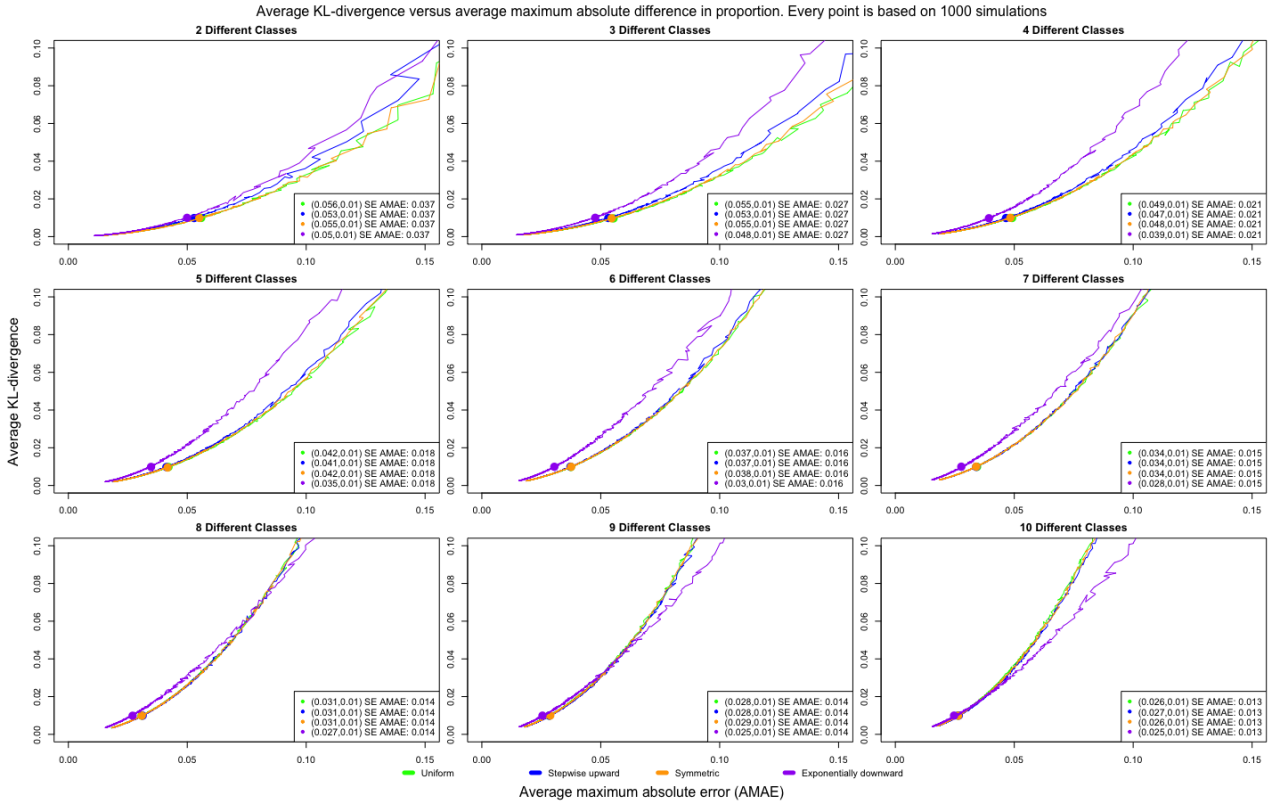

Figure A.15: Average KL-Divergence plotted against the average maximum absolute error (AMAE) between the generated density and underlying distributions for the uniform, stepwise upward, symmetric, and exponentially downward distributions for 2 up to 10 different classes.

to determine a the minimum amount of required observations, R_N. For this, we need to take into account the number of distinct classes (delivery promises), as well as the shape of the distribution. For example if we take the worst case scenario of the plots in Figure A.14, we require on average a value of R_N of around 450. However, we believe that this amount is too pessimistic, since we assume in this case that all 10 different delivery promise have high probability masses. In our opinion, it is much more realistic to have only a couple of the delivery promises with high probability mass, and the other either being absent, or having only very low probability mass. Therefore, we believe that if we consider the plots up to 6 different delivery promises, we are in a much more realistic scenario. Based on these plots, we take the worst case scenario of 6 different delivery promises, for which a value for R_N of around 250 observations should satisfy the threshold on average. Therefore, for convenience we set $R_N = 250$.

Implementation of Mode Imputation. Given the decision rule for imputation of Equation A.5, and a value of R_N of 100, we can illustrate our imputation method by means of an example. Similar to the imputation of Section Appendix A.5.1 we take account for weekends and holidays. That is for partners which we know do not delivery on a particular day (or all days) in the weekend, and/or holidays we add extra delivery promises. In case we do not know if there is a delivery in the weekend and/or on holidays, we add extra delivery promises for Sunday, and the holidays.

The approach of imputation is described by the following two-step procedure:

1. **Determine Product Group Level**: Find the lowest product group level for which holds that the number of observations of partner s in product group level g, denoted by N_{sg}, is larger or equal than R_N: $N_{sg} \geq R_N$. In case no N_{sg} satisfies this condition, we do not impute.

2. **Apply Mode Imputation**: Based on the selected product group level, apply the decision rule of Equation A.5.

We can apply this imputation by means of a query.

Results Mode Imputation. In Figure A.16, we have plotted the percentages of recovered products using mode imputation per shop. Unfortunately, we were not able to impute the majority of the data for most shops (Mobile being the exception). This is mainly because of three reasons. First, we have many partners which only have a couple of products. For some of these partners, we do not have any other products with usable delivery information. Hence, it is impossible to impute the missing data using mode imputation. For other partners, we have some products which we can use to impute, but these amounts are far below the set threshold of R_N of 250. However, as there are many of these partners, the total number of products we cannot impute is automatically large.

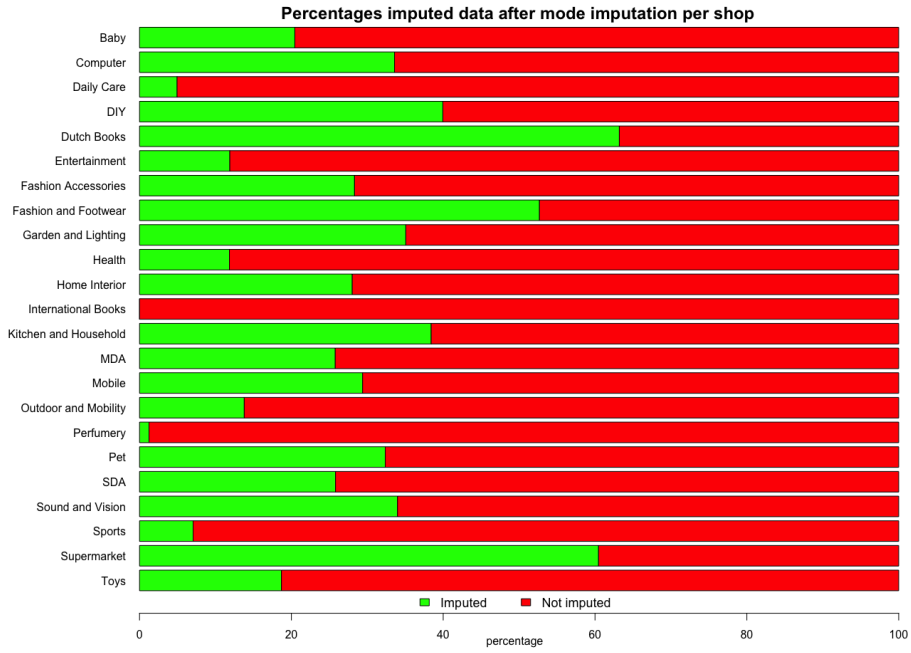

Figure A.16: Percentages of products which we are able to impute given the values of $R_N = 250$ and the decision rule of Equation A.5 per shop.

Second, by using a value of 250 for R_N we often use distributions of delivery promises of the higher product group levels (product group or shop). As distributions generally become more spread out the higher the product group level, this implies that our imputation becomes less specific. As a result, given the constraints of Table A.15, the decision rule of Equation A.5 leads to returning a none value (or deciding not to impute).

This last point leads to the last reason, namely that the penalties of A.15 might generally be too strict. Consequently, we could have imputed more products with looser bounds.

Although we could recover more products by either lowering the value of R_N, or by loosening the penalties of Table A.15, we believe that the possible risk of creating systematic biases out weights the additional benefit we obtain by doing so. For this reason, we take the results of Figure A.16 as they are.

Appendix A.6. Results after Imputation

Based on the methods described in Sections Appendix A.4, Appendix A.5.1 and Appendix A.5.2, we have plotted in Figure A.17 the results after imputation over all shops. In this figure, we find that for most shops the majority of products have usable products after imputation. The exceptions on this rule are the shops related to books (Dutch Books and International Books). This is partly the reason why we have relatively small amount of products from the two book shops. Additionally, we see that the shop Entertainment still has a large proportion of products which have unusable information in terms of the delivery promise. However, this does not to seem have any large effect on the number of products from this shop which we use in this study.

Figure A.17: Top Plot: Overview of usability levels before imputation is applied as depicted in Figure A.11. Bottom Plot: Usability levels after imputation.

Appendix B. More Extensive Overview Data

Appendix B.1. Variability Variables of Study

In this part of Section 4.3, we provide an overview of the variability of the study variables $\sigma_{9.21}(\text{RP}_p)$, $\sigma_{9.21}(\text{RP}_d)$, RC, WTP and UTP by means of histograms of the observations split over the different shops. We treat the regular period and holiday period separately. In Figures B.18 (regular period) and B.20 (holiday period) we plot the variability for respectively $\sigma_{9.21}(\text{RP}_p)$ and $\sigma_{9.21}(\text{RP}_d)$, while in Figures B.18 (regular period) and B.20 (holiday period) we do the same for RC, WTP and UTP. Regarding Figures B.18 and B.20 we would like to stress that we have splitted the variability into two parts. First we have plotted the proportion of inactive and active observations (plots on the left side). Then for all observations which are active, we subsequently plot the variability within the active part (plots on the right).

Regular Period.

- $\boldsymbol{\sigma_{9.21}(\text{RP}_p)}$: In the top plot of Figure B.18, we have depicted the variability for the $\sigma_{9.21}(\text{RP}_p)$ during the regular period over the different shops. Based on this plot, we can first of all see that the mass of values of $\sigma_{9.21}(\text{RP}_p)$ are larger than 0.5 for nearly all shops (Dutch Books and International Books being the exception). This indicates that in the majority of the time the prices of the the internal retailer are significantly lower compared to that of the market.

  Secondly, we observe some peaks around a $\sigma_{9.21}(\text{RP}_p)$ value of 0.5. For example, for the shop Daily Care, we see that the $\sigma_{9.21}(\text{RP}_p)$ gradually increases, with the exception at 0.5, in which we a sudden peak. These peaks can be explained by the fact that during some days, we do not observe any competitor. This is especially true for the products which are less popular (have less daily sales). As a result, the only competitor in the market is the internal retailer, which automatically implies that the price of the internal retailer equals the market price. Consequently we obtain a value for $\sigma_{9.21}(\text{RP}_p)$ of 0.5.

  Thirdly, for the shops Dutch Books and International Books, we do not find much variation in values of $\sigma_{9.21}(\text{RP}_p)$. This can partly be explained by the small number of products which we have available for these two shops (see Table 5).

- $\boldsymbol{\sigma_{9.21}(\text{RP}_p)}$: In the bottom plot of Figure B.18 we obtain the variability for the variable $\sigma_{9.21}(\text{RP}_d)$ during the regular period. At a first glance, we observe values of $\sigma_{9.21}(\text{RP}_d)$ overall have a mode at a value of 1. This indicates that the internal retailer generally offers much faster delivery promises compared to the market.

  What is more, we observe much less variability compared to the plot of $\sigma_{9.21}(\text{RP}_p)$. This can partly be explained for two reasons. First, the delivery promises are variables in the range of $[1, 14]$, while prices tend to to have larger values in general. As a result, an absolute difference of 1 day has relatively speaking a much larger impact on the relative delivery promise position than an absolute difference of 1 euro. Secondly, delivery promises increment in much larger steps than prices. Although we make delivery promises continues by the aggregation process,

delivery promises we observe that the absolute difference of delivery promises takes place in number of days, while for prices we more relatively observe more absolute differences in terms of euro cents.

Given these observations, we can also make a couple of remarks which are comparable to those we made for $\sigma_{9.21}(\text{RP}_p)$. First, we see sharp peaks at a $\sigma_{9.21}(\text{RP}_d)$ value of 0.5, which we can explain by the fact that for some observations we do not observe any competitors. Secondly, we do not observe much variability in values of $\sigma_{9.21}(\text{RP}_d)$ for the shops Dutch Books and International Books.

- **RC**: The plots in the first row of Figure B.19 show variability for the variable RC during the holiday period for the different shops. If we consider the left plot (top left) of this figure, we first of all see that for a majority of the observations (on average a little over 60% of the observations) we find that RC is active. This is true for almost all shops. The shops which form an exception to this rule are Dutch Books and International Books. This should not be very surprising given the observations we made earlier about the variability of $\sigma_{9.21}(\text{RP}_p)$ and $\sigma_{9.21}(\text{RP}_d)$ of these shops.

  For those observations for which we observe that RC is active, we can find the variability by means of consulting the right plot (top right). Here we can see that for all shops RC mostly takes values in the range $[0, 1]$. This indicates that the internal retailer outperforms the market both in terms of price and delivery promise in a majority of the time. This is in line with the analysis we made about the plots of Figure B.18, in which we concluded that the internal retailer has a offer position which is generally better than the market both in terms of price and delivery promise.

- **WTP**: In the two middle plots of Figure B.19, we have shown the variability of variable WTP during the regular period. By first considering the left plot (middle left), we find that for most shops during a majority of the time WTP is inactive (on average a little over 80% of the time). Given the top left plot of Figure B.19, this is not entirely unexpected, since we observed that RC is active for the bulk of the observations.

  For those observations for which we have that WTP is active, we observe most observations are clustered around a value of 0.4 for most shops. This implies moderate trade-offs between faster delivery promises and higher prices. Furthermore, we see that the full range of values WTP can attain ($[0, 1]$) is covered for most shops. The shops which only have a proportion of the range covered are Dutch Books, Home Interior and International Books.

- **UTP**: In the bottom two plots of Figure B.19, we observe the variability of the variable UTP during the regular period. The histograms in the left (bottom left) plot show that most of the time UTP (a little above 80% of the time for most shops) is inactive. This matches our view for the variable WTP, where we could make a similar observation.

  By zooming into the part in which UTP is active (see bottom right plot), we generally observe a pattern in which the density of the value of UTP increases as UTP becomes higher. This leads

ultimately to a peak where UTP equal 1. This shows that within our sample of products, we observe high trade-off values for this variable. Consequently, we observe situations in which the price of the internal retailer is much lower than the market, at the cost of relative slow delivery promises.

Holiday Period Compared to Regular Period. For the holiday period, we observe similar plots as for the regular periods in terms of variability in $\sigma_{9.21}(\text{RP}_p)$, $\sigma_{9.21}(\text{RP}_d)$, RC, WTP and UTP. Therefore, in stead providing similar comments as for the regular period, we compare the holiday period to the regular period and analyse to what extent the variability is similar during these two periods. The idea behind this analysis is to see to what extend we can compare the possible results during the regular and holiday period based on the variability we observe for variables we want to study during these two periods.

- $\sigma_{\mathbf{9.21}}(\mathbf{RP_p})$: When we contrast the top plot Figure B.20 to the top plot of Figure B.18, we mainly observe similar patterns. For starters, we observe for most shops that $\sigma_{9.21}(\text{RP}_p) > 0.5$ during the holiday period. Second, we observe peak of $\sigma_{9.21}(\text{RP}_p)$ at a value of 0.5 during the holiday period. Lastly, we find that Dutch Books and International Books deviate most from the ordinary pattern.

  By consulting Figure B.20 a little bit more closely, we also can observe some minor differences between Figure B.20 and B.18. For instance, for the shops Baby, Home Interior, Health, and Toys we observe slightly more right skew $\sigma_{9.21}(\text{RP}_p)$ (the area where $(\sigma_{9.21}(\text{RP}_p) > 0.5)$ during the holiday period compared to the regular period, while we also observe less clustering around the values of 0.5 during the holiday period compared to the regular period (contrast the shop Perfumery during those two periods for example).

- $\sigma_{\mathbf{9.21}}(\mathbf{RP_d})$: In the bottom plot of Figure B.20 we observe the variability of $\sigma_{9.21}(\text{RP}_d)$ during the holiday period. Comparing this plot to the bottom plot of Figure B.18 shows that the variability of between these two periods is similar in the sense that the observe most observations within the edges of the histograms. Additionally, most observations are clustered at or close to 1. Furthermore, we observe a spike where $\sigma_{9.21}(\text{RP}_d)$ equals 0.5.

  In terms of differences between the two periods, we find that during the holiday period the internal retailer generally seems to have faster delivery promises compared to the market than during the regular period. This can be concluded from the fact that the peaks at 1 are higher during the holiday period, and additionally since we observe relatively less spread around the values of 1.

- **RC**: If we have a look at the top plots (first row) of Figure B.21 and compare this to the top plots of Figure B.19, the first notable difference is that during the holiday period the proportion of values for which RC is active is lower. Although we still observe that RC is active for a majority of the observations, the gap between active and inactive observations is closer for most shops. In some instances this gap is totally vanished. For example, for the shop Perfumery, we

find that during the holiday period the proportion between active and inactive is approximately the same, while this is not the case for the regular period.

For the observations which are active, we see that the distribution of values behaves similarly during holiday- and regular periods. Consequently, we have that during the holiday the majority of the observations is in the range $[0, 1]$ for RC.

- **WTP**: By considering the middle plots (second row) of Figure B.21 and contrasting these to the middle plots of Figure B.19 we can compare the variability of WTP between the holiday and regular period. Similar to our observations about RC, we find that during the holiday period the gap between inactive and active variable decreases. In this situation, this implies that we relatively have more observations which are active for the variable WTP during the holiday period compared to the regular period.

  Within the active part of WTP of the holiday period (right middle plot), we observe that the distribution has generally similar shapes compared to the regular period. The two main findings which contribute to this conclusion are that (1) we observe peaks around a value of 0.4, and (2) most observations are clustered in the neighbourhood of 0.5. However, we also observe some differences. First of all, during the regular period, the right part of the distribution (the area in which WTP > 0.5) seems to be more populated for the shops Baby, DIY, and Health compared to the holiday period. The opposite seems to be true for the shops MDA, Mobile and Perfumery.

- **UTP**: If we consult the bottom plots (third row) of Figure B.21, and compare this to the bottom plots of Figure B.19, we generally see that the proportion of observations in which UTP is active is similar between the two periods over the different shops. However, by considering individual shops, we are able to find some (noteable) differences. By comparing the proportions for the shop Perfumery for example, we observe that during the holiday period we have relatively more observations which are active compared to the regular period. For the shop Sound and Vision on the other hand, we are able to observe the opposite.

  In terms of variability of the observations in which UTP is active, we see that although the general shape the distributions over the shops during the two periods looks similar, the areas where most observations are clustered differs. The extend to which this occurs is furthermore varying between the different shops. For instance, for the shop Supermarket, we see the the shapes of the distributions roughly have similar shapes and areas where the observations are clustered. However, for the shop Perfumery, we observe that during the holiday period most observations are clustered around 1, while for the regular period this is more gradually increasing to 1.

All-in-all, we find that the variability between the regular and holiday period behaves similarly for the variables $\sigma_{9.21}(\mathrm{RP}_p)$ and $\sigma_{9.21}(\mathrm{RP}_d)$ over the different shops. For the variable RC, we have that during the regular period we have more information for which this variable is active, while the distributions for the observations which are active is roughly speaking the same for both periods. For WTP on the other hand, we observe that during the holiday period more observations are active for

this variable compared to the regular period. In terms of distributions over the different values for which WTP is active, we do not observe any shocking differences. Lastly, for UTP, we find that we have differences from shop to shop both in terms of the proportion of products which is active, as well as the distribution over the different values UTP can attain for those observations which are active between the regular- and holiday period.

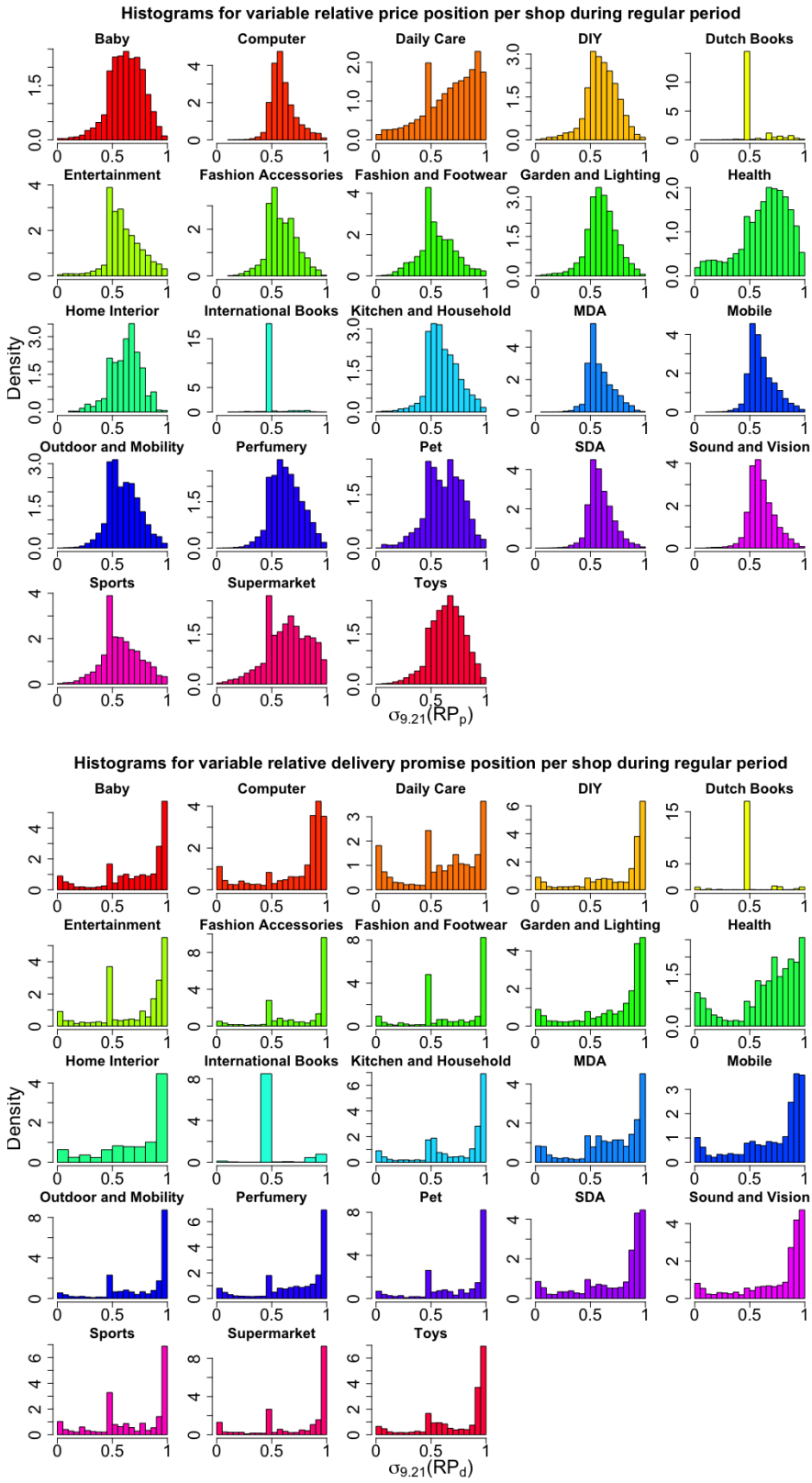

Figure B.18: Histograms for relative price positions, $\sigma_{9.21}(\mathrm{RP}_p)$ (top), and relative delivery promise positions, $\sigma_{9.21}(\mathrm{RP}_d)$ (bottom), over the different shops during the regular period

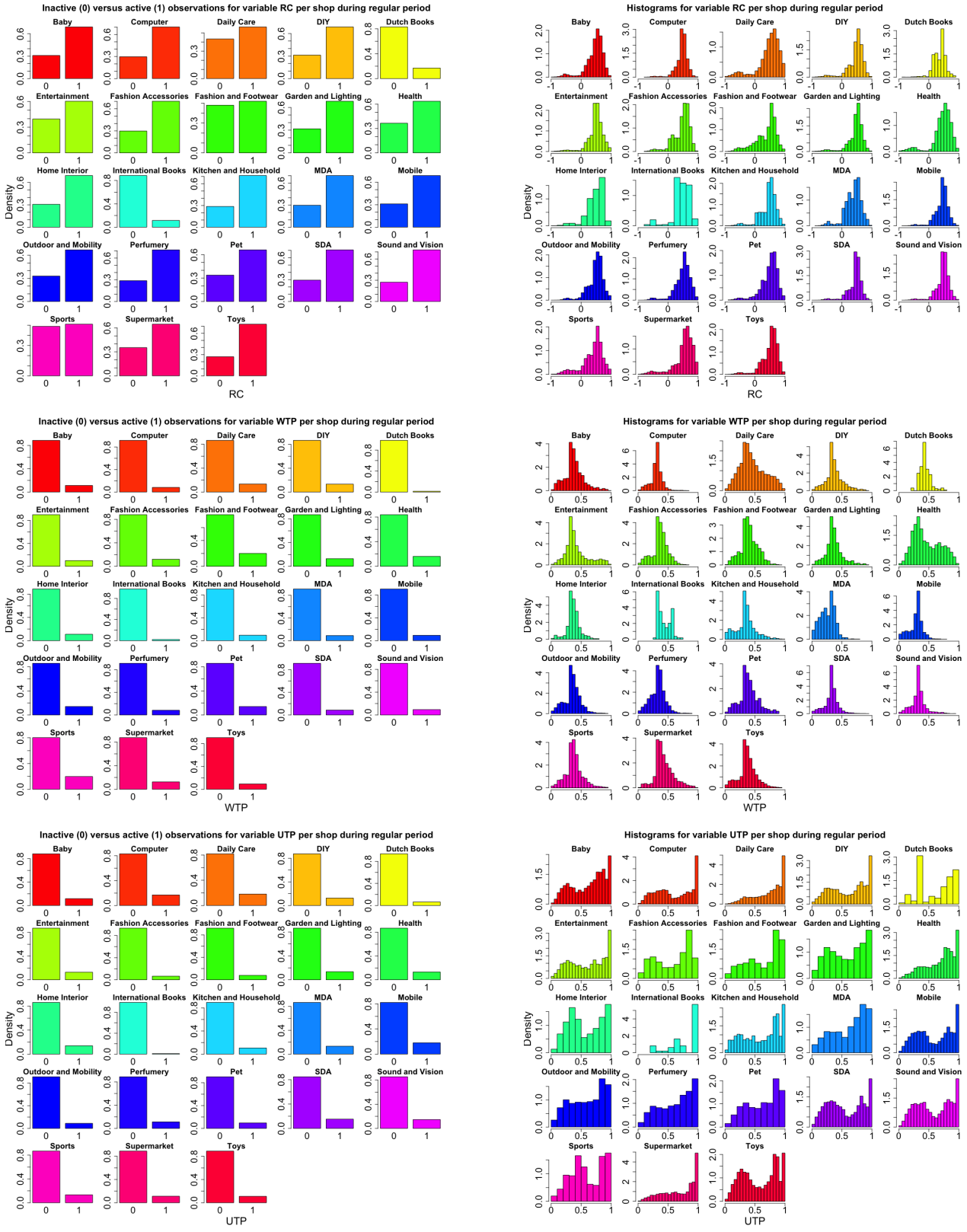

Figure B.19: Left columns: Splits between observations of products without variation (denoted by 0) in RC (top), WTP (middle) and UTP (bottom) and with variation (denoted by 1) over the different shops during the regular period. Right column: Variation of the trade-off variables RC (top), WTP (middle) and UTP (bottom) for those observations which are active during the regular period. Hence we disregard all observations which have 0 values for the in the split histograms.

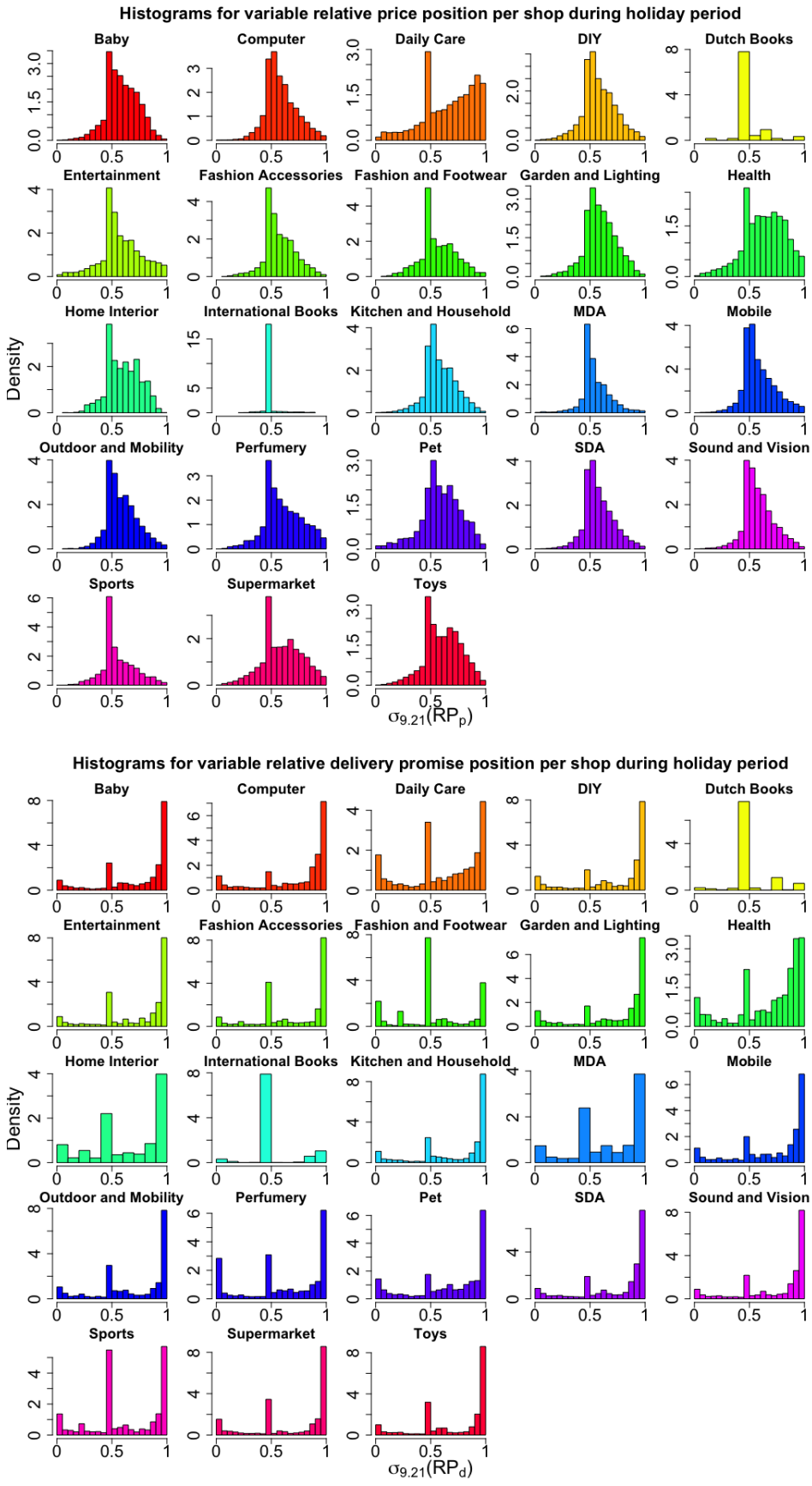

Figure B.20: Histograms for relative price positions, $\sigma_{9.21}(\mathrm{RP}_p)$ (top), and relative delivery promise positions, $\sigma_{9.21}(\mathrm{RP}_d)$ (bottom), over the different shops during the holiday period.

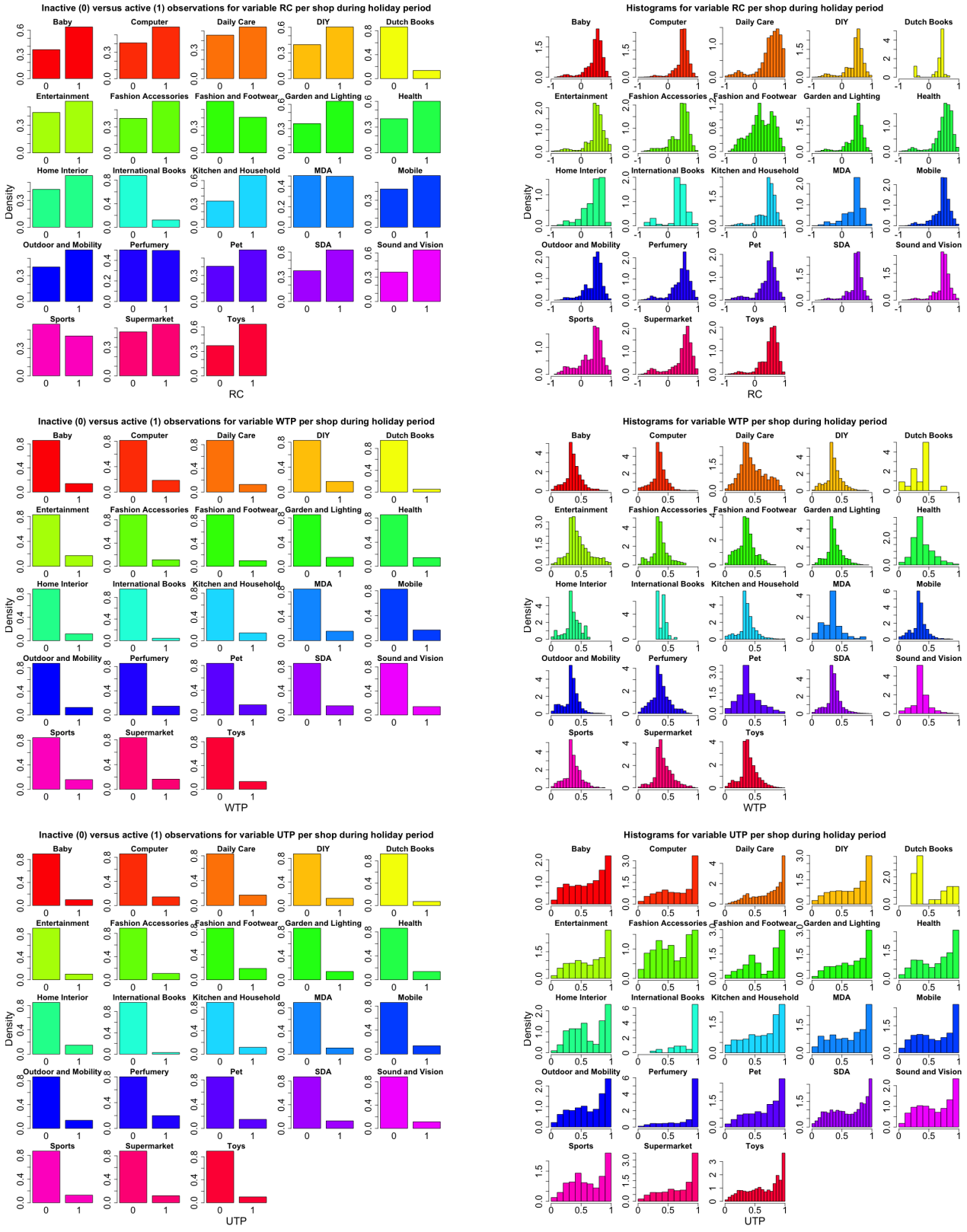

Figure B.21: Left columns: Splits between observations of products without variation (denoted by 0) in RC (top), WTP (middle) and UTP (bottom) and with variation (denoted by 1) over the different shops during the regular period. Right column: Variation of the trade-off variables RC (top), WTP (middle) and UTP (bottom) for those observations which are active during holiday period. Hence we disregard all observations which have 0 values for the in the split histograms.

Appendix B.2. Sample Contrasted to Population

In this part of Section 4.3, we compare products used in this study (the sample) to the underlying population of products which we could have used. Here we define the population as the 500.000 most popular products of the internal retailer which have at least one product per day during 50% of the days between May 2021 and December 2021. Therefore, the difference between the population and the sample of products we use in this study is a direct consequence of the selection criteria we have applied. Within this part of Section 4.3, the goal is to investigate to what extent we can make claims about the underlying population based on the sample of products we use in this study (see Table 5 for the overview of products over the different shops).

For this analysis, we compare the sample to the population based on three different aspects: price, delivery promise and product popularity. The price and delivery promise are based on the different prices and delivery promises of the internal retailer. Here we do not consider competitive offers. The popularity relates to different gradations in which products are sold. Based on these three levels, we divide products into different brackets. These brackets are the following:

- **Price**:
  1. Bracket 1: Median Price $\leq$ €10
  2. Bracket 2: €10 $<$ Median Price $\leq$ €20
  3. Bracket 3: €20 $<$ Median Price $\leq$ €50
  4. Bracket 4: €50 $<$ Median Price $\leq$ €100
  5. Bracket 5: Median Price $>$ €100
- **Delivery Promise**:
  1. Bracket 1: Median Delivery Promise = 1 day
  2. Bracket 2: 1 day $<$ Median Delivery Promise $\leq$ 2 days
  3. Bracket 3: 2 days $<$ Median Delivery Promise $\leq$ 5 days
  4. Bracket 4: 5 days $<$ Median Delivery Promise $\leq$ 7 days
  5. Bracket 5: median Delivery Promise $>$ 7 days
- **Popularity**:
  1. Bracket 1: Median popularity rank $\leq$ 30% Popularity Percentile
  2. Bracket 2: 30% Popularity Percentile $<$ Median Popularity Rank $\leq$ 50% Popularity Percentile
  3. Bracket 3: 50% Popularity Percentile $<$ Median Popularity Rank $\leq$ 70% Popularity Percentile
  4. Bracket 4: 70% Percentile $<$ Median Popularity Rank $\leq$ 90% Popularity Percentile
  5. Bracket 5: Median Popularity Rank $>$ 90% Popularity Percentile

Furthermore, as we consider in this study three different samples (over two different time periods), we compare three different samples to two underlying populations. More specifically, we compare the

sample taken during the regular period to the population of the regular period, while we compare the other two samples (see second and third column of Table 5) to population of the holiday period.

Based on these different specifications, we obtain in total 9 different plots (for the combination of the three different brackets and samples). These are plotted in Figure B.22. In these plots we compare the sample of products per shop (colored distributions) to the population per shop (distributions in white). If we read the plots horizontally, we have plots based on price on top, plots based on delivery promises in the middle, and plots based on popularity in the bottom. Vertically, we have the regular sample on the left, the standard holiday period in the middle, and the holiday period conditioned on willingness to pay around Sinterklaas and Christmas on the right. Next, we provide an analysis per sample (hence we treat the plots vertically).

Regular Period.

- **Price:** In the top left plot of Figure B.22 we find the comparison between the sample and population for prices during the regular period. Generally, we see that our product sample matches the population quite well. For those shops which we observe some differences, across these shops the differences are not the same. For example, for the shop Home Interior we have a small under representation of the third price bracket, while for the shop Sports this holds true for the fourth price bracket. The shops with the largest deviation seem to be Dutch Books and Entertainment.

- **Delivery Promise:** In the top left plot of Figure B.22 we can see the he comparison between the sample and population for delivery promises during the regular period. Generally, we observe that the sample matches the population quite well. The shops Entertainment and Homer Interior seem to have the largest differences between sample and population.

- **Popularity:** In the bottom left plot of Figure B.22 we can see the he comparison between the sample and population for product popularity during the regular period. For all shops, we see that the first bracket is underrepresented in our sample compared to the population. An possible explanation for this could be that we require that products need to have observed competitors before we regard them in the dataset. Products which are less popular, generally also tend to have fewer competitors (or none). This is partly the case, because these products are more obscure, and hence no competitor exists. An explanation which complements the preceding is that the internal retailer overlooks the competitors for these products, since the products in the first popularity bracket are considered to be less relevant for the internal retailer.

  The underrepresentation of the first bracket results in overrepresentation of the second (and sometimes) third brackets. The fourth and fifth brackets seem quite well to be represented in our sample. All-in-all, we can conclude that products which are totally not popular are underrepresented in our data for the regular period.

Based on the observations for price, delivery promise and product popularity, we can conclude that overall the sample matches the population quite well. The only caveat here is that we have severe

underrepresentation of products which fall in the first popularity bracket. However, we argue that this is not too problematic as we do not regard these products to be very relevant in the first place.

Holiday Period.

- **Price:** In the top middle plot of Figure B.22 we find the comparison between the sample and population for prices during the holiday period. Generally, we see that our product sample matches the population quite well. The shops which have the largest deviation from the population are Dutch Books, Entertainment and International Books.

- **Delivery Promise:** In the middle middle plot of Figure B.22 we can see the he comparison between the sample and population for delivery promises during the holiday period. Generally, we observe that the sample matches the population quite well. The shop International Books seems to form the biggest exception to this rule, given the underrepresenation of the first bracket and overrepresentation of the last bracket .

- **Popularity:** In the bottom middle plot of Figure B.22 we can see the he comparison between the sample and population for product popularity during the holiday period. Similar to the plot of the regular period, we find that the first bracket is underrepresented in our sample compared to the population. However, compared to the regular period, the underrepresenation seems to be relatively less severe during the holiday period. As a possible explanation for this observation, we can note that during the holiday period more products sell, which implies that the first bracket is less populated during the holiday period. This is also true if we contrast the heights of the first bracket of the holiday period to the regular period, in which we see that during the regular period the first bracket generally has higher densities compared to the holiday period.

  A consequence of the underrepresenation that remains for first bracket is an overrepresentation of the second (and sometimes) third brackets. This is similar to that of the regular period.

Overall, we find that the sample of this study matches the underlying population quite well. In fact it seems to match the population better compared to the regular period, due to the less underrepresentation of the first popularity bracket. Shops which are exhibit some bias in terms of the population are Dutch Books, International Books and possibly Entertainment.

Holiday Period WTP around Holidays.

- **Price:** In the top right plot of Figure B.22 we find the comparison between the sample and population for prices of willingness to pay around Sinterklaas and Christmas. Overall, the distribution of the sample matches that of the population quite well. However, compared to the holiday period (top middle plot), we observe that for some shops we have relatively larger deviations. For example. we see underrepresentation for the the second bracket of the shop Baby (which leads to overrepresentation of the fourth and fifth bracket). Other shops with moderate differences between the population are Computer, MDA and Mobile. For the shop

Dutch Books we observe the largest deviation compared to the population. This can simply be explained by the sample size of only 1 product.

- **Delivery Promise:** In the middle right plot of Figure B.22 we can see the he comparison between the sample and population of willingness to pay around Sinterklaas and Christmas. We find that the first bracket has an underrepresentation for most shops. As a consequence, the second and third brackets exhibit overrepresentation. The shop Dutch books seems not to be very well represented at all.

- **Popularity:** In the bottom right plot of Figure B.22 we can see the he comparison between the sample and population for product popularity of willingness to pay around Sinterklaas and Christmas. We find that resemblance of the sample compared to the population here is similar as that of the holiday period (bottom middle plot), with the difference that the first bracket is more underrepresented.

Overall, we find that the this sample matches the population reasonably well. Compared to the sample of the holiday period, we see that this sample matches the holiday population less in terms of the delivery promise, but this does not lead to severe deviations.

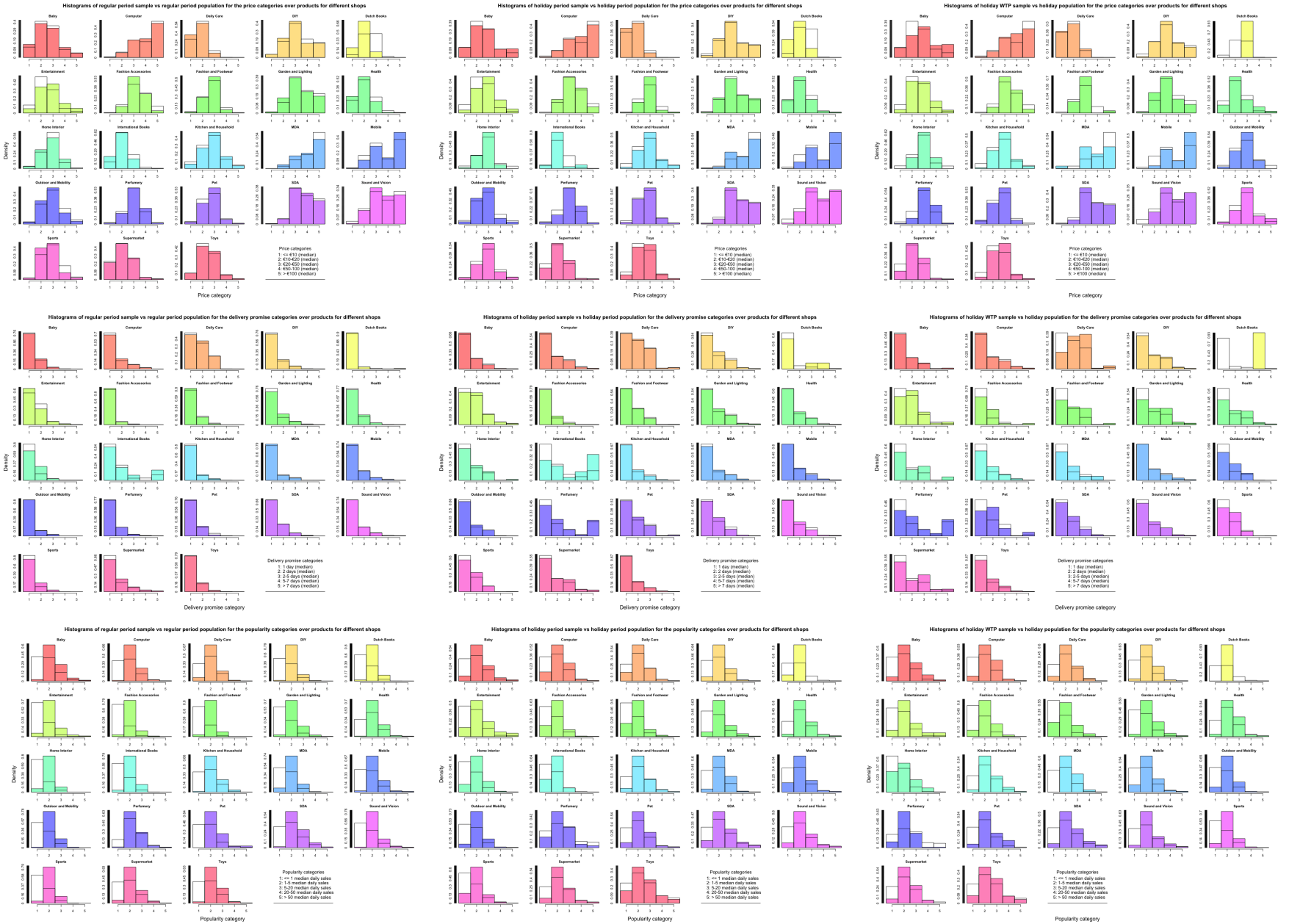

Figure B.22: Sample distribution compared to the underlying populations for different price- (first row), delivery promise- (second row) and product popularity (third row) brackets over different. First column shows the distributions for the regular period, the second column for the holiday period, and the third column for willingness to pay around Sinterklaas and Christmas

Appendix C. Econometric Methods

Appendix C.1. Poisson Regression

Poisson regression depends on the Poisson distribution, which is defined as follows. For some random variable Y, $Y \sim \text{Pois}(\lambda)$ implies the following probability mass function (pmf):

$$\text{P}(Y = y) = \frac{e^{-\lambda}\lambda^{y}}{y!} \tag{C.1}$$

Where y is the realisation of Y and can be any non-negative integer. For a random variable which follows a Poisson distribution, we have the following two central moments:

$$\text{E}(Y) = \lambda \tag{C.2}$$

$$\text{VAR}(Y) = \lambda \tag{C.3}$$

Since the variance and mean of a Poisson distributed random variable are the same, we say the the Poisson distribution satisfies the equidispersion property (Cameron and Trivedi (2005) (section 20.2.2). can convert to Poisson regression (for panel data) by introducing the subscripts i for every individual $i = 1, 2, ..., N$ and t for every time period $t = 1, 2, ..., T$. Then given some outcome variable y_{it}, regressors x_{it} and parameter λ_{it} we express the conditional mean of y_{it} given x_{it} by means of the log-link:

$$E(y_{it}|x_{it}) = \lambda_{it} = e^{x'_{it}\beta} \tag{C.4}$$

With the use of Equations C.1 and C.4, we find that the log-likelihood function is:

$$\mathcal{L}(\beta) = \sum_{i}^{N}\sum_{t}^{T}\left[y_{it}x'_{it}\beta - e^{x'_{it}\beta} - \log(y_{it}!)\right] \tag{C.5}$$

Taking the partial derivative with respect to β, and noting that the log-likelihood function of Equation C.5 is globally concave, results in the following requirement which needs to be solved:

$$\frac{\Delta\mathcal{L}(\beta)}{\Delta\beta} \overset{\text{s}}{=} 0 \iff \sum_{i}^{N}\sum_{t}^{T}\left[x_{it}(y_{it} - e^{x'_{it}\beta})\right] = 0 \tag{C.6}$$

Equation C.6 is usually solved using Gauss-Newton or Newton-Raphson algorithms.

Appendix C.1.1. Underdispersion/Overdispersion

One of the limitations of the Poisson distribution lies in the fact that the variance equals the mean. In many real world applications (including the one we consider in this thesis) this is an unrealistic assumption and it is much more likely that we either observe overdispersion (variance exceeds the mean) or underdispersion (mean exceeds the variance). There exist statistical tests for overdispersion (Cameron and Trivedi (1990)) and underdispersion (Gurmu and Trivedi (1992)). Next we provide two approaches on how deal with overdispersion, as this it the type we encounter in our study.

- **Negative Binomial:** A model specification which is able to deal with overdispersed data is the negative binomial distribution. In Cameron and Trivedi (2005) section 20.4.1 a derivation is given of how to obtain the negative binomial specification. Borrowing the notation of the section, let $f(y|\lambda)$ be a Poisson density as defined in Equation C.1 in which now assume that λ is the product of a deterministic part and random part. Hence let $\lambda = \mu\nu$, where μ denotes the deterministic part and ν the random part which follows a $g(\nu|\delta)$ density. In order to derive the negative binomial density, let and $g(\nu|\delta) = \frac{\nu^{\delta-1}e^{-\nu\delta}\delta^{\delta}}{\Gamma(\delta)}, \nu, \delta > 0$ be a gamma density in which $\mathrm{E}(\nu) = \delta$ and $\mathrm{VAR}(\nu) = \frac{1}{\delta}$. The negative binomial density is then defined as follows. We write the marginal density of y conditioned on the deterministic parameters μ, δ by taking the mixture of densities of $f(y|\lambda)$ and $g(\nu|\delta)$, and integrating out ν:

$$h(y|\lambda,\delta) = \int f(y|\lambda)g(\nu|\delta)d\nu = \int f(y|\mu,\nu)g(\nu|\delta)d\nu = \frac{\Gamma(\alpha^{-1}+y)}{\Gamma(\alpha^{-1})\Gamma(y)}\left(\frac{\alpha^{-1}}{\alpha^{-1}+\mu}\right)^{\alpha^{-1}}\left(\frac{\mu}{\mu+\alpha^{-1}}\right)^{y} \tag{C.7}$$

Where $\alpha = \frac{1}{\delta}$. For the full derivation of Formula C.7 we refer to section 20.4.1 of Cameron and Trivedi (2005). Note that the Gamma term ($\Gamma(\cdot)$) becomes a factorial if the argument is integer (which is the case for y). FOR Equation C.7 we find that the first two central moments are:

$$\mathrm{E}(y|\mu,\alpha) = \mu \tag{C.8}$$

$$\mathrm{VAR}(y|\mu,\alpha) = \mu(1+\alpha\mu) \tag{C.9}$$

If we compare these two moments to those of the Poisson distribution, we find that the two coincide if $\alpha = 0$. For $\alpha > 0$, we find that the variance of the negative binomial distribution exceeds the variance of Poisson distribution (and the mean of both the negative binomial and Poisson distributions). Hence, by applying a regression model under the specification of Equation C.7, we account for overdispersion.

In regression applications, usually two different specifications can be used. The difference between the two lies in the way $\mathrm{VAR}(y|\mu,\alpha)$ and how α is treated. In the first specification α is estimated from the data and the expression of $\mathrm{VAR}(y|\mu,\alpha) = \mu(1+\alpha\mu)$ is quadratic in μ. This type is denoted as NB2 (Cameron and Trivedi (2013)). For the other specification, we the has a linear function and is written as $\mathrm{VAR}(y|\mu,\alpha) = \mu(1+\gamma)$, where $\gamma = \mu\alpha \iff \alpha = \frac{\gamma}{\mu}$. This type is denoted as NB1 (Cameron and Trivedi (2013))

- **Finite Mixture Models:** Another method to deal with overdispersion is by means of Finite Mixture Models. We explain this method in greater detail in Section Appendix C.3. In the context of overdispersion, Finite Mixture Models fit a finite discrete number separate mixture components, each with varying values of λ (as defined in Equation C.1). Therefore, although within every mixture s it is assumed that $\mathrm{E}(y) = \mathrm{VAR}(y) = \lambda_s$, as we have a different number of mixtures the total variance can exceed the mean. Note that we also can allow for overdispersion within a cluster by using the negative binomial specification for every mixture component.

Different applications show that Finite Mixture Models are suitable to deal with overdispersed data. For example in Deb and Trivedi (2002) it is shown performs well for medicine data in which the population can be split different health statuses which are latent, while in Park and Lord (2009) it is shown that a finite mixture of Poisson or negative binomial have better fit than merely applying a negative binomial regression on vehicle crash data.

Appendix C.1.2. Excess Zeros

In many real world applications (including ours) a vast majority of the observations have zero outcomes. This is called the excess-zero problem. In these situations, Poisson Regression has a tendency to underestimate the amount of zeros. This problem can be solved by several methods, such as the Hurdle or Two-Part Models and the Zero-Inflated Model. In the former, we assume that the zero-outcomes and non-zero outcomes are generated by two different data generating processes. Here the non-zero outcomes are assumed to be generated from a truncated density. We refer to section 20.4.5 of Cameron and Trivedi (2005) for a more detailed explanation of this method.

In the Zero-Inflated-Model, a slightly different approach is taken. In this model, we assume a binary process, in which we have with probability $f_1(0)$ that this process takes on the value zero. In this case, we find that our outcome equals zero. With probability $f_1(1)$, we find that the value 1 is taken. In this situation the outcome variable takes on all values in the range of possible outcomes. Based on this binary process, we can conclude that we have two types of zero-outcomes: 'true' zeros which follow the same data generating process as the non-zero outcomes and 'false' zeros, which are excluded from the other outcomes (including both the 'true' zeros and non-zeros). See section section 20.4.5 Cameron and Trivedi (2005).

Practical applications show that Finite Mixture Models with latent classes can also be used to deal with excess zeros. For example, in Dalrymple et al. (2003) it is shown that Finite Mixtures can have a similar fit zero-inflated Poisson and hurdle models on a dataset concerning sudden infant death syndrome (SIDS). To mention another study, in Bermúdez and Karlis (2012) the researchers show that a Finite Mixture Model with a Bivariate Poisson density is better able to deal with overdispersion than zero-inflated and hurdle-models without finite mixtures.

Appendix C.2. Approaches to Deal With Unobserved Heterogeneity in Panel Data Models

Within panel data we generally distinguish three types of models. The difference between these models has to to with the way in which the unobserved heterogeneity is treated. First we have pooled models, which do not account for heterogeneity. Second, we have fixed effects (FE), in which it is assumed that in which we assume that all individual-specific unobserved variables are correlated with the included explanatory variables of our model. Thirdly, we have Random Effects (RE). Thirdly, we have Random Effects (RE). Within this approach we assume that all individual-specific unobserved variables are uncorrelated with the included explanatory variables of our model. By imposing this assumption, we can consider these effects as part of the error term (assuming that our explanatory variables are not correlated with the error term). From a consistency perspective, models using the FE assumption are always consistent, while models using the pooled or RE assumption are only consistent in case the RE assumption is true. It should be noted that whenever the pooled or RE

assumption hold true, models based on the FE assumption are less efficient. The Hausman Test (Hausman (1978)) can be used to test which of the two specifications is valid.

Issues concerning unobserved heterogeneity usually arise in the context of micro panel datasets (or short panels). Here we assume that T is moderately small, while $N \to \infty$. As a consequence, we obtain biases for the estimation of the term involving the unobserved heterogeneity (α_i as introduced earlier). The bias in this estimation result in a carry over effect of inconsistency for the other parameters in the model. In the econometrics context, this is called the incidental parameter problem (see Lancaster (2000)). Especially for models which use a FE approach this implies that it is more desirable to first remove the unobserved heterogeneity. For certain non linear specifications it is shown that using dummy variables fixed effects can be estimated in an asymptotically unbiased way (see Heckman (1981) Greene (2004) and Allison (2009)).

Appendix C.2.1. Eliminating Unobserved Heterogeneity using Fixed Effects

Within FE frameworks, the idea is to remove the unobserved heterogeneity. For example, in linear regression the unobserved individual heterogeneity can be removed by demeaning, or first differencing.

For non linear models, two methods are usually considered. First we have conditional likelihood approach. Here the idea is to find a sufficient statistic for the unobserved heterogeneity. Then by conditioning on this sufficient statistic, we can eliminate the unobserved heterogeneity from the likelihood. The second approach is called concentrated likelihood. Here the idea is to write the likelihood only in terms of focus parameters, while the other (auxiliary) parameters are concentrated out.

As examples are more illustrative than merely words, let us illustrate the concept of concentrated likelihood in the case for Poisson regression in a panel data setting (the model structure we use in this study). For this, we borrow notation from Cameron and Trivedi (2005) (Section 25.7.3) which on its turn is based on Hausman et al. (1984) and Blundell et al. (1995). By doing so, consider the following specification:

$$y_{it} \sim \text{Pois}(\lambda_{it}\alpha_i) \tag{C.10}$$

$$\lambda_{it} = e^{(x'_{it}\beta)} \tag{C.11}$$

Here y_{it} corresponds to the outcome variable for observation i measured at time t, λ_{it} is the parameter of the Poisson distribution, α_i is the individual specific effect, and x'_{it} correspond to the regressors. Note here that we assume that $_i$ has an multiplicative effect on λ_{it}.

The first step is to find a sufficient statistic for α_i. It can be shown that this equals $\Sigma_{i,t} y_{it}$. Then consider the the log-likelihood function for a Poisson specification:

$$\mathcal{L}(\beta, \alpha) = \log\left[\Pi_i \Pi_t \left(\frac{(\alpha_i \lambda_{it})^{y_{it}} e^{(-\alpha_i \lambda_{it})}}{y_{it}!}\right)\right] = \Sigma_i \left[-\alpha_i \Sigma_t \lambda_{it} + \log(\alpha_i)\Sigma_t y_{it} + \Sigma_t y_{it} \log(\lambda_{it}) - \Sigma_t \log(y_{it}!)\right] \tag{C.12}$$

If we differentiate in Equation C.12 with respect to α_i and set the derivative equal to zero (analysing the first order condition), we obtain:

$$\frac{\Delta \mathcal{L}(\beta, \alpha)}{\Delta \alpha} \stackrel{s}{=} 0 \iff \hat{\alpha}_i = \frac{\Sigma_t y_{it}}{\Sigma_t \lambda_{it}} = \frac{\bar{y}_i}{\bar{\lambda}_i} \tag{C.13}$$

Where $\bar{y}_i = \frac{1}{T}\sum_t y_{it}$ and $\bar{\lambda}_i = \frac{1}{T}\sum_t \lambda_{it} = \frac{1}{T}\Sigma_t e^{x'_{it}\beta}$. Next, let us consider the first order condition of Equation C.12 given than we use the sufficient statistic $\hat{\alpha}_i$ for α_i. For this we consider the concentrated likelihood function

$$\mathcal{L}_{\text{conc}}(\beta) = \Sigma_i \left[-\hat{\alpha}_i \Sigma_t \lambda_{it} + \log(\hat{\alpha}_i)\Sigma_t y_{it} + \Sigma_t y_{it} \log(\lambda_{it}) - \Sigma_t \log(y_{it}!)\right] \tag{C.14}$$

The first order condition of Equation C.14 then is

$$\frac{\Delta \mathcal{L}_{\text{conc}}(\beta)}{\Delta \beta} \stackrel{s}{=} 0 \iff \sum_{i=1}^{N}\sum_{t=1}^{T} x_{it}\left(y_{it} - \hat{\alpha}_i \lambda_{it}\right) = \sum_{i=1}^{N}\sum_{t=1}^{T} x_{it}\left(y_{it} - \frac{\lambda_{it}}{\bar{\lambda}_i}\bar{y}_i\right) = 0 \tag{C.15}$$

As a consequence of the Formula C.15, time-invariant regressors are dropped out from the model. For fixed T and $N \to \infty$ consistent estimates can be obtained (see Hausman et al. (1984)). Estimation of C.15 can be done by Newton Raphson type algorithms (iteratively reweighted least squares).

Appendix C.2.2. Random Effects Models in the Context of Unobserved Heterogeneity

Under the assumption that the Random Effects assumption holds, for linear regression models parameter estimation is usually applied by means of Feasible Generalised Least Squares (FGLS), see Cameron and Trivedi (2005) (Section 21.7.1).

In the context of non linear models, the parameters can be estimated using maximal likelihood. For this let us borrow some notation from Cameron and Trivedi (2005) (Section 23.2.3). For individuals $i = 1, 2, ..., N$ and time period $t = 1, 2, ..., T$ Let $f(y_{it}|x_{it}, \alpha_i, \beta)$ be some density function (for example Poisson) for outcome variable y_{it} as a function of regressors x_{it} and model parameters $_i$ and β. Here α_i is the individual specific parameter and β the other model parameters. Additionally, let $g(\alpha_i, \beta)$ be a density function for α_i. Then the complete marginal likelihood function for y_i can be written as:

$$f(y|x, \beta) = \prod_{i=1}^{N}\left[\int \left(\prod_{t=1}^{T} f(y_{it}|x_{it}, \alpha_i, \beta)\right) g(\alpha_i, \beta) d\alpha_i\right] \tag{C.16}$$

The idea behind Formula Appendix C.2.2 is to treat α_i as a random variable following some distribution $g(\alpha_i, \beta)$ and then removing α_i by means of integration out α_i. For some specifications of $f(y_{it}|x_{it}, \alpha_i, \beta)$ and $g(\alpha_i, \beta)$ a closed form solution of Equation can be obtained. For example in case $f(y_{it}|x_{it}, \alpha_i, \beta)$ is a density following the Poisson distribution and $g(\alpha_i, \beta)$ a distribution following a gamma distribution, the Formula becomes a negative binomial distribution (see Cameron and Trivedi (2005) section 23.7.2). In most applications however, we do not find specifications which lead to a closed form solution. In these circumstances simulation methods can be used (such as Monte Carlo Simulation).

Appendix C.3. Finite Mixture Models

In the context of Finite Mixture Models two concepts are of main interest. First we have the model specification as a mixture of S different components, and second the group memberships (posterior probabilities) for an individual i belonging to a segment j. Let us next introduce these two concepts.

Let i denote an individual for $i = 1, 2, ..., N$, t a time measurement for $t = 1, 2, ..., T$. Given i and t, y_{it} denotes the outcome for individual i measured at time t, x_{it} a vector of length K containing the regressors $k = 1, 2, ..K$ measured for individual i at time t. For individual i, we assume that individual i belongs to one of S_i clusters/segments, where $S_i \in \{1, 2, ..., S\}$, for some $S \in \mathbf{N}$. We denote the probability of individual i belonging to S_i as $\mathrm{P}(S_i = s) = \pi_s$. Since we state that π_s is a probability, we implicitly set the following conditions:

$$\pi_s \geq 0 \tag{C.17}$$

$$\sum_{s=1}^{S} \pi_s = 1 \tag{C.18}$$

For every segment s, we have besides π_s a set of parameters, denoted as θ_s. Combining all these parameters for all $s = 1, 2, ..., S$ into one vector gives us $\psi = \left(\pi_1, \pi_2, ..., \pi_S, \theta_1', \theta_2', ..., \theta_S'\right)$. Using this notation, we define a S-finite mixture as follows:

$$h(y_i|x_i, \psi) = \sum_{s=1}^{S} \pi_s \prod_{t=1}^{T} f_s(y_{it}|x_{it}, \theta_s) = \sum_{s=1}^{S} \pi_s f(y_i|x_i, \theta_s) \tag{C.19}$$

Where $f_s(y_{it}|x_{it}, \theta_s)$ is some arbitrary density in which the subscript s indicates that we are considering the density (and parameters) of segment s. Given the S different segment we define the posterior probability of individual i belonging to segment s as:

$$p_{is} = \mathrm{P}(j|y_i, x_i, \psi) = \frac{\pi_s f_s(y_i|x_i, \theta_s)}{\sum_{m=1}^{S} \pi_m f(y_i|x_i, \theta_m)} \tag{C.20}$$

Based on Equation C.19 we can divide the types of models into two families, namely those who specify linear regression models (DeSarbo and Cron (1988)) and generalised linear models (Wedel and DeSarbo (1995)). As we in this study consider the Poisson specification, our model falls in the family of general linear models.

In order to obtain estimates for all parameters in Finite Mixture Models the Expectation Maximization (EM) (first derived by Dempster et al. (1977)) is usually used, although sometimes other methods such as Bayesian approaches are also seen in the literature (see Diebolt and Robert (1994) for an example). In this study we will also make use of the EM-algorithm. In the next paragraph we formulate the steps needed to derive a general EM-algorithm.

Appendix C.3.1. Derivation EM-Algorithm

We derive the EM-algorithm in two steps. First we show a formula for the complete likelihood function for some arbitrary density function. Given this complete likelihood function, we then derive the EM-algorithm, which in the process also results in the formula of the group membership as introduced in Equation C.20.

1. *Deriving Complete Log-likelihood*:

We start the derivation of the complete log-likelihood by means of Equation C.19:

$$h(y_{it}|, x_{it}, \psi) = \sum_{s=1}^{S} \pi_s f_s(\theta_s|y_i, x_i)$$

If we then would take this function for all N individuals, we would obtain the general likelihood-function:

$$h(y|x, \psi) = \prod_{i=1}^{N} \sum_{s=1}^{S} \pi_s f_s(y_i|x_i, \theta_s) \tag{C.21}$$

Taking logs with respect to equation (C.21) therefore should result in the log-likelihood function:

$$\mathcal{L}(y|x, \psi) = \sum_{i=1}^{N} \log(\sum_{s=1}^{S} \pi_s f_s(y_i|x_i, \theta_s) \tag{C.22}$$

The log-likelihood function as defined in equation (C.22) makes it hard to find estimates for ϕ, due to the sum over the segments c in the log. Therefore, we define the complete likelihood function, by assuming that the segment S_i is known. By doing so we obtain the following formula:

$$L_c(y, s|x, \psi) = \prod_{i=1}^{N} \prod_{s=1}^{S} (\pi_c f_s(y_i|x_i, \theta_s))^{\mathbb{I}(S_i=s)} \tag{C.23}$$

Taking logs, we should obtain therefore the complete log-likelihood function:

$$\mathcal{L}_c(y, s|x, \psi) = \sum_{i=1}^{N} \sum_{s=1}^{S} \mathbb{I}(S_i = s)[\log(\pi_c) + \log(f_s(y_i|x_i, \theta_s))] \tag{C.24}$$

2. *Deriving E-M steps*

The E-M algorithm repeatedly alternates between the E-step and M step. In the E-step the posterior probabilities p_{is} as defined by Equation C.20 are calculated, using fixed values of the parameter vector ψ. Given the estimates for p_{is} we then update our estimates for ψ. The process then repeats itself until convergence is achieved. Let us next show the derivation for these two steps.

E-step:. Note that $\mathbb{I}(S_i = s)$ in equation (C.24) is latent and hence cannot be used as input. Therefore, we need to replace this by something which we could give as input. For this we

consider the expectation of $\mathbb{I}(S_i = s)$ conditional on y_i:

$$\begin{aligned} E(\mathbb{I}(S_i = s)|y_i) &= P(S_i = s|y_i) \\ &= \frac{f_s(y_i, S_i = s|x, \theta_s)}{f_s(y_i|x, \theta_s)} \\ &= \frac{\pi_s f_s(y_i|x, \theta_s)}{\sum_{m=1}^{S} \pi_m f_s(y_i|x, \theta_m)} = p_{is} \end{aligned} \tag{C.25}$$

Here the result of Equation C.25 are the posterior probabilities as defined in Equation C.20. In order to derive numerical values for the result in equation (C.25), we assume that we know the values in ψ (π and θ). Therefore, if we would replace $\mathbb{I}(S_i = s)$ by p_{is}, we are able to find numerical results for equation C.24.

M-step:. After we have computed the E-step, and therefore assume that the p_{is} values are known, we are able to update our estimates for π and θ. In order to do so, we need to derive first order conditions. These will then be used to find the updates for π and θ. Therefore, to compute the M-step, let us first fill the result of equation (C.25) into equation (C.24) and split the terms, such that we can write equation (C.24) into two parts:

$$\mathcal{L}_c(\theta, \pi|y, s; x) = \sum_{i=1}^{N}\sum_{c=1}^{K} p_{is}\log(\pi_s) + \sum_{i=1}^{N}\sum_{s=1}^{S} p_{is}\log(f_s(y_i|x_i, \theta_s)) \tag{C.26}$$

Since equation (C.26) is the sum of two functions, we can estimate the π- and θ-vectors independently from each other. Estimating the parameters in π boils down to:

$$\hat{\pi}_s = \arg\max_{\pi_s} \sum_{i=1}^{N}\sum_{s=1}^{S} p_{is}\log(\pi_s), \text{ for } s \in \{1, 2, ..., S\} \tag{C.27}$$

$$\text{subject to: } \pi_s \geq 0 \; s \in \{1, 2, ..., S\} \text{ and } \sum_{s=1}^{S} \pi_s = 1$$

Equation (C.27) can easily be solved if we write this problem down in a Lagrangian form and then find the first order conditions with respect to this form. Furthermore, since the log-function is concave, we will attain a maximum. By doing so, we obtain that our estimates for π are:

$$\hat{\pi}_s = \frac{1}{N}\sum_{i=1}^{N} p_{is}, \text{ for } s \in \{1, 2, ..., S\} \tag{C.28}$$

Note that the result in equation (C.28) could be interpreted the average of the conditional segment probabilities over the individuals. Given the solution for π as defined in Equation C.28, we can find estimates for θ_s by equation (C.26). In order to find estimates for θ, we need

to solve:

$$\hat{\theta}_s = \arg\max_{\theta_s}(\sum_{i=1}^{N}\sum_{s=1}^{S} p_{is}\log(f_s(y_i|x_i,\theta_s))), \text{ for } s \in \{1,2,...,S\} \tag{C.29}$$

We can achieve this by solving the following first order condition:

$$\sum_{i=1}^{N}\sum_{s=1}^{S} p_{is}\frac{\Delta\log(f_s(y_i|x_i,\theta_s))}{\Delta\theta_s} \overset{s}{=} 0 \tag{C.30}$$

The complexity of solving the first order condition of Equation C.30 depends on the complexity of the specific form of $f(y_i|x_i,\theta_s)$. In this study, $f(y_i|x_i,\theta_s)$ would be the Poisson density. In the next paragraph we show the specific derivation for this distribution.

Appendix C.3.2. M-step under (Fixed Effects) Poisson Specification

We want to solve the first order condition of Equation C.30 for $f(y_i|x_i,\theta_s)$ following a Poisson density. Recall again the first order condition

$$\sum_{i=1}^{N}\sum_{s=1}^{S} p_{is}\frac{\Delta\log(f_s(y_i|x_i,\theta_s))}{\Delta\theta_s} \overset{s}{=} 0$$

The first we observation we can make is that we can treat the derivative of every segment s separately, since the derivative of a sum (here over the segments) equals the sum of the derivatives and the terms p_{is}, θ_s and $\log(f_s(y_i|x_i\theta_s)$ only appear in their own segments, which implies that if we take the derivative for one segment s all other terms in the sum equal zero. Therefore, we need to solve S different derivatives of the same form:

$$\sum_{i=1}^{N} p_{is}\frac{\Delta\log(f_s(y_i|x_i,\theta_s))}{\Delta\theta_s} \overset{s}{=} 0 \ \forall s = 1,2,...,S \tag{C.31}$$

The next step is to replace $f(y_i|x_i,\theta_s)$ by the Poisson density, taking the log of this density and deriving the first order condition. For this recall, Equations C.5 and C.6 in which we did this already. Compared to the steps in these equations now we also need to include the term p_{is}. Using these observations, we obtain the following first order condition:

$$\sum_{i=1}^{N} p_{is}\left(\frac{\Delta\sum_{t=1}^{T}\left[y_{it}x_{it}'\beta_s - e^{x_{it}'\beta_s} - \log(y_{it}!)\right]}{\Delta\beta_s}\right) \overset{s}{=} 0 \iff \sum_{i}^{N} p_{is}\sum_{t}^{T}\left[x_{it}(y_{it} - e^{x_{it}'\beta_s})\right] = 0 \tag{C.32}$$

The solution of Equation C.32 can be found using iterative reweighed least-squares (see Wedel and DeSarbo (1995)).

In Cameron and Trivedi (2013) the authors show how to use a Poisson Fixed Effects specification as chosen form of $f_s(y_i|x_i,\theta_s)$ in Equation C.31. Recall from Formula C.12 the structure of the log-likelihood for this situation. Based on this specification the authors propose to first purge the fixed

effects from the mixture components and then form a mixture of concentrated marginals. The purge of the fixed effects is done by means of conditional likelihood for which they condition on a sufficient statistic for α_i. In Equation C.13 we found that under the Poisson density this sufficient statistic is equal to

$$\hat{\alpha}_i = \frac{\bar{y_i}}{\bar{\lambda i}}$$

Where $\bar{y}_i = \frac{1}{T}\sum_{t=1}^{T} y_{it}$ and $\bar{\lambda_i} = \frac{1}{T}\sum_{t=1}^{T} \lambda_{it}$. In contrast to the sufficient statistic of Equation C.13, we now have S different segments all with different parameters λ_{its}. As $\hat{\alpha_i}$ depends on λ_{it}, we now write $\hat{\alpha}_{is} = \frac{\bar{y_i}}{\bar{\lambda is}}$. Accounting for this factor, we can write Equation C.31 in terms of a Fixed Effects Poisson specification as

$$\begin{aligned} &\sum_{i=1}^{N} p_{is} \frac{\Delta\left[-\hat{\alpha}_{is}\Sigma_t\lambda_{its} + \log(\hat{\alpha}_{is})\Sigma_t y_{it} + \Sigma_t y_{it}\log(\lambda_{its}) - \Sigma_t \log(y_{it}!)\right]}{\Delta\beta_s} \overset{\mathsf{S}}{=} 0 \\ &\iff \sum_{i=1}^{N} p_{is} \sum_{t=1}^{T} x_{it}\left(y_{it} - \hat{\alpha_{is}}\lambda_{its}\right) = \sum_{i=1}^{N} p_{is} \sum_{t=1}^{T} x_{it}\left(y_{it} - \frac{\lambda_{its}}{\bar{\lambda_{is}}}\bar{y}_i\right) = 0 \end{aligned} \tag{C.33}$$

Estimation of Equation C.33 can be done using Newton-Raphson type algorithms (iterative reweighed least-squares) (see McLachlan and Peel (2000)).

Appendix C.3.3. Determining the Number of Clusters

As the number of clusters is unknown a-priori, one of the major topics within the Finite Mixture Model framework deals with determining the optimal number of clusters. In Melnykov and Maitra (2010) we can find an overview of different approaches which are used. The author of this paper distinguishes two types of approaches: those based on (penalized) versions of the log likelihood (parsimony based selection), and approaches based on hypothesis testing.

Parsimoniuos Approaches Within parsimonious based approaches, the intuition is to fit the model for a different number of clusters and select the configuration which minimizes some selection criterion. Within this area we can roughly distinguish two types of criteria. First we have a set of criteria which directly penalisation on the log-likelihood. These criteria are most commonly based on some variant of the Akaike Information Criterion (AIC) by Akaike (1973), or the Bayesian Information Criterion (BIC) by Schwarz (1978). AIC is an estimator derived from Kullback-Leibler Divergence which has the following form:

$$\text{AIC}(S) = 2|\psi_S| - 2\mathcal{L}_S(y|x, \psi_S) \tag{C.34}$$

where $|\psi_S|$ denotes the number of estimated free parameters in the model under different S segments. BIC can be seen as an asymptotic approximation of the integrated likelihood:

$$\text{BIC}(S) = |\psi_S|\log(NT) - 2\mathcal{L}_S(y|x, \psi_S) \tag{C.35}$$

Based on AIC and BIC, we also have adaptations such as Consistent AIC (CAIC) by Bozdogan (1987):

$$\text{CAIC} = |\psi_S|(\log(NT) + 1)) - 2\mathcal{L}_S(y|x, \psi_S) \tag{C.36}$$

Another criterion which is somewhat related to AIC and BIC is the Approximate Weight of Evidence (AWE) by Banfield and Raftery (1993):

$$\text{AWE}(S) = 2|\psi_S|(\frac{3}{2} + \log(NT)) - 2\mathcal{L}_S(y|x, \psi_S) \tag{C.37}$$

Within the literature, the consensus seems to be that AIC has a tendency to overestimate the true number of clusters (see Koehler and Murphree (1988) for example). In contrast, BIC has a better reputation to find the true number of segments. However, there is no theoretical guarantee that using BIC (or AIC) it is possible to find the optimal number of clusters. In Titterington et al. (1985) the authors explain that the reason for this might be because one of the regularity conditions formulated by Cramer (1946) is not satisfied in the finite mixture context. As a consequence the usual asymptotic theory which are based on the regularity conditions is invalid.

Besides AIC and BIC, we also have information criteria which aim to penalise based on the cluster separation and hence try to take the cluster quality into account. One of these criteria is the Normalized Entropy Criterion (NEC) by Celeux and Soromenho (1996). The idea behind NEC is to calculate cluster separability based on the posterior probabilities p_{is} of Equation C.20 for a number of segments S. The separability is calculated based on the entropy measure:

$$E_S = -\sum_{s=1}^{S}\sum_{i=1}^{N} p_{is}\ \log(p_{is}) \tag{C.38}$$

The entropy measure of Equation C.38 is then normalised based on taking the difference of the the maximised log-likelihoods under S segments and 1 segment:

$$NEC(S) = \frac{E_S}{\mathcal{L}_S(y|x, \psi_S) - \mathcal{L}_1(y|x, \psi_1)} \tag{C.39}$$

The interpretation behind the definition of NEC as shown in Formula C.39 is as follows. The better the cluster separability, the closer E_S is to zero. In case of perfect cluster separability, E_S is in fact exactly zero. We then E_S by $\mathcal{L}_S(y|x, \psi_S) - \mathcal{L}_1(y|x, \psi_1)$ as $\mathcal{L}_S(y|x, \psi_S)$ is an increasing function of S, which makes comparing E_S for different values of S not possible. Furthermore, Celeux and Soromenho (1996) shows that $\mathcal{L}_S(y|x, \psi_S)$ can be written in terms of E_S, which after some algebra gives us the result of Equation C.39.

Another criterion which aims to take the cluster quality into account is the Classification Likelihood information Criterion (CLC) by Biernacki and Govaert (1997) . The form of CLC stems from a relationship first derived by Hathaway (1986) which shows the relationship between the log-likelihood and the entropy measure as defined in Equation C.38. In case for CLC this takes the form

$$\text{CLC}(S) = -2\mathcal{L}_S(y|x, \psi_S) + 2E_S \tag{C.40}$$

The authors of Biernacki et al. (1998) propose a measure based on the complete data likelihood by means of the Integrated Classification Likelihood (ICL). In Biernacki et al. (2000) this is combined with BIC such that we obtain ICL-BIC:

$$\text{ICL-BIC}(S) = \text{BIC}(S) + 2E_S \tag{C.41}$$

Comparing the standard BIC to ICL-BIC, we see that the term $2E_S$ is added to penalise poorly separated clusters. Therefore, in case the separation becomes worse than the decrease of BIC, ICL-BIC can increase.

Approaches based on Hypothesis Testing Compared to the parsimonious approach, hypothesis test based approaches have the advantage that a more complex model can directly be tested against a simpler model using likelihood ratio tests (LRT), since the the simpler model is nested in the more complex model. However in the context of Finite Mixture Models, the parameter vector lies on the boundary of the parameter space under the null hypothesis, which violates one of the regularity conditions as proposed in Cramer (1946). Consequently, the asymptotic null distribution of the likelihood ratio test statistic is invalid. In Aitkin and Rubin (1985) the authors try to move the parameter vector into the parameter space by postulating a prior probability distribution on the mixing proportions. As an alternative, bootstrapping can be used. For example, in McLachlan (1987) it is explained how bootstrapping can be used for Gaussian Finite Mixture Models.

Appendix C.3.4. Technical Difficulties with Finite Mixture Models

Identifiability Problems related to the identification of Finite Mixture Models can be decomposed into two parts. First we have the general identifiability of the model. We find that a model is identifiable if no two different set of parameters can explain the same distribution. Hence if the mapping of the parameter space to the statistical model is one-to-one, we say that the model is identifiable. Under some mild conditions, it has been shown by Teicher (1961) that Finite Mixture Models under a Poisson density are identifiable.

Secondly, we have the arbitrarily labeling of components. Within Finite Mixture Models the labels assigned to every cluster are arbitrary and can be different from training session to training session. As a result the interpretation of every cluster should be done with caution. In order to retain the labels which are similar from session to session, one could try to relabel the clusters based on their cluster size.

Local Optima and Sensibility of Starting Values The results of Finite Mixture models are sensitive to the starting values. As a result, the results of Finite Mixture models are susceptible of being stuck in local optima. In order to overcome this different strategies can be used. The simplest strategy is to run the algorithm for different (randomly) chosen starting values and select the output for which the log-likelihood is maximised. Alternatively, more advanced methods can be used, such as classification EM (CEM), or stochastic EM (SEM) both derived by Celeux and Govaert (1992).

Appendix C.4. Auxiliary Methods of Presenting Additional Results

In this subsection we provide an overview of the different methods we use to show the (additional) results of Section 6 and Appendix D once we have chosen the number of different clusters under a model specification. We present the results with respect to cluster dissimilarity, cluster interpretability, statistical power, and coefficient effects.First we show how we measure cluster dissimilarity using

Kullback-Leibler Divergence (KL-divergence). Second, we we elaborate on our approach for measuring the statistical power of the output models. Lastly, we explain our methodology of showing the effects of the study variables.

Appendix C.4.1. Cluster Dissimilarity using KL-Divergence

We compute the cluster dissimilarity using the Kullback-Leibler Divergence derived by Kullback and Leibler (1951) (KL-Divergence), which we define as follows. Let P be the reference distribution, and Q the observed empirical distribution which are both defined over the same probability space $\mathcal{X}$. Then we write the KL-Divergence between Q and P as:

$$D_{KL}(Q||P) = \sum_{x \in \mathcal{X}} Q(x) \log \left(\frac{Q(X)}{P(X)} \right) \tag{C.42}$$

In Leisch (2004) the formula is shown which can be used to calculate the KL-divergence between two mixture components. For this let s_1 and s_2 be two mixtures. Then the KL-divergence between these two mixtures can be approximated by

$$\begin{aligned} D_{KL}(f_{s_1}||f_{s_2}) &\approx \sum_{i=1}^{N} p_{is_1} \log \left(\frac{p_{is_1}}{p_{is_2}} \right) \\ \text{Where } p_{is_1} &= \pi_{s_1} \prod_{t=1}^{T} f(y_{it}|x_{it}, \kappa_{s_1}) \end{aligned} \tag{C.43}$$

Larger values of the KL-divergence indicate that two mixture components are more separated. It should be noted that KL-divergence is not a symmetric metric. That is $D_{KL}(f_{s_1}||f_{s_2}) \neq D_{KL}(f_{s_2}||f_{s_1})$. Therefore, we can expect that obtain an asymmetric metric of pairwise KL-divergences.

Appendix C.4.2. Statistical Power

We explore the statistical power by means of the methods proposed by Signorini (1991), Hsieh et al. (1998) and Hsieh and Lavori (2000), which show how statistical power can be computed for respectively simple and multivariate Poisson Regression. To follow the line of these papers, say that for a variable θ_j we want to test the hypothesis that $\theta_j = 0$ versus the alternative that $\theta_j = E_j$ for some non-zero effect E_j. Given an intercept ω, probability of a Type I-error α, probability of a Type II-error β, and regressor X_j, Signorini (1991) provides the following formula to determine the sample size NT under these conditions for simple Poisson Regression

$$NT = \frac{\left(z_{1-\alpha/2} \sqrt{V(b_1|\theta_j = 0)} + z_{1-\beta} \sqrt{V(b_1|\theta_j = E_j)} \right)^2}{\exp(\omega) E_j} \tag{C.44}$$

Where z denotes the z-score under a normal distribution, $V(b_1|\theta_j = 0) = \frac{1}{\text{VAR}(X_j)}$, and $V(b_1|\theta_j = E_j)$ is the variance under the non-null case. This variance depends on the assumption of the distribution of X_j. In this study we assume that this is a normal density, such that we obtain

$$V(b_1|\theta_j = E_j) = \frac{1}{\sigma^2_{X_j}} e^{-\left(E_j \mu_{X_j} + \frac{E_j^2 \sigma^2_{X_j}}{2}\right)} \tag{C.45}$$

The authors of Hsieh et al. (1998) and Hsieh and Lavori (2000) show an approximation in case we also add different regressors to the Poisson Regression model

$$NT = \frac{\left(z_{1-\alpha/2}\sqrt{V(b_1|\theta_j = 0)} + z_{1-\beta}\sqrt{V(b_1|\theta_j = E_j)}\right)^2}{\exp(\omega)E_j(1 - R^2)} \tag{C.46}$$

Here R^2 is the coefficient of determination which we obtain when we regress x_j on the other regressors. Rewriting Equation C.46 gives us the corresponding power

$$\text{Statistical Power} = 1 - \beta = \Phi\left(\frac{\sqrt{NT\exp(\omega)E_j(1 - R^2)} - z_{1-\alpha/2}\sqrt{V(b_1|\theta_j = 0)}}{\sqrt{V(b_1|\theta_j = E_j)}}\right) \tag{C.47}$$

Where $\Phi(\cdot)$ corresponds to the cdf of a normal density. We use the result of Equation C.47 as a guideline to assess the statistical power of clusters for the variables we want to study. For this we consider the estimated effect size of the study variable in segment s, E_{js}, the number of observations in segment s of the shop category on which the estimated effect is based, NT_{SCs}, and a specified Type-I error probability of 0.05. We calculate the statistical power of variables which are significant at a 5% significance level.

Appendix C.4.3. Coefficient Effects

We present the results in terms of coefficient estimates and marginal effects. The role of coefficient estimates should be clear, as these are an immediate result of the models we train. We include marginal effects to obtain more insight into the size of the effects of our parameter estimates. For linear models, the marginal effects are equal to the coefficient estimates. However, in non linear models, this is not the case. For exponential models (of which Poisson Regression forms a part of), we can write the marginal effect for some regressor x_j with exponential conditional mean as:

$$\frac{\partial \mathrm{E}(y|x)}{\partial x_j} = \theta_j \exp(x'\kappa)) \tag{C.48}$$

Clearly, the partial derivative of Equation C.48 depends on both the parameter θ_j and the regressors. This implies that the marginal effect is affected by the observational values at hand. In Cameron and Trivedi (2005) Section 5.2.4, several methods are proposed to represent marginal effects for models with an exponential conditional mean. In this study, we report the marginal effects based on percentiles and boxplots on a bi-symmetric log scale (see Webber (2012) for an explanation on bi-symmetric logarithmic transformations).

Compared to Equation C.48 we add one more level of complexity to the marginal effects by including interaction terms with respect to the different shop categories. Specifically, for shop category SC_g, the marginal effect for regressor x_j with an interaction with SC_g is

$$\frac{\partial \mathrm{E}(y|x)}{\partial x_j} = (\theta_j + \gamma_{11+g} SC_g)\exp(x'\kappa)) \tag{C.49}$$

Besides marginal effects, we conduct hypothesis tests to compare the effects of different study variables. In particular, for $\sigma_{9.21}(\mathrm{RP}_p)$ and $\sigma_{9.21}(\mathrm{RP}_d)$ we want to determine which of the two variables has an larger impact on sales. For WTP and UTP, we want to determine to what extent we observe a trade-off between these two variables.

Appendix D. Additional Results

In this Appendix we present the results with regards to the additional results of this thesis. We kick-off by presenting the complete output tables of the different model specifications. These can be found in Appendix D.1. Secondly, we present additional results for the five different model specifications. These respectively are estimating $\sigma_{9.21}(\text{RP}_p)$ and $\sigma_{9.21}(\text{RP}_d)$ during the regular period, estimating $\sigma_{9.21}(\text{RP}_p)$ and $\sigma_{9.21}(\text{RP}_d)$ during the holiday period, estimating RC, WTP and UTP during the regular period, estimating RC, WTP and UTP during the holiday period, and estimating willingness to pay around Sinterklaas and Christmas. We present the results of these five different model specifications in a similar fashion. We first show the model training results, by means of a motivation of the selected number of clusters, posterior cluster sizes and cluster similarity. Then we elaborate on the coefficient estimates as presented in 6.4 in terms of statistical power and significant marginal effects. We conclude every model specification with results of heterogeneity of the different effect types based on sales, price propositions and delivery promise propositions. Within the discussion the results of the model specifications, we rely on additional methods, such as KL-divergence, statistical power and marginal effects. These are explained in Appendix C.4.

Appendix D.1. Coefficient Estimates Full Model Specifications

Table D.16: Full model coefficient estimates for studying RC, WTP and WTPSC around Sinterklaas and Christmas

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7	Cluster 8	Cluster 9	Cluster 10	Cluster 11	Cluster 12	Cluster 13
Intercept	0.03 (0.02)	-1.26 (0.04)$_L$	-0.88 (0.05)$_L$	-1.38 (0.03)$_L$	1.16 (0.04)$_L$	-2.28 (0.04)$_L$	-0.53 (0.03)$_L$	-0.56 (0.07)$_L$	-1.23 (0.03)$_L$	-1.15 (0.08)$_L$	-1.11 (0.04)$_L$	-0.07 (0.06)	-1.72 (0.06)$_L$
Proportion of day for sale	2.92 (0.02)$_L$	2.79 (0.02)$_L$	3.00 (0.02)$_L$	3.02 (0.02)$_L$	2.70 (0.02)$_L$	3.20 (0.02)$_L$	2.46 (0.02)$_L$	2.58 (0.02)$_L$	3.55 (0.02)$_L$	3.22 (0.02)$_L$	3.03 (0.02)$_L$	2.23 (0.02)$_L$	2.94 (0.03)$_L$
Discount	1.66 (0.06)$_L$	5.50 (865537066.16)	2.72 (0.02)$_L$	1.15 (0.06)$_L$	4.11 (0.04)$_L$	4.14 (0.04)$_L$	1.17 (0.04)$_L$	1.35 (0.03)$_L$	1.25 (0.05)$_L$	0.29 (0.05)$_L$	0.74 (0.04)$_L$	2.83 (0.01)$_L$	4.64 (0.18)$_L$
Monday	-0.06 (0.01)$_L$	-0.09 (0.01)$_L$	0.00 (0.01)	-0.11 (0.01)$_L$	-0.14 (0.01)$_L$	-0.08 (0.01)$_L$	-0.12 (0.01)$_L$	-0.12 (0.01)$_L$	-0.17 (0.01)$_L$	-0.10 (0.01)$_L$	0.01 (0.01)	0.27 (0.01)$_L$	-0.18 (0.01)$_L$
Tuesday	-0.08 (0.01)$_L$	-0.07 (0.01)$_L$	-0.17 (0.01)$_L$	-0.20 (0.01)$_L$	-0.23 (0.01)$_L$	-0.18 (0.01)$_L$	-0.24 (0.01)$_L$	-0.24 (0.01)$_L$	-0.25 (0.01)$_L$	-0.22 (0.01)$_L$	-0.21 (0.01)$_L$	-0.23 (0.01)$_L$	-0.32 (0.01)$_L$
Wednesday	-0.15 (0.01)$_L$	-0.12 (0.01)$_L$	-0.12 (0.01)$_L$	-0.20 (0.01)$_L$	-0.16 (0.01)$_L$	-0.23 (0.01)$_L$	-0.28 (0.01)$_L$	-0.24 (0.01)$_L$	-0.16 (0.01)$_L$	-0.22 (0.01)$_L$	-0.18 (0.01)$_L$	-0.24 (0.01)$_L$	-0.31 (0.01)$_L$
Thursday	-0.26 (0.01)$_L$	-0.26 (0.01)$_L$	-0.24 (0.01)$_L$	-0.37 (0.01)$_L$	-0.38 (0.01)$_L$	-0.34 (0.01)$_L$	-0.46 (0.01)$_L$	-0.38 (0.01)$_L$	-0.41 (0.01)$_L$	-0.32 (0.01)$_L$	-0.26 (0.01)$_L$	-0.39 (0.01)$_L$	-0.38 (0.01)$_L$
Friday	-0.30 (0.01)$_L$	-0.48 (0.01)$_L$	-0.43 (0.01)$_L$	-0.46 (0.01)$_L$	-0.52 (0.01)$_L$	-0.41 (0.01)$_L$	-0.39 (0.01)$_L$	-0.54 (0.01)$_L$	-0.50 (0.01)$_L$	-0.48 (0.01)$_L$	-0.55 (0.01)$_L$	-0.46 (0.01)$_L$	-0.60 (0.01)$_L$
Saturday	-0.12 (0.01)$_L$	-0.34 (0.01)$_L$	-0.17 (0.01)$_L$	-0.28 (0.01)$_L$	-0.28 (0.01)$_L$	-0.19 (0.01)$_L$	-0.34 (0.01)$_L$	-0.22 (0.01)$_L$	0.02 (0.01)	0.31 (0.01)$_L$	0.20 (0.01)$_L$	-0.21 (0.01)$_L$	-0.10 (0.01)$_L$
Holiday	-0.48 (0.01)$_L$	-0.52 (0.02)$_L$	-0.41 (0.01)$_L$	-0.47 (0.01)$_L$	-0.72 (0.01)$_L$	-0.58 (0.01)$_L$	-0.57 (0.01)$_L$	-0.72 (0.02)$_L$	-0.71 (0.01)$_L$	-0.68 (0.02)$_L$	-0.66 (0.01)$_L$	-0.67 (0.01)$_L$	-0.90 (0.03)$_L$
Black Friday	0.83 (0.02)$_L$	0.94 (0.02)$_L$	1.31 (0.01)$_L$	1.18 (0.02)$_L$	1.18 (0.01)$_L$	1.02 (0.02)$_L$	1.12 (0.02)$_L$	0.86 (0.02)$_L$	0.88 (0.01)$_L$	1.39 (0.02)$_L$	1.41 (0.01)$_L$	1.25 (0.01)$_L$	1.10 (0.02)$_L$
Lockdown	0.33 (0.01)$_L$	0.03 (0.01)	0.07 (0.01)$_L$	0.31 (0.01)$_L$	0.11 (0.01)$_L$	0.59 (0.01)$_L$	0.45 (0.01)$_L$	-0.14 (0.01)$_L$	0.29 (0.01)$_L$	0.16 (0.01)$_L$	0.46 (0.01)$_L$	0.33 (0.01)$_L$	-0.47 (0.01)$_L$
Drugs and Baby	-1.16 (0.02)$_L$	-0.57 (0.04)$_L$	1.23 (0.05)$_L$	0.83 (0.03)$_L$	-0.93 (0.04)$_L$	0.57 (0.04)$_L$	3.11 (0.03)$_L$	3.21 (0.07)$_L$	0.97 (0.03)$_L$	1.12 (0.08)$_L$	1.67 (0.04)$_L$	0.75 (0.06)$_L$	0.76 (0.06)$_L$
Entertainment	-0.78 (0.02)$_L$	1.69 (0.08)$_L$	2.12 (0.04)$_L$	1.73 (0.04)$_L$	-2.06 (0.03)$_L$	1.80 (0.04)$_L$	1.75 (0.05)$_L$	0.61 (0.07)$_L$	-1.15 (0.03)$_L$	-1.58 (0.10)$_L$	2.88 (0.04)$_L$	3.94 (0.05)$_L$	2.28 (0.05)$_L$
Hardware	0.90 (0.03)$_L$	0.60 (0.04)$_L$	0.67 (0.04)$_L$	-0.23 (0.03)$_L$	-2.84 (0.04)$_L$	1.41 (0.04)$_L$	0.67 (0.03)$_L$	0.11 (0.07)	1.22 (0.03)$_L$	-0.60 (0.08)$_L$	3.23 (0.04)$_L$	-0.38 (0.06)$_L$	-0.15 (0.08)
Kitchen and Household	-1.74 (0.03)$_L$	3.03 (0.03)$_L$	0.12 (0.05)	1.39 (0.05)$_L$	-1.13 (0.10)$_L$	1.62 (0.04)$_L$	-0.10 (0.03)	2.63 (0.07)$_L$	0.91 (0.03)$_L$	-0.79 (0.08)$_L$	0.75 (0.04)$_L$	-1.14 (0.13)$_L$	-0.18 (0.07)
other	-2.08 (0.03)$_L$	0.79 (0.04)$_L$	0.90 (0.04)$_L$	-0.20 (0.03)$_L$	-2.39 (0.05)$_L$	1.12 (0.04)$_L$	0.19 (0.03)$_L$	1.82 (0.07)$_L$	-0.93 (0.07)$_L$	1.51 (0.07)$_L$	-0.50 (0.06)$_L$	1.65 (0.06)$_L$	1.09 (0.06)$_L$
Personal Care	-1.10 (0.02)$_L$	-0.41 (0.03)$_L$	-0.64 (0.05)$_L$	1.19 (0.04)$_L$	-2.22 (0.03)$_L$	2.25 (0.04)$_L$	0.29 (0.04)$_L$	-0.53 (0.07)$_L$	-0.51 (0.05)$_L$	1.81 (0.07)$_L$	0.08 (0.04)	0.15 (0.06)	-0.75 (0.09)$_L$
Domestic Appliances	-1.13 (0.02)$_L$	-0.01 (0.03)	0.55 (0.05)$_L$	2.70 (0.03)$_L$	-1.71 (0.04)$_L$	2.62 (0.03)$_L$	1.06 (0.03)$_L$	-0.90 (0.07)$_L$	0.04 (0.03)	0.06 (0.07)	1.96 (0.04)$_L$	0.64 (0.06)$_L$	0.20 (0.07)
Sound and Vision	0.36 (0.02)$_L$	1.22 (0.04)$_L$	-0.79 (0.05)$_L$	1.40 (0.04)$_L$	0.61 (0.03)$_L$	0.95 (0.04)$_L$	3.00 (0.03)$_L$	0.70 (0.07)$_L$	-0.34 (0.05)$_L$	-0.60 (0.08)$_L$	-1.09 (0.04)$_L$	-0.96 (0.07)$_L$	1.56 (0.08)$_L$
Sports and Activity	-0.73 (0.03)$_L$	0.67 (0.05)$_L$	-1.45 (0.06)$_L$	-0.27 (0.04)$_L$	-1.91 (0.04)$_L$	2.80 (0.04)$_L$	0.66 (0.06)$_L$	-0.85 (0.08)$_L$	0.73 (0.03)$_L$	-1.82 (0.12)$_L$	-0.78 (0.05)$_L$	-0.78 (0.08)$_L$	0.95 (0.07)$_L$
Toys	-0.59 (0.02)$_L$	1.74 (0.03)$_L$	-0.33 (0.04)$_L$	1.35 (0.03)$_L$	1.86 (0.03)$_L$	2.96 (0.03)$_L$	-0.96 (0.03)$_L$	0.48 (0.07)$_L$	1.93 (0.03)$_L$	-0.84 (0.07)$_L$	0.99 (0.04)$_L$	0.17 (0.06)	2.73 (0.05)$_L$
UTP	-0.26 (0.05)$_L$	-0.37 (0.08)$_M$	0.53 (0.11)$_L$	-0.12 (0.08)	0.65 (0.08)$_L$	-1.08 (0.11)$_L$	0.23 (0.07)	-0.93 (0.31)	0.28 (0.06)$_L$	-0.58 (0.23)	0.15 (0.08)	-3.57 (0.55)$_L$	0.71 (0.10)$_L$
RC	0.21 (0.03)$_L$	-0.67 (0.06)$_L$	1.38 (0.08)$_L$	0.15 (0.05)	0.68 (0.06)$_L$	0.25 (0.06)$_M$	0.14 (0.05)	0.29 (0.11)	0.36 (0.05)$_L$	-0.28 (0.13)	-0.40 (0.07)$_L$	0.10 (0.10)	0.66 (0.09)$_L$
WTP	-0.32 (0.10)	-1.82 (0.13)$_L$	0.06 (0.18)	0.42 (0.10)$_M$	0.06 (0.13)	0.64 (0.10)$_L$	-0.95 (0.13)$_L$	-1.59 (0.23)$_L$	-0.31 (0.08)$_S$	1.43 (0.19)$_L$	0.96 (0.16)$_L$	-0.20 (0.17)	0.61 (0.15)$_S$
WTPSC	-1.76 (0.34)$_L$	-1.52 (0.27)$_L$	-0.30 (0.40)	-0.69 (0.38)	-2.38 (0.36)$_L$	-0.21 (0.25)	0.09 (0.30)	-0.58 (0.59)	-0.47 (0.19)	2.48 (0.32)$_L$	-0.82 (0.53)	0.24 (0.28)	0.74 (0.30)
Drugs and Baby:UTP	0.21 (0.06)	0.58 (0.09)$_L$	0.26 (0.13)	0.26 (0.09)	-1.09 (0.12)$_L$	1.16 (0.12)$_L$	-0.06 (0.08)	1.57 (0.32)$_L$	-0.18 (0.08)	0.44 (0.24)	-1.37 (0.11)$_L$	3.27 (0.56)$_L$	-0.81 (0.14)$_L$
Entertainment:UTP	0.68 (0.06)$_L$	1.44 (0.24)$_L$	-1.26 (0.12)$_L$	0.57 (0.13)$_M$	-0.38 (0.09)$_M$	1.15 (0.13)$_L$	-1.96 (0.46)$_M$	2.02 (0.32)$_L$	-0.09 (0.07)	3.35 (0.27)$_L$	-1.25 (0.10)$_L$	3.71 (0.55)$_L$	-0.58 (0.12)$_L$
Hardware:UTP	0.76 (0.07)$_L$	0.69 (0.10)$_L$	-2.46 (0.15)$_L$	0.09 (0.09)	-1.84 (0.13)$_L$	1.33 (0.13)$_L$	0.88 (0.08)$_L$	0.82 (0.32)	0.04 (0.08)	0.34 (0.24)	-1.73 (0.13)$_L$	1.86 (0.57)	1.28 (0.16)$_L$
Kitchen and Household:UTP	0.56 (0.06)$_L$	-0.77 (0.11)$_L$	-0.48 (0.13)	-0.54 (0.12)$_M$	-1.17 (0.34)	0.99 (0.12)$_L$	-0.26 (0.08)	0.35 (0.32)	-0.27 (0.08)	-0.32 (0.26)	-0.09 (0.10)	7.39 (0.68)$_L$	-2.52 (0.39)$_L$
other:UTP	-0.08 (0.07)	0.10 (0.12)	-0.32 (0.12)	0.11 (0.09)	-1.84 (0.18)$_L$	1.06 (0.13)$_L$	-0.88 (0.09)$_L$	0.01 (0.32)	1.75 (0.10)$_L$	0.49 (0.23)	0.60 (0.11)$_L$	5.58 (0.55)$_L$	-0.86 (0.13)$_L$
Personal Care:UTP	-0.31 (0.06)$_L$	0.56 (0.09)$_L$	-2.72 (0.16)$_L$	-1.24 (0.11)$_L$	-0.52 (0.09)$_L$	1.56 (0.12)$_L$	0.35 (0.09)$_S$	1.46 (0.32)$_M$	2.05 (0.09)$_L$	3.49 (0.23)$_L$	0.09 (0.09)	3.51 (0.55)$_L$	-0.28 (0.17)
Domestic Appliances:UTP	0.13 (0.06)	-0.49 (0.11)$_M$	0.43 (0.12)	0.81 (0.08)$_L$	-0.09 (0.10)	1.11 (0.12)$_L$	-0.50 (0.09)$_L$	1.44 (0.32)$_M$	-0.41 (0.08)$_L$	2.38 (0.23)$_L$	0.49 (0.09)$_L$	2.64 (0.56)$_L$	-2.38 (0.21)$_L$
Sound and Vision:UTP	0.61 (0.07)$_L$	-0.16 (0.13)	-0.50 (0.13)$_S$	0.24 (0.10)	-0.93 (0.11)$_L$	1.45 (0.12)$_L$	0.74 (0.08)$_L$	1.20 (0.32)$_S$	-0.75 (0.18)$_M$	-0.02 (0.25)	-1.10 (0.12)$_L$	3.89 (0.56)$_L$	-1.66 (0.31)$_L$
Sports and Activity:UTP	-0.03 (0.11)	0.06 (0.24)	0.14 (0.14)	0.38 (0.11)	-0.38 (0.13)	1.11 (0.13)$_L$	0.66 (0.11)$_L$	-0.35 (0.38)	-0.94 (0.09)$_L$	1.07 (0.33)	-0.35 (0.14)	4.11 (0.56)$_L$	-1.45 (0.22)$_L$
Toys:UTP	0.26 (0.07)	0.43 (0.08)$_L$	-0.54 (0.12)$_M$	0.10 (0.09)	-0.89 (0.09)$_L$	0.57 (0.12)$_L$	0.49 (0.08)$_L$	1.06 (0.31)	0.35 (0.07)$_L$	0.13 (0.23)	0.61 (0.09)$_L$	3.27 (0.55)$_L$	-0.32 (0.11)
Drugs and Baby:RC	0.38 (0.04)$_L$	0.91 (0.07)$_L$	0.65 (0.10)$_L$	0.50 (0.06)$_L$	0.74 (0.10)$_L$	-0.04 (0.07)	0.47 (0.06)$_L$	1.12 (0.12)$_L$	-0.17 (0.06)	1.60 (0.14)$_L$	1.67 (0.08)$_L$	0.70 (0.10)$_L$	0.73 (0.11)$_L$
Entertainment:RC	0.29 (0.04)$_L$	2.29 (0.14)$_L$	-1.08 (0.08)$_L$	0.68 (0.08)$_L$	-0.71 (0.06)$_L$	0.74 (0.08)$_L$	0.39 (0.09)$_M$	-0.17 (0.12)	-0.37 (0.06)$_L$	7.27 (0.19)$_L$	1.21 (0.08)$_L$	0.44 (0.10)$_M$	-0.55 (0.10)$_L$
Hardware:RC	1.84 (0.05)$_L$	1.33 (0.08)$_L$	-1.25 (0.08)$_L$	-0.06 (0.06)	-0.78 (0.08)$_L$	-0.22 (0.07)	1.13 (0.06)$_L$	-0.30 (0.12)	0.21 (0.06)	2.34 (0.15)$_L$	0.25 (0.09)	-0.01 (0.11)	3.37 (0.14)$_L$
Kitchen and Household:RC	-0.53 (0.05)$_L$	-0.36 (0.07)$_L$	-0.85 (0.09)$_L$	-0.51 (0.09)$_L$	0.58 (0.21)	-0.24 (0.07)	-0.20 (0.06)	0.03 (0.13)	0.03 (0.07)	1.14 (0.15)$_L$	1.51 (0.09)$_L$	2.97 (0.20)$_L$	-1.19 (0.16)$_L$
other:RC	-0.01 (0.05)	1.13 (0.07)$_L$	-0.98 (0.08)$_L$	-0.23 (0.06)$_S$	0.14 (0.10)	-0.05 (0.08)	-0.88 (0.07)$_L$	-1.59 (0.14)$_L$	2.23 (0.12)$_L$	0.97 (0.14)$_L$	1.52 (0.11)$_L$	1.71 (0.11)$_L$	-0.40 (0.11)
Personal Care:RC	-0.34 (0.04)$_L$	0.80 (0.07)$_L$	-1.57 (0.09)$_L$	-0.56 (0.07)$_L$	-0.22 (0.07)	0.22 (0.07)	1.49 (0.07)$_L$	1.67 (0.13)$_L$	0.74 (0.08)$_L$	1.13 (0.14)$_L$	0.76 (0.08)$_L$	0.27 (0.10)	0.41 (0.15)
Domestic Appliances:RC	-0.02 (0.04)	0.28 (0.07)$_S$	-0.31 (0.09)	0.12 (0.05)	0.47 (0.08)$_L$	-0.02 (0.07)	-0.25 (0.06)$_M$	-0.61 (0.13)$_L$	-0.12 (0.07)	3.72 (0.14)$_L$	3.32 (0.08)$_L$	-1.22 (0.11)$_L$	0.47 (0.14)
Sound and Vision:RC	0.40 (0.04)$_L$	0.65 (0.07)$_L$	-1.20 (0.09)$_L$	0.09 (0.07)	-0.89 (0.07)$_L$	-0.20 (0.08)	0.54 (0.06)$_L$	-0.81 (0.13)$_L$	1.26 (0.09)$_L$	1.25 (0.15)$_L$	0.49 (0.09)$_L$	0.18 (0.13)	-0.92 (0.16)$_L$
Sports and Activity:RC	0.14 (0.07)	-0.05 (0.10)	-0.98 (0.12)$_L$	-0.84 (0.08)$_L$	-0.71 (0.09)$_L$	0.62 (0.10)$_L$	1.42 (0.11)$_L$	-0.57 (0.17)	-0.57 (0.07)$_L$	2.24 (0.20)$_L$	1.16 (0.12)$_L$	0.13 (0.15)	-2.04 (0.15)$_L$
Toys:RC	1.24 (0.04)$_L$	0.95 (0.06)$_L$	-0.67 (0.08)$_L$	-0.42 (0.06)$_L$	-0.49 (0.06)$_L$	0.09 (0.07)	0.14 (0.06)	0.25 (0.12)	1.14 (0.05)$_L$	1.00 (0.14)$_L$	1.64 (0.07)$_L$	-0.86 (0.10)$_L$	0.38 (0.09)$_M$
Drugs and Baby:WTP	0.26 (0.11)	1.73 (0.15)$_L$	0.45 (0.20)	-0.36 (0.11)	-2.95 (0.61)$_L$	-0.96 (0.12)$_L$	-0.22 (0.14)	-0.14 (0.24)	0.58 (0.10)$_L$	-2.51 (0.21)$_L$	-2.08 (0.17)$_L$	-0.03 (0.18)	2.09 (0.20)$_L$
Entertainment:WTP	0.52 (0.11)$_L$	2.65 (0.29)$_L$	0.15 (0.18)	-1.28 (0.14)$_L$	-0.02 (0.13)	-0.85 (0.14)$_L$	0.31 (0.20)	0.46 (0.25)	0.01 (0.09)	3.48 (0.29)$_L$	-0.09 (0.16)	-0.88 (0.17)$_L$	-1.48 (0.18)$_L$
Hardware:WTP	-0.90 (0.14)$_L$	2.60 (0.16)$_L$	0.27 (0.19)	-0.78 (0.12)$_L$	0.42 (0.15)	-0.81 (0.12)$_L$	1.52 (0.15)$_L$	1.15 (0.24)$_L$	0.75 (0.10)$_L$	-1.25 (0.22)$_L$	-3.12 (0.37)$_L$	-0.01 (0.19)	3.51 (0.24)$_L$
Kitchen and Household:WTP	-0.35 (0.14)	1.26 (0.14)$_L$	-0.69 (0.20)	2.50 (0.16)$_L$	-4.80 (0.58)$_L$	-0.60 (0.12)$_L$	0.60 (0.14)$_M$	3.00 (0.25)$_L$	0.80 (0.11)$_L$	0.76 (0.23)	-0.80 (0.19)$_M$	2.24 (0.47)$_L$	0.16 (0.26)
other:WTP	0.25 (0.13)	1.95 (0.16)$_L$	0.19 (0.18)	-0.60 (0.12)$_L$	1.99 (0.23)$_L$	-0.76 (0.15)$_L$	0.08 (0.15)	0.09 (0.27)	4.39 (0.26)$_L$	-1.20 (0.20)$_L$	-0.46 (0.24)	3.66 (0.20)$_L$	-1.22 (0.21)$_L$
Personal Care:WTP	0.22 (0.11)	1.07 (0.16)$_L$	-1.00 (0.21)$_L$	-2.96 (0.17)$_L$	-1.05 (0.16)$_L$	-0.83 (0.12)$_L$	0.64 (0.18)	2.25 (0.25)$_L$	0.26 (0.16)	-1.72 (0.20)$_L$	0.71 (0.18)$_S$	-1.11 (0.34)	
Domestic Appliances:WTP	0.00 (0.11)	2.19 (0.15)$_L$	0.51 (0.19)	-0.58 (0.10)$_L$	-0.44 (0.17)	-1.22 (0.11)$_L$	1.85 (0.14)$_L$	1.80 (0.24)$_L$	0.15 (0.12)	0.62 (0.21)	0.87 (0.17)$_L$	0.02 (0.19)	-0.43 (0.23)
Sound and Vision:WTP	0.21 (0.12)	1.27 (0.16)$_L$	-0.50 (0.20)	-0.38 (0.13)	-0.62 (0.15)$_S$	-0.44 (0.13)	-0.42 (0.16)	1.02 (0.26)$_S$	-0.16 (0.17)	-1.36 (0.22)$_L$	-0.83 (0.19)$_M$	2.89 (0.20)$_L$	0.61 (0.28)
Sports and Activity:WTP	-0.39 (0.14)	2.96 (0.17)$_L$	0.09 (0.26)	-1.35 (0.17)$_L$	-0.38 (0.19)	-0.31 (0.14)	-1.39 (0.24)$_L$	2.51 (0.31)$_L$	-0.51 (0.12)$_M$	0.72 (0.39)	-0.40 (0.22)	-0.75 (0.28)	-1.87 (0.28)$_L$
Toys:WTP	0.05 (0.12)	1.77 (0.14)$_L$	-0.35 (0.18)	-0.71 (0.11)$_L$	-0.62 (0.13)$_L$	-2.21 (0.11)$_L$	0.57 (0.14)$_S$	1.20 (0.23)$_L$	0.14 (0.09)	-1.08 (0.20)$_L$	-1.06 (0.16)$_L$	-0.37 (0.18)	0.13 (0.16)
Drugs and Baby:WTPSC	1.67 (0.36)$_M$	1.60 (0.32)$_L$	0.74 (0.47)	0.81 (0.40)	-9.66 (7.95)	-0.54 (0.28)	-1.12 (0.33)	0.11 (0.60)	0.61 (0.23)	-3.74 (0.39)$_L$	-0.03 (0.54)	0.17 (0.31)	0.71 (0.47)
Entertainment:WTPSC	2.18 (0.35)$_L$	-625.16 (104.26)$_L$	-0.46 (0.42)	-0.05 (0.43)	2.34 (0.36)$_L$	0.63 (0.30)	-2.37 (0.56)$_M$	-1.07 (0.65)	-0.02 (0.21)	-0.13 (0.72)	1.15 (0.53)	-1.21 (0.28)$_M$	-1.52 (0.39)$_S$
Hardware:WTPSC	1.58 (0.37)$_M$	1.64 (0.31)$_L$	0.10 (0.42)	0.49 (0.40)	2.59 (0.38)$_L$	0.02 (0.27)	0.23 (0.32)	-0.11 (0.61)	0.82 (0.20)$_S$	-2.18 (0.36)$_L$	-1.18 (0.63)	-0.08 (0.32)	3.27 (0.40)$_L$
Kitchen and Household:WTPSC	1.28 (0.41)	0.79 (0.29)	0.16 (0.45)	-0.01 (0.51)	-0.57 (645256349.60)	-0.70 (0.31)	-0.05 (0.33)	0.88 (0.66)	0.65 (0.35)	-1.39 (0.40)	1.59 (0.55)	3.25 (0.67)$_L$	0.73 (0.66)
other:WTPSC	1.85 (0.38)$_L$	1.94 (0.33)$_L$	0.55 (0.42)	0.06 (0.42)	4.96 (0.49)$_L$	-0.45 (0.34)	-1.63 (0.40)$_S$	-7.56 (2.51)	1.64 (0.86)	-2.41 (0.39)$_L$	0.85 (0.65)	3.71 (0.32)$_L$	-1.43 (0.53)
Personal Care:WTPSC	1.90 (0.37)$_L$	0.30 (0.47)	0.24 (0.51)	0.15 (0.55)	1.87 (0.46)$_S$	0.28 (0.35)	-0.77 (0.49)	0.34 (0.78)	0.26 (0.38)	-3.13 (0.36)$_L$	-0.10 (0.57)	0.31 (0.35)	1.23 (0.97)
Domestic Appliances:WTPSC	1.23 (0.35)	1.11 (0.31)	0.81 (0.43)	-0.16 (0.39)	1.30 (0.42)	0.37 (0.26)	0.83 (0.32)	1.10 (0.61)	-0.26 (0.25)	-0.04 (0.36)	3.17 (0.53)$_L$	0.20 (0.37)	-0.75 (0.44)
Sound and Vision:WTPSC	1.43 (0.35)$_S$	1.15 (0.31)	0.15 (0.44)	0.84 (0.42)	2.63 (0.39)$_L$	-0.34 (0.30)	-1.64 (0.39)$_M$	-0.50 (0.64)	0.09 (0.33)	-2.39 (0.39)$_L$	0.66 (0.56)	1.91 (0.41)$_M$	2.15 (0.51)$_M$
Sports and Activity:WTPSC	0.42 (0.53)	1.24 (0.50)	-0.32 (0.78)	-0.80 (0.52)	0.63 (0.63)	0.29 (0.31)	-2.22 (0.55)$_S$	0.45 (0.81)	-0.46 (0.35)	3.12 (0.53)$_L$	1.56 (0.62)	-1.93 (0.89)	-0.42 (0.61)
Toys:WTPSC	1.67 (0.35)$_L$	1.13 (0.28)$_S$	-0.21 (0.42)	0.95 (0.39)	1.64 (0.36)$_M$	-0.83 (0.26)	-0.60 (0.33)	-0.06 (0.59)	0.50 (0.20)	-3.14 (0.35)$_L$	0.37 (0.53)	-0.38 (0.32)	0.38 (0.31)

$_S$: $p < 5\%$ α-level
$_M$: $p < 1\%$ α-level
$_L$: $p < 0.1\%$ α-level

Table D.17: Full model coefficient estimates for studying $\sigma_{9.21}(\text{RP}_p)$ and $\sigma_{9.21}(\text{RP}_d)$ during the regular period

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
Intercept	-0.73 (0.04)$_L$	-1.80 (0.04)$_L$	-1.82 (0.05)$_L$	-4.07 (0.23)$_L$	-2.51 (0.05)$_L$	-1.52 (0.07)$_L$
Proportion of day for sale	3.10 (0.01)$_L$	2.89 (0.01)$_L$	2.75 (0.01)$_L$	2.85 (0.01)$_L$	2.56 (0.01)$_L$	2.43 (0.01)$_L$
temp	-0.02 (0.00)$_L$	-0.01 (0.00)$_L$	-0.03 (0.00)$_L$	-0.01 (0.00)$_L$	-0.04 (0.00)$_L$	-0.04 (0.00)$_L$
Holiday	0.01 (0.01)	0.09 (0.01)$_L$	0.06 (0.01)$_L$	0.12 (0.01)$_L$	0.07 (0.01)$_L$	-0.01 (0.01)
Discount	1.18 (0.04)$_L$	3.57 (0.02)$_L$	2.81 (0.03)$_L$	4.17 (0.01)$_L$	2.50 (0.04)$_L$	1.54 (0.03)$_L$
Display	0.29 (0.01)$_L$	0.28 (0.01)$_L$	0.37 (0.01)$_L$	0.35 (0.01)$_L$	0.37 (0.01)$_L$	0.15 (0.01)$_L$
Monday	0.05 (0.01)$_L$	0.04 (0.01)$_S$	0.05 (0.01)$_L$	0.08 (0.01)$_L$	0.06 (0.01)$_L$	0.04 (0.01)$_S$
Tuesday	-0.01 (0.01)	-0.05 (0.01)$_L$	-0.02 (0.01)	0.02 (0.01)	-0.04 (0.01)$_S$	-0.01 (0.01)
Wednesday	-0.03 (0.01)	-0.07 (0.01)$_L$	-0.02 (0.01)	-0.03 (0.01)	-0.05 (0.01)$_L$	-0.02 (0.01)
Thursday	-0.10 (0.01)$_L$	-0.12 (0.01)$_L$	-0.09 (0.01)$_L$	-0.08 (0.01)$_L$	-0.11 (0.01)$_L$	-0.11 (0.01)$_L$
Friday	-0.16 (0.01)$_L$	-0.19 (0.01)$_L$	-0.18 (0.01)$_L$	-0.16 (0.01)$_L$	-0.22 (0.01)$_L$	-0.18 (0.01)$_L$
Saturday	-0.32 (0.01)$_L$	-0.38 (0.01)$_L$	-0.36 (0.01)$_L$	-0.34 (0.01)$_L$	-0.44 (0.01)$_L$	-0.30 (0.01)$_L$
Domestic Appliances	-2.31 (0.05)$_L$	1.92 (0.05)$_L$	-0.93 (0.05)$_L$	4.55 (0.23)$_L$	0.73 (0.06)$_L$	1.11 (0.07)$_L$
Drugs and Baby	-1.77 (0.04)$_L$	-1.08 (0.05)$_L$	-0.69 (0.05)$_L$	2.95 (0.23)$_L$	-1.46 (0.06)$_L$	-0.08 (0.07)
Entertainment	-1.38 (0.05)$_L$	0.15 (0.05)	-0.56 (0.07)$_L$	0.72 (0.23)	0.60 (0.07)$_L$	-1.70 (0.09)$_L$
Hardware	-0.90 (0.05)$_L$	-0.58 (0.06)$_L$	-0.30 (0.06)$_L$	1.69 (0.23)$_L$	2.26 (0.09)$_L$	0.05 (0.09)
Kitchen and Household	-1.90 (0.05)$_L$	-0.62 (0.05)$_L$	0.82 (0.05)$_L$	4.02 (0.23)$_L$	2.13 (0.06)$_L$	0.27 (0.07)$_S$
other	-1.76 (0.05)$_L$	-0.53 (0.05)$_L$	0.86 (0.05)$_L$	2.68 (0.23)$_L$	2.02 (0.06)$_L$	1.34 (0.08)$_L$
Personal Care	-5.81 (0.14)$_L$	-1.17 (0.05)$_L$	-0.19 (0.05)$_S$	1.11 (0.23)$_L$	1.57 (0.05)$_L$	0.50 (0.07)$_L$
Sound and Vision	-2.82 (0.09)$_L$	1.01 (0.05)$_L$	0.63 (0.06)$_L$	-0.01 (0.23)	1.77 (0.08)$_L$	-0.49 (0.12)$_M$
Sports and Activity	-0.70 (0.05)$_L$	0.02 (0.06)	-4.65 (0.13)$_L$	1.35 (0.23)$_L$	5.01 (0.07)$_L$	-2.37 (0.10)$_L$
Toys	-1.47 (0.04)$_L$	-2.63 (0.05)$_L$	0.62 (0.05)$_L$	-2.85 (0.23)$_L$	3.20 (0.05)$_L$	-0.49 (0.07)$_L$
$\sigma_{9.21}(\text{RP}_p)$	0.55 (0.05)$_L$	0.37 (0.05)$_L$	1.58 (0.06)$_L$	6.60 (0.36)$_L$	5.09 (0.07)$_L$	5.64 (0.11)$_L$
$\sigma_{9.21}(\text{RP}_d)$	0.36 (0.03)$_L$	-0.03 (0.03)	-0.22 (0.03)$_L$	-2.44 (0.13)$_L$	-0.17 (0.03)$_L$	0.27 (0.03)$_L$
Domestic Appliances:$\sigma_{9.21}(\text{RP}_p)$	1.80 (0.06)$_L$	-0.07 (0.07)	1.56 (0.07)$_L$	-5.49 (0.37)$_L$	-4.00 (0.08)$_L$	-4.14 (0.11)$_L$
Drugs and Baby:$\sigma_{9.21}(\text{RP}_p)$	0.03 (0.06)	3.18 (0.06)$_L$	1.32 (0.06)$_L$	-6.56 (0.36)$_L$	-1.08 (0.08)$_L$	-3.77 (0.11)$_L$
Entertainment:$\sigma_{9.21}(\text{RP}_p)$	0.39 (0.07)$_L$	-0.47 (0.07)$_L$	1.66 (0.09)$_L$	-3.06 (0.37)$_L$	-3.67 (0.09)$_L$	-1.94 (0.13)$_L$
Hardware:$\sigma_{9.21}(\text{RP}_p)$	2.33 (0.06)$_L$	-0.21 (0.08)	0.03 (0.07)	-3.85 (0.37)$_L$	-4.27 (0.13)$_L$	-4.07 (0.13)$_L$
Kitchen and Household:$\sigma_{9.21}(\text{RP}_p)$	0.49 (0.07)$_L$	1.29 (0.07)$_L$	-0.67 (0.07)$_L$	-6.03 (0.37)$_L$	-3.99 (0.08)$_L$	-2.09 (0.11)$_L$
other:$\sigma_{9.21}(\text{RP}_p)$	0.76 (0.06)$_L$	0.28 (0.07)$_S$	-1.55 (0.07)$_L$	-7.42 (0.37)$_L$	-3.68 (0.08)$_L$	-3.69 (0.12)$_L$
Personal Care:$\sigma_{9.21}(\text{RP}_p)$	3.95 (0.15)$_L$	2.07 (0.06)$_L$	-1.27 (0.06)$_L$	-4.61 (0.37)$_L$	-4.72 (0.07)$_L$	-4.31 (0.11)$_L$
Sound and Vision:$\sigma_{9.21}(\text{RP}_p)$	3.38 (0.13)$_L$	1.26 (0.06)$_L$	0.19 (0.09)	-1.41 (0.37)$_S$	-3.98 (0.10)$_L$	-1.87 (0.16)$_L$
Sports and Activity:$\sigma_{9.21}(\text{RP}_p)$	-0.23 (0.07)	0.24 (0.07)	4.73 (0.15)$_L$	-4.98 (0.37)$_L$	-7.34 (0.09)$_L$	0.99 (0.14)$_L$
Toys:$\sigma_{9.21}(\text{RP}_p)$	-0.17 (0.06)	3.27 (0.07)$_L$	-1.00 (0.06)$_L$	1.28 (0.37)	-4.81 (0.07)$_L$	-3.45 (0.11)$_L$
Domestic Appliances:$\sigma_{9.21}(\text{RP}_d)$	-0.40 (0.03)$_L$	-0.27 (0.04)$_L$	0.25 (0.03)$_L$	2.50 (0.13)$_L$	0.05 (0.04)	0.06 (0.03)
Drugs and Baby:$\sigma_{9.21}(\text{RP}_d)$	-0.28 (0.03)$_L$	0.10 (0.03)	0.28 (0.03)$_L$	2.45 (0.13)$_L$	-0.20 (0.04)$_L$	-0.18 (0.03)$_L$
Entertainment:$\sigma_{9.21}(\text{RP}_d)$	-0.45 (0.04)$_L$	-0.15 (0.04)$_S$	0.46 (0.04)$_L$	2.75 (0.14)$_L$	-0.39 (0.05)$_L$	-0.20 (0.05)$_S$
Hardware:$\sigma_{9.21}(\text{RP}_d)$	-0.17 (0.03)$_L$	0.42 (0.04)$_L$	0.24 (0.04)$_L$	2.74 (0.13)$_L$	-0.37 (0.05)$_L$	0.61 (0.05)$_L$
Kitchen and Household:$\sigma_{9.21}(\text{RP}_d)$	-0.56 (0.04)$_L$	-0.27 (0.04)$_L$	0.10 (0.04)	2.50 (0.13)$_L$	0.03 (0.04)	-0.21 (0.04)$_L$
other:$\sigma_{9.21}(\text{RP}_d)$	-0.58 (0.03)$_L$	-0.11 (0.04)	0.05 (0.04)	2.61 (0.13)$_L$	0.31 (0.04)$_L$	0.05 (0.04)
Personal Care:$\sigma_{9.21}(\text{RP}_d)$	3.23 (0.10)$_L$	0.06 (0.03)	0.26 (0.03)$_L$	2.30 (0.13)$_L$	0.12 (0.04)	0.08 (0.03)
Sound and Vision:$\sigma_{9.21}(\text{RP}_d)$	-0.24 (0.05)$_L$	0.15 (0.03)$_L$	0.33 (0.04)$_L$	2.82 (0.13)$_L$	0.37 (0.06)$_L$	0.34 (0.07)$_L$
Sports and Activity:$\sigma_{9.21}(\text{RP}_d)$	-0.47 (0.04)$_L$	0.01 (0.04)	0.66 (0.08)$_L$	2.33 (0.13)$_L$	0.10 (0.05)	-0.93 (0.05)$_L$
Toys:$\sigma_{9.21}(\text{RP}_d)$	-0.33 (0.03)$_L$	-0.17 (0.03)$_L$	0.18 (0.03)$_L$	2.11 (0.13)$_L$	0.02 (0.04)	-0.38 (0.03)$_L$

	Cluster 7	Cluster 8	Cluster 9	Cluster 10	Cluster 11	Cluster 12
Intercept	-4.98 (0.09)$_L$	-2.40 (0.04)$_L$	-2.86 (0.06)$_L$	-3.19 (0.07)$_L$	-2.10 (0.11)$_L$	-3.21 (0.10)$_L$
Proportion of day for sale	2.88 (0.01)$_L$	2.88 (0.01)$_L$	2.88 (0.02)$_L$	2.99 (0.02)$_L$	2.85 (0.01)$_L$	2.40 (0.01)$_L$
temp	-0.01 (0.00)$_L$	-0.01 (0.00)$_L$	0.00 (0.00)	-0.01 (0.00)$_L$	-0.02 (0.00)$_L$	-0.05 (0.00)$_L$
Holiday	0.07 (0.01)$_L$	0.07 (0.01)$_L$	0.02 (0.01)	0.13 (0.01)$_L$	-0.19 (0.01)$_L$	-0.18 (0.01)$_L$
Discount	1.07 (0.03)$_L$	3.70 (0.02)$_L$	0.54 (0.06)$_L$	1.28 (0.03)$_L$	0.49 (0.03)$_L$	1.00 (0.02)$_L$
Display	0.50 (0.01)$_L$	0.23 (0.01)$_L$	0.33 (0.01)$_L$	0.35 (0.01)$_L$	0.58 (0.00)$_L$	0.73 (0.00)$_L$
Monday	0.10 (0.01)$_L$	0.08 (0.01)$_L$	0.08 (0.01)$_L$	0.05 (0.01)$_L$	0.20 (0.01)$_L$	0.05 (0.01)$_L$
Tuesday	0.03 (0.01)	-0.02 (0.01)	0.01 (0.01)	-0.05 (0.01)$_L$	0.05 (0.01)$_L$	-0.09 (0.01)$_L$
Wednesday	0.00 (0.01)	-0.04 (0.01)$_S$	-0.03 (0.01)	-0.07 (0.01)$_L$	0.03 (0.01)	-0.06 (0.01)$_L$
Thursday	-0.07 (0.01)$_L$	-0.08 (0.01)$_L$	-0.11 (0.01)$_L$	-0.15 (0.01)$_L$	-0.07 (0.01)$_L$	-0.21 (0.01)$_L$
Friday	-0.13 (0.01)$_L$	-0.18 (0.01)$_L$	-0.17 (0.01)$_L$	-0.22 (0.01)$_L$	-0.12 (0.01)$_L$	-0.29 (0.01)$_L$
Saturday	-0.17 (0.01)$_L$	-0.32 (0.01)$_L$	-0.40 (0.01)$_L$	-0.35 (0.01)$_L$	-0.17 (0.01)$_L$	-0.31 (0.01)$_L$
Domestic Appliances	4.88 (0.09)$_L$	0.91 (0.05)$_L$	-0.77 (0.06)$_L$	1.45 (0.07)$_L$	-0.53 (0.11)$_L$	2.90 (0.10)$_L$
Drugs and Baby	2.96 (0.09)$_L$	2.44 (0.04)$_L$	2.21 (0.06)$_L$	-0.11 (0.07)	1.01 (0.11)$_L$	2.63 (0.10)$_L$
Entertainment	4.14 (0.10)$_L$	0.71 (0.06)$_L$	0.48 (0.07)$_L$	0.32 (0.08)$_S$	-1.58 (0.12)$_L$	4.50 (0.11)$_L$
Hardware	2.35 (0.09)$_L$	1.67 (0.05)$_L$	-2.93 (0.07)$_L$	1.65 (0.08)$_L$	0.05 (0.11)	-0.35 (0.12)
Kitchen and Household	2.44 (0.09)$_L$	1.86 (0.04)$_L$	0.95 (0.07)$_L$	1.40 (0.07)$_L$	-0.68 (0.12)$_L$	2.20 (0.11)$_L$
other	5.88 (0.11)$_L$	0.86 (0.04)$_L$	1.42 (0.06)$_L$	-0.88 (0.08)$_L$	-0.29 (0.11)	4.37 (0.11)$_L$
Personal Care	3.52 (0.09)$_L$	-1.64 (0.05)$_L$	1.28 (0.06)$_L$	1.69 (0.07)$_L$	0.14 (0.11)	0.34 (0.11)
Sound and Vision	2.26 (0.10)$_L$	-0.13 (0.06)	1.04 (0.07)$_L$	-0.82 (0.08)$_L$	-0.38 (0.13)	4.17 (0.14)$_L$
Sports and Activity	2.56 (0.10)$_L$	0.67 (0.05)$_L$	-0.38 (0.06)$_L$	-0.19 (0.08)	-1.32 (0.12)$_L$	2.66 (0.12)$_L$
Toys	1.57 (0.09)$_L$	0.02 (0.05)	1.42 (0.06)$_L$	-1.42 (0.07)$_L$	1.31 (0.11)$_L$	1.64 (0.10)$_L$
$\sigma_{9.21}(\text{RP}_p)$	4.62 (0.13)$_L$	0.28 (0.05)$_L$	2.08 (0.08)$_L$	3.59 (0.10)$_L$	0.56 (0.18)	4.17 (0.14)$_L$
$\sigma_{9.21}(\text{RP}_d)$	0.00 (0.06)	0.13 (0.03)$_M$	-0.43 (0.04)$_L$	-0.11 (0.04)	1.02 (0.07)$_L$	0.11 (0.05)
Domestic Appliances:$\sigma_{9.21}(\text{RP}_p)$	-3.03 (0.13)$_L$	2.43 (0.06)$_L$	2.31 (0.09)$_L$	-0.44 (0.10)$_M$	3.56 (0.18)$_L$	-1.04 (0.14)$_L$
Drugs and Baby:$\sigma_{9.21}(\text{RP}_p)$	-4.14 (0.13)$_L$	0.50 (0.05)$_L$	-1.58 (0.08)$_L$	0.91 (0.10)$_L$	2.83 (0.18)$_L$	-0.78 (0.14)$_L$
Entertainment:$\sigma_{9.21}(\text{RP}_p)$	-2.72 (0.14)$_L$	1.87 (0.08)$_L$	-0.41 (0.09)$_M$	0.64 (0.11)$_L$	1.14 (0.19)$_L$	-4.46 (0.16)$_L$
Hardware:$\sigma_{9.21}(\text{RP}_p)$	-3.64 (0.14)$_L$	1.61 (0.06)$_L$	4.47 (0.10)$_L$	1.29 (0.11)$_L$	2.35 (0.18)$_L$	-0.81 (0.16)$_L$
Kitchen and Household:$\sigma_{9.21}(\text{RP}_p)$	-1.77 (0.13)$_L$	0.40 (0.05)$_L$	-1.98 (0.09)$_L$	-2.70 (0.10)$_L$	2.62 (0.20)$_L$	-2.98 (0.14)$_L$
other:$\sigma_{9.21}(\text{RP}_p)$	-8.75 (0.16)$_L$	0.49 (0.06)$_L$	-1.41 (0.08)$_L$	2.17 (0.11)$_L$	1.21 (0.18)$_L$	-5.50 (0.14)$_L$
Personal Care:$\sigma_{9.21}(\text{RP}_p)$	-3.46 (0.13)$_L$	2.28 (0.06)$_L$	-0.84 (0.08)$_L$	-3.25 (0.10)$_L$	-0.26 (0.18)	-1.53 (0.14)$_L$
Sound and Vision:$\sigma_{9.21}(\text{RP}_p)$	-3.40 (0.14)$_L$	2.07 (0.09)$_L$	-2.36 (0.10)$_L$	-1.15 (0.11)$_L$	1.98 (0.21)$_L$	-4.74 (0.19)$_L$
Sports and Activity:$\sigma_{9.21}(\text{RP}_p)$	-2.49 (0.14)$_L$	-0.70 (0.07)$_L$	-0.38 (0.09)$_M$	0.02 (0.11)	2.44 (0.19)$_L$	-2.48 (0.18)$_L$
Toys:$\sigma_{9.21}(\text{RP}_p)$	-2.28 (0.14)$_L$	2.34 (0.06)$_L$	0.12 (0.08)	1.19 (0.10)$_L$	-0.58 (0.18)	-1.88 (0.14)$_L$
Domestic Appliances:$\sigma_{9.21}(\text{RP}_d)$	0.62 (0.06)$_L$	-0.08 (0.03)	0.51 (0.05)$_L$	0.35 (0.04)$_L$	-0.89 (0.08)$_L$	0.32 (0.06)$_L$
Drugs and Baby:$\sigma_{9.21}(\text{RP}_d)$	0.04 (0.06)	0.10 (0.03)	0.57 (0.04)$_L$	0.41 (0.04)$_L$	-0.25 (0.07)	0.25 (0.06)$_M$
Entertainment:$\sigma_{9.21}(\text{RP}_d)$	0.31 (0.06)$_L$	0.20 (0.04)$_L$	0.33 (0.05)$_L$	-0.03 (0.05)	-0.01 (0.08)	0.08 (0.07)
Hardware:$\sigma_{9.21}(\text{RP}_d)$	0.18 (0.06)	0.32 (0.03)$_L$	0.31 (0.05)$_L$	0.29 (0.04)$_L$	-0.67 (0.08)$_L$	1.05 (0.07)$_L$
Kitchen and Household:$\sigma_{9.21}(\text{RP}_d)$	0.31 (0.06)$_L$	-0.23 (0.03)$_L$	0.54 (0.05)$_L$	-0.02 (0.05)	-0.98 (0.08)$_L$	-0.15 (0.06)
other:$\sigma_{9.21}(\text{RP}_d)$	0.39 (0.07)$_L$	-0.22 (0.03)$_L$	0.80 (0.05)$_L$	-0.03 (0.05)	-1.00 (0.08)$_L$	0.17 (0.06)
Personal Care:$\sigma_{9.21}(\text{RP}_d)$	0.26 (0.06)$_M$	-0.09 (0.03)	0.22 (0.04)$_L$	0.01 (0.04)	-0.95 (0.08)$_L$	0.47 (0.06)$_L$
Sound and Vision:$\sigma_{9.21}(\text{RP}_d)$	0.44 (0.07)$_L$	-0.27 (0.04)$_L$	0.31 (0.05)$_L$	0.44 (0.05)$_L$	-0.68 (0.09)$_L$	-0.30 (0.08)$_S$
Sports and Activity:$\sigma_{9.21}(\text{RP}_d)$	0.42 (0.07)$_L$	-0.18 (0.04)$_M$	0.11 (0.05)	-0.26 (0.05)$_L$	-0.22 (0.08)	-0.99 (0.09)$_L$
Toys:$\sigma_{9.21}(\text{RP}_d)$	1.03 (0.06)$_L$	-0.05 (0.03)	0.49 (0.04)$_L$	-0.05 (0.05)	-0.66 (0.08)$_L$	-0.05 (0.06)

	Cluster 13	Cluster 14	Cluster 15	Cluster 16	Cluster 17	Cluster 18
Intercept	-0.01 (0.06)	-5.22 (0.15)$_L$	0.09 (0.05)	-0.06 (0.06)	-3.67 (0.09)$_L$	-2.14 (0.08)$_L$
Proportion of day for sale	2.47 (0.02)$_L$	2.56 (0.02)$_L$	2.58 (0.01)$_L$	2.65 (0.01)$_L$	2.67 (0.02)$_L$	2.73 (0.02)$_L$
temp	-0.04 (0.00)$_L$	0.03 (0.00)$_L$	-0.04 (0.00)$_L$	-0.04 (0.00)$_L$	0.07 (0.00)$_L$	-0.04 (0.00)$_L$
Holiday	-0.16 (0.01)$_L$	0.12 (0.01)$_L$	-0.03 (0.01)	0.07 (0.01)$_L$	0.14 (0.02)$_L$	-0.13 (0.01)$_L$
Discount	1.23 (0.05)$_L$	0.93 (0.06)$_L$	0.89 (0.03)$_L$	1.66 (0.03)$_L$	0.82 (0.05)$_L$	1.40 (0.04)$_L$
Display	0.11 (0.01)$_L$	0.22 (0.01)$_L$	0.66 (0.00)$_L$	0.60 (0.01)$_L$	0.30 (0.01)$_L$	0.84 (0.00)$_L$
Monday	0.06 (0.01)$_L$	0.12 (0.01)$_L$	0.02 (0.01)	0.06 (0.00)$_L$	0.07 (0.01)$_L$	0.08 (0.01)$_L$
Tuesday	-0.04 (0.01)$_S$	0.02 (0.01)	-0.01 (0.01)	-0.03 (0.01)	0.00 (0.01)	-0.03 (0.01)
Wednesday	0.00 (0.01)	0.00 (0.01)	-0.03 (0.01)	-0.01 (0.01)	-0.03 (0.01)	0.01 (0.01)
Thursday	-0.12 (0.01)$_L$	-0.10 (0.01)$_L$	-0.11 (0.01)$_L$	-0.13 (0.01)$_L$	-0.14 (0.01)$_L$	-0.11 (0.01)$_L$
Friday	-0.24 (0.01)$_L$	-0.17 (0.01)$_L$	-0.21 (0.01)$_L$	-0.21 (0.01)$_L$	-0.22 (0.01)$_L$	-0.20 (0.01)$_L$
Saturday	-0.32 (0.01)$_L$	-0.32 (0.01)$_L$	-0.44 (0.01)$_L$	-0.28 (0.01)$_L$	-0.31 (0.01)$_L$	-0.27 (0.01)$_L$
Domestic Appliances	-2.90 (0.07)$_L$	3.67 (0.15)$_L$	-1.34 (0.07)$_L$	-0.86 (0.06)$_L$	2.31 (0.11)$_L$	1.39 (0.09)$_L$
Drugs and Baby	-3.49 (0.06)$_L$	3.63 (0.15)$_L$	-0.33 (0.05)$_L$	-4.49 (0.07)$_L$	0.98 (0.09)$_L$	1.03 (0.08)$_L$
Entertainment	1.12 (0.10)$_L$	3.76 (0.16)$_L$	-0.51 (0.07)$_L$	0.24 (0.07)	-1.68 (0.12)$_L$	0.48 (0.08)$_L$
Hardware	1.08 (0.09)$_L$	2.58 (0.15)$_L$	-3.31 (0.08)$_L$	-3.55 (0.08)$_L$	-0.41 (0.11)$_S$	-5.29 (0.09)$_L$
Kitchen and Household	-0.57 (0.06)$_L$	2.09 (0.16)$_L$	0.79 (0.06)$_L$	0.23 (0.06)$_S$	-1.21 (0.11)$_L$	2.22 (0.09)$_L$
other	-1.11 (0.06)$_L$	3.12 (0.15)$_L$	-3.42 (0.07)$_L$	-3.45 (0.08)$_L$	1.83 (0.09)$_L$	3.16 (0.08)$_L$
Personal Care	-2.50 (0.06)$_L$	-2.07 (0.17)$_L$	0.55 (0.05)$_L$	0.04 (0.06)	0.10 (0.10)	0.61 (0.08)$_L$
Sound and Vision	-4.33 (0.21)$_L$	1.22 (0.15)$_L$	-3.73 (0.08)$_L$	-6.39 (0.22)$_L$	-2.13 (0.13)$_L$	-0.65 (0.11)$_L$
Sports and Activity	0.32 (0.09)	4.46 (0.15)$_L$	0.01 (0.10)	-1.07 (0.07)$_L$	0.30 (0.09)	0.37 (0.12)
Toys	-0.12 (0.06)	3.57 (0.15)$_L$	-1.10 (0.05)$_L$	-1.25 (0.06)$_L$	0.32 (0.10)	2.87 (0.08)$_L$
$\sigma_{9.21}(\text{RP}_p)$	-0.05 (0.08)	4.19 (0.18)$_L$	0.24 (0.06)$_S$	-0.94 (0.09)$_L$	1.76 (0.12)$_L$	0.84 (0.10)$_L$
$\sigma_{9.21}(\text{RP}_d)$	0.14 (0.04)	-0.29 (0.07)$_M$	0.04 (0.03)	0.00 (0.04)	0.28 (0.06)$_L$	1.09 (0.06)$_L$
Domestic Appliances:$\sigma_{9.21}(\text{RP}_p)$	5.01 (0.11)$_L$	-3.06 (0.19)$_L$	2.48 (0.08)$_L$	1.54 (0.09)$_L$	-4.58 (0.15)$_L$	-0.18 (0.11)
Drugs and Baby:$\sigma_{9.21}(\text{RP}_p)$	4.21 (0.09)$_L$	-3.48 (0.18)$_L$	1.46 (0.06)$_L$	7.23 (0.10)$_L$	0.24 (0.13)	1.05 (0.10)$_L$
Entertainment:$\sigma_{9.21}(\text{RP}_p)$	-1.10 (0.14)$_L$	-3.09 (0.20)$_L$	0.43 (0.09)$_L$	3.54 (0.10)$_L$	5.32 (0.15)$_L$	0.19 (0.11)
Hardware:$\sigma_{9.21}(\text{RP}_p)$	-3.46 (0.13)$_L$	-2.37 (0.19)$_L$	4.80 (0.11)$_L$	6.68 (0.12)$_L$	2.08 (0.14)$_L$	10.02 (0.11)$_L$
Kitchen and Household:$\sigma_{9.21}(\text{RP}_p)$	1.89 (0.09)$_L$	-1.09 (0.21)$_L$	-0.72 (0.08)$_L$	2.54 (0.09)$_L$	2.50 (0.15)$_L$	-2.70 (0.13)$_L$
other:$\sigma_{9.21}(\text{RP}_p)$	1.55 (0.09)$_L$	-3.66 (0.19)$_L$	3.25 (0.10)$_L$	6.01 (0.11)$_L$	-0.66 (0.12)$_L$	-1.10 (0.10)$_L$
Personal Care:$\sigma_{9.21}(\text{RP}_p)$	3.71 (0.08)$_L$	3.13 (0.20)$_L$	1.91 (0.06)$_L$	0.63 (0.09)$_L$	0.40 (0.13)	0.51 (0.10)$_L$
Sound and Vision:$\sigma_{9.21}(\text{RP}_p)$	7.24 (0.29)$_L$	2.52 (0.19)$_L$	3.91 (0.10)$_L$	8.50 (0.32)$_L$	4.26 (0.18)$_L$	1.82 (0.13)$_L$
Sports and Activity:$\sigma_{9.21}(\text{RP}_p)$	-0.69 (0.13)$_L$	-4.08 (0.18)$_L$	-1.96 (0.12)$_L$	3.20 (0.09)$_L$	-0.45 (0.13)	0.32 (0.16)
Toys:$\sigma_{9.21}(\text{RP}_p)$	2.39 (0.08)$_L$	-3.63 (0.19)$_L$	1.59 (0.06)$_L$	3.35 (0.09)$_L$	-0.61 (0.13)$_L$	0.52 (0.10)$_L$
Domestic Appliances:$\sigma_{9.21}(\text{RP}_d)$	-0.31 (0.04)$_L$	0.38 (0.07)$_L$	-0.30 (0.04)$_L$	0.09 (0.04)	0.21 (0.07)	-0.76 (0.06)$_L$
Drugs and Baby:$\sigma_{9.21}(\text{RP}_d)$	-0.36 (0.04)$_L$	0.29 (0.07)$_M$	0.33 (0.04)$_L$	0.56 (0.05)$_L$	-0.13 (0.06)	-0.78 (0.06)$_L$
Entertainment:$\sigma_{9.21}(\text{RP}_d)$	-0.31 (0.07)$_M$	-0.04 (0.08)	-0.11 (0.05)	0.40 (0.05)$_L$	-0.08 (0.08)	-1.40 (0.06)$_L$
Hardware:$\sigma_{9.21}(\text{RP}_d)$	0.11 (0.05)	0.70 (0.08)$_L$	-0.12 (0.05)	0.36 (0.05)$_L$	0.25 (0.07)	-0.27 (0.07)$_S$
Kitchen and Household:$\sigma_{9.21}(\text{RP}_d)$	-0.13 (0.04)	-0.94 (0.08)$_L$	-0.31 (0.04)$_L$	0.43 (0.04)$_L$	-0.45 (0.08)$_L$	-0.47 (0.07)$_L$
other:$\sigma_{9.21}(\text{RP}_d)$	0.21 (0.04)$_L$	0.38 (0.07)$_L$	-0.31 (0.05)$_L$	-0.06 (0.05)	-0.14 (0.06)	-0.89 (0.06)$_L$
Personal Care:$\sigma_{9.21}(\text{RP}_d)$	0.12 (0.04)	0.40 (0.09)$_M$	-0.03 (0.04)	0.16 (0.05)	-0.25 (0.07)	-0.96 (0.06)$_L$
Sound and Vision:$\sigma_{9.21}(\text{RP}_d)$	-0.24 (0.10)	0.75 (0.07)$_L$	-0.03 (0.05)	1.45 (0.09)$_L$	-0.30 (0.08)$_S$	-0.47 (0.07)$_L$
Sports and Activity:$\sigma_{9.21}(\text{RP}_d)$	-0.44 (0.07)$_L$	0.55 (0.07)$_L$	0.45 (0.09)$_L$	0.32 (0.05)$_L$	-0.38 (0.06)$_L$	-0.57 (0.09)$_L$
Toys:$\sigma_{9.21}(\text{RP}_d)$	0.15 (0.04)$_S$	0.28 (0.07)$_S$	-0.12 (0.04)	0.19 (0.04)$_L$	-0.19 (0.06)	-0.62 (0.06)$_L$

	Cluster 19	Cluster 20	Cluster 21	Cluster 22	Cluster 23
Intercept	-1.85 (0.08)$_L$	0.26 (0.07)$_S$	-0.64 (0.06)$_L$	-2.26 (0.09)$_L$	-3.41 (0.28)$_L$
Proportion of day for sale	2.59 (0.02)$_L$	2.35 (0.02)$_L$	2.45 (0.02)$_L$	2.61 (0.02)$_L$	2.44 (0.02)$_L$
temp	0.05 (0.00)$_L$	-0.03 (0.00)$_L$	-0.07 (0.00)$_L$	0.11 (0.00)$_L$	0.17 (0.00)$_L$
Holiday	0.11 (0.02)$_L$	0.00 (0.01)	-0.16 (0.01)$_L$	0.07 (0.03)	0.17 (0.03)$_L$
Discount	1.26 (0.03)$_L$	1.61 (0.04)$_L$	3.48 (0.02)$_L$	0.99 (0.04)$_L$	0.13 (0.06)
Display	0.84 (0.01)$_L$	0.26 (0.01)$_L$	0.47 (0.00)$_L$	0.53 (0.01)$_L$	-0.64 (0.02)$_L$
Monday	0.09 (0.01)$_L$	0.10 (0.01)$_L$	0.05 (0.01)$_L$	0.09 (0.01)$_L$	-0.03 (0.01)
Tuesday	0.03 (0.01)	0.03 (0.01)	0.02 (0.01)	0.02 (0.01)	-0.14 (0.01)$_L$
Wednesday	-0.04 (0.01)$_S$	0.01 (0.01)	0.00 (0.01)	-0.07 (0.01)$_L$	-0.19 (0.01)$_L$
Thursday	-0.13 (0.01)$_L$	-0.07 (0.01)$_L$	-0.07 (0.01)$_L$	-0.20 (0.01)$_L$	-0.34 (0.01)$_L$
Friday	-0.25 (0.01)$_L$	-0.11 (0.01)$_L$	-0.19 (0.01)$_L$	-0.30 (0.01)$_L$	-0.45 (0.01)$_L$
Saturday	-0.47 (0.01)$_L$	-0.45 (0.01)$_L$	-0.40 (0.01)$_L$	-0.46 (0.01)$_L$	-0.38 (0.01)$_L$
Domestic Appliances	-6.86 (0.15)$_L$	0.78 (0.07)$_L$	-0.60 (0.07)$_L$	0.27 (0.12)	3.96 (0.29)$_L$
Drugs and Baby	0.89 (0.08)$_L$	-4.88 (0.08)$_L$	1.21 (0.06)$_L$	-3.15 (0.10)$_L$	-2.83 (0.29)$_L$
Entertainment	-0.68 (0.12)$_L$	-0.35 (0.09)$_S$	-0.60 (0.08)$_L$	-1.96 (3.87)	-0.88 (0.30)
Hardware	-0.86 (0.09)$_L$	-0.75 (0.08)$_L$	2.10 (0.09)$_L$	-3.45 (0.15)$_L$	-11.36 (0.57)$_L$
Kitchen and Household	0.68 (0.09)$_L$	1.11 (0.08)$_L$	1.62 (0.09)$_L$	-2.57 (0.15)$_L$	-0.90 (0.34)
other	-3.39 (0.09)$_L$	1.39 (0.07)$_L$	1.46 (0.07)$_L$	-0.86 (0.10)$_L$	-1.04 (0.28)$_S$
Personal Care	-1.41 (0.08)$_L$	-0.64 (0.07)$_L$	1.21 (0.06)$_L$	-2.15 (0.10)$_L$	-2.69 (0.28)$_L$
Sound and Vision	2.06 (0.09)$_L$	0.48 (0.12)$_S$	0.16 (0.09)	-0.56 (0.14)$_S$	-3.75 (0.36)$_L$
Sports and Activity	0.46 (0.08)$_L$	-0.39 (0.08)$_L$	-3.09 (0.11)$_L$	1.46 (0.09)$_L$	-0.86 (0.29)
Toys	1.62 (0.08)$_L$	-4.48 (0.08)$_L$	0.30 (0.06)$_L$	-2.72 (0.19)$_L$	1.70 (0.29)$_L$
$\sigma_{9.21}(\text{RP}_p)$	-0.70 (0.12)$_L$	-1.26 (0.10)$_L$	0.83 (0.07)$_L$	0.03 (0.11)	1.48 (0.42)
$\sigma_{9.21}(\text{RP}_d)$	-0.46 (0.06)$_L$	-0.75 (0.05)$_L$	0.22 (0.04)$_L$	0.49 (0.10)$_L$	-1.51 (0.16)$_L$
Domestic Appliances:$\sigma_{9.21}(\text{RP}_p)$	12.79 (0.25)$_L$	1.58 (0.11)$_L$	1.84 (0.10)$_L$	-1.43 (0.17)$_L$	-6.29 (0.43)$_L$
Drugs and Baby:$\sigma_{9.21}(\text{RP}_p)$	0.57 (0.12)$_L$	6.83 (0.12)$_L$	-0.78 (0.08)$_L$	3.13 (0.12)$_L$	3.23 (0.43)$_L$
Entertainment:$\sigma_{9.21}(\text{RP}_p)$	2.90 (0.18)$_L$	1.05 (0.12)$_L$	1.35 (0.11)$_L$	0.45 (4.51)	-0.72 (0.44)
Hardware:$\sigma_{9.21}(\text{RP}_p)$	2.00 (0.13)$_L$	1.59 (0.12)$_L$	-1.47 (0.12)$_L$	3.59 (0.18)$_L$	19.31 (0.95)$_L$
Kitchen and Household:$\sigma_{9.21}(\text{RP}_p)$	0.94 (0.14)$_L$	-1.64 (0.12)$_L$	-1.23 (0.13)$_L$	2.39 (0.20)$_L$	1.42 (0.49)
other:$\sigma_{9.21}(\text{RP}_p)$	5.33 (0.13)$_L$	2.59 (0.11)$_L$	-1.87 (0.10)$_L$	1.21 (0.12)$_L$	-0.61 (0.42)
Personal Care:$\sigma_{9.21}(\text{RP}_p)$	4.05 (0.12)$_L$	3.19 (0.10)$_L$	1.13 (0.08)$_L$	2.74 (0.12)$_L$	4.04 (0.42)$_L$
Sound and Vision:$\sigma_{9.21}(\text{RP}_p)$	1.65 (0.13)$_L$	-0.25 (0.18)	0.49 (0.11)$_M$	0.54 (0.21)	3.91 (0.53)$_L$
Sports and Activity:$\sigma_{9.21}(\text{RP}_p)$	1.08 (0.12)$_L$	1.39 (0.12)$_L$	4.43 (0.13)$_L$	0.08 (0.12)	0.03 (0.43)
Toys:$\sigma_{9.21}(\text{RP}_p)$	-0.06 (0.12)	8.26 (0.11)$_L$	1.80 (0.08)$_L$	4.44 (0.22)$_L$	-2.04 (0.43)$_L$
Domestic Appliances:$\sigma_{9.21}(\text{RP}_d)$	0.37 (0.10)$_S$	0.82 (0.05)$_L$	0.16 (0.05)	-0.27 (0.11)	2.70 (0.16)$_L$
Drugs and Baby:$\sigma_{9.21}(\text{RP}_d)$	0.55 (0.06)$_L$	1.24 (0.06)$_L$	-0.14 (0.05)	-0.42 (0.10)$_M$	1.77 (0.16)$_L$
Entertainment:$\sigma_{9.21}(\text{RP}_d)$	-0.81 (0.09)$_L$	0.74 (0.07)$_L$	-0.11 (0.06)	1.07 (3.13)	0.97 (0.18)$_L$
Hardware:$\sigma_{9.21}(\text{RP}_d)$	0.50 (0.07)$_L$	0.78 (0.06)$_L$	-0.27 (0.06)$_M$	-0.90 (0.13)$_L$	2.17 (0.21)$_L$
Kitchen and Household:$\sigma_{9.21}(\text{RP}_d)$	0.10 (0.07)	1.81 (0.07)$_L$	-0.60 (0.06)$_L$	-0.89 (0.12)$_L$	1.33 (0.18)$_L$
other:$\sigma_{9.21}(\text{RP}_d)$	0.55 (0.07)$_L$	0.37 (0.05)$_L$	-0.14 (0.05)	-0.68 (0.10)$_L$	1.23 (0.16)$_L$
Personal Care:$\sigma_{9.21}(\text{RP}_d)$	0.70 (0.06)$_L$	0.71 (0.05)$_L$	-0.26 (0.04)$_L$	-0.31 (0.10)	2.30 (0.16)$_L$
Sound and Vision:$\sigma_{9.21}(\text{RP}_d)$	0.23 (0.06)$_S$	0.85 (0.10)$_L$	-0.58 (0.06)$_L$	-0.63 (0.12)$_L$	1.39 (0.20)$_L$
Sports and Activity:$\sigma_{9.21}(\text{RP}_d)$	0.19 (0.06)	0.52 (0.06)$_L$	-0.44 (0.08)$_L$	-0.36 (0.10)	1.36 (0.16)$_L$
Toys:$\sigma_{9.21}(\text{RP}_d)$	0.49 (0.06)$_L$	0.52 (0.05)$_L$	-0.05 (0.04)	-1.73 (0.12)$_L$	2.80 (0.16)$_L$

S: $p < 5\%$ α-level
M: $p < 1\%$ α-level
L: $p < 0.1\%$ α-level

Table D.18: Full model coefficient estimates for studying $\sigma_{9.21}(\text{RP}_p)$ and $\sigma_{9.21}(\text{RP}_d)$ during the holiday period

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
Intercept	-1.62 (0.05)$_L$	-1.61 (0.04)$_L$	-2.85 (0.06)$_L$	0.59 (0.05)$_L$	-1.09 (0.06)$_L$	-1.05 (0.05)$_L$
Proportion of day for sale	3.09 (0.01)$_L$	2.89 (0.02)$_L$	3.01 (0.01)$_L$	2.57 (0.02)$_L$	3.41 (0.02)$_L$	2.68 (0.02)$_L$
Discount	-181.09 (38.56)$_L$	1.53 (0.05)$_L$	-0.21 (0.02)$_L$	4.68 (0.02)$_L$	1.72 (0.03)$_L$	0.92 (0.05)$_L$
Monday	0.00 (0.01)	-0.13 (0.01)$_L$	-0.13 (0.01)$_L$	-0.07 (0.01)$_L$	-0.14 (0.01)$_L$	-0.02 (0.01)
Tuesday	-0.09 (0.01)$_L$	-0.19 (0.01)$_L$	-0.19 (0.01)$_L$	-0.14 (0.01)$_L$	-0.20 (0.01)$_L$	-0.14 (0.01)$_L$
Wednesday	-0.11 (0.01)$_L$	-0.18 (0.01)$_L$	-0.19 (0.01)$_L$	-0.16 (0.01)$_L$	-0.16 (0.01)$_L$	-0.15 (0.01)$_L$
Thursday	-0.20 (0.01)$_L$	-0.31 (0.01)$_L$	-0.28 (0.01)$_L$	-0.30 (0.01)$_L$	-0.29 (0.01)$_L$	-0.25 (0.01)$_L$
Friday	-0.33 (0.01)$_L$	-0.42 (0.01)$_L$	-0.48 (0.01)$_L$	-0.40 (0.01)$_L$	-0.50 (0.01)$_L$	-0.38 (0.01)$_L$
Saturday	-0.24 (0.01)$_L$	-0.37 (0.01)$_L$	-0.42 (0.01)$_L$	-0.36 (0.01)$_L$	-0.37 (0.01)$_L$	-0.03 (0.01)
Holiday	-0.35 (0.01)$_L$	-0.49 (0.01)$_L$	-0.53 (0.01)$_L$	-0.51 (0.01)$_L$	-0.53 (0.01)$_L$	-0.44 (0.01)$_L$
Black Friday	0.77 (0.01)$_L$	0.78 (0.01)$_L$	0.83 (0.01)$_L$	0.89 (0.01)$_L$	1.27 (0.01)$_L$	0.80 (0.01)$_L$
Lockdown	-0.08 (0.01)$_L$	0.08 (0.01)$_L$	-0.11 (0.00)$_L$	0.16 (0.01)$_L$	0.23 (0.00)$_L$	0.42 (0.01)$_L$
Drugs and Baby	-0.66 (0.05)$_L$	1.12 (0.14)$_L$	1.97 (0.07)$_L$	-2.10 (0.05)$_L$	0.87 (0.07)$_L$	-0.20 (0.05)$_S$
Entertainment	1.49 (0.05)$_L$	1.57 (0.06)$_L$	1.18 (0.06)$_L$	0.17 (0.07)	-0.55 (0.08)$_L$	0.19 (0.06)
Hardware	0.95 (0.06)$_L$	-0.46 (0.06)$_L$	4.36 (0.08)$_L$	-1.06 (0.06)$_L$	-3.11 (0.06)$_L$	-1.00 (0.06)$_L$
Kitchen and Household	-0.39 (0.07)$_L$	1.23 (0.08)$_L$	2.45 (0.08)$_L$	-0.72 (0.14)$_L$	0.19 (0.07)	0.27 (0.07)$_S$
other	-6.13 (0.11)$_L$	0.08 (0.06)	0.92 (0.07)$_L$	-1.50 (0.11)$_L$	-3.66 (0.07)$_L$	0.22 (0.07)
Personal Care	-0.69 (0.05)$_L$	-1.13 (0.05)$_L$	4.82 (0.08)$_L$	-2.31 (0.06)$_L$	-0.91 (0.07)$_L$	-1.05 (0.05)$_L$
Domestic Appliances	1.47 (0.06)$_L$	0.30 (0.10)	2.85 (0.08)$_L$	-0.99 (0.07)$_L$	2.39 (0.07)$_L$	2.57 (0.05)$_L$
Sound and Vision	0.81 (0.06)$_L$	-0.29 (0.04)$_L$	-2.74 (0.07)$_L$	0.08 (0.09)	-0.16 (0.08)	-0.19 (0.06)
Sports and Activity	-0.36 (0.07)$_L$	0.44 (0.10)$_M$T	1.89 (0.10)$_L$	-0.30 (0.13)	-0.97 (0.13)$_L$	-0.60 (0.07)$_L$
Toys	-0.07 (0.05)	0.00 (0.06)	1.64 (0.06)$_L$	-4.15 (0.05)$_L$	-3.01 (0.07)$_L$	-5.08 (0.05)$_L$
$\sigma_{9.21}(\text{RP}_p)$	0.09 (0.07)	-0.08 (0.06)	4.04 (0.07)$_L$	-2.29 (0.06)$_L$	0.06 (0.09)	1.10 (0.07)$_L$
$\sigma_{9.21}(\text{RP}_d)$	-0.02 (0.04)	-0.25 (0.03)$_L$	-0.52 (0.05)$_L$	-0.01 (0.03)	-0.37 (0.04)$_L$	0.17 (0.04)$_M$T
Drugs and Baby:$\sigma_{9.21}(\text{RP}_p)$	0.19 (0.07)	0.72 (0.20)	-3.51 (0.08)$_L$	3.18 (0.06)$_L$	0.50 (0.10)$_L$	1.43 (0.08)$_L$
Entertainment:$\sigma_{9.21}(\text{RP}_p)$	1.09 (0.08)$_L$	1.19 (0.08)$_L$	-3.87 (0.07)$_L$	2.65 (0.08)$_L$	2.02 (0.11)$_L$	-1.15 (0.09)$_L$
Hardware:$\sigma_{9.21}(\text{RP}_p)$	-0.45 (0.08)$_L$	3.38 (0.09)$_L$	-4.60 (0.09)$_L$	3.05 (0.09)$_L$	3.31 (0.10)$_L$	-1.59 (0.09)$_L$
Kitchen and Household:$\sigma_{9.21}(\text{RP}_p)$	0.75 (0.10)$_L$	0.39 (0.11)	-5.29 (0.11)$_L$	2.49 (0.19)$_L$	-2.18 (0.10)$_L$	0.18 (0.12)
other:$\sigma_{9.21}(\text{RP}_p)$	8.16 (0.14)$_L$	0.57 (0.09)$_L$	-3.69 (0.08)$_L$	4.92 (0.17)$_L$	4.17 (0.11)$_L$	-1.48 (0.10)$_L$
Personal Care:$\sigma_{9.21}(\text{RP}_p)$	0.53 (0.07)$_L$	4.12 (0.07)$_L$	-5.31 (0.09)$_L$	5.38 (0.07)$_L$	0.56 (0.10)$_L$	0.23 (0.08)
Domestic Appliances:$\sigma_{9.21}(\text{RP}_p)$	0.25 (0.09)	-0.39 (0.12)	-4.18 (0.09)$_L$	2.48 (0.09)$_L$	0.41 (0.10)$_M$T	-2.31 (0.08)$_L$
Sound and Vision:$\sigma_{9.21}(\text{RP}_p)$	-0.26 (0.09)	-0.02 (0.06)	3.66 (0.08)$_L$	1.92 (0.11)$_L$	0.93 (0.12)$_L$	-1.86 (0.10)$_L$
Sports and Activity:$\sigma_{9.21}(\text{RP}_p)$	-0.71 (0.10)$_L$	0.49 (0.16)	-3.25 (0.14)$_L$	2.78 (0.17)$_L$	0.36 (0.20)	1.93 (0.10)$_L$
Toys:$\sigma_{9.21}(\text{RP}_p)$	-0.24 (0.07)	1.20 (0.08)$_L$	-2.88 (0.07)$_L$	5.84 (0.06)$_L$	5.43 (0.10)$_L$	11.34 (0.08)$_L$
Drugs and Baby:$\sigma_{9.21}(\text{RP}_d)$	0.08 (0.04)	0.40 (0.08)$_L$	0.63 (0.06)$_L$	-0.09 (0.04)	0.30 (0.05)$_L$	0.68 (0.04)$_L$
Entertainment:$\sigma_{9.21}(\text{RP}_d)$	0.33 (0.04)$_L$	-1.01 (0.05)$_L$	0.19 (0.05)$_S$	-0.30 (0.05)$_L$	1.09 (0.06)$_L$	0.19 (0.05)$_S$
Hardware:$\sigma_{9.21}(\text{RP}_d)$	0.19 (0.04)$_L$	0.43 (0.04)$_L$	0.81 (0.06)$_L$	-0.90 (0.05)$_L$	0.90 (0.05)$_L$	0.70 (0.05)$_L$
Kitchen and Household:$\sigma_{9.21}(\text{RP}_d)$	0.18 (0.05)	0.42 (0.06)$_L$	0.26 (0.07)$_S$	-0.37 (0.11)	0.12 (0.05)	0.07 (0.05)
other:$\sigma_{9.21}(\text{RP}_d)$	1.55 (0.07)$_L$	0.00 (0.04)	0.24 (0.06)$_S$	0.27 (0.07)$_S$	0.20 (0.05)$_S$	-0.09 (0.05)
Personal Care:$\sigma_{9.21}(\text{RP}_d)$	0.13 (0.04)	-0.93 (0.03)$_L$	-0.06 (0.06)	0.07 (0.05)	0.28 (0.05)$_L$	0.39 (0.04)$_L$
Domestic Appliances:$\sigma_{9.21}(\text{RP}_d)$	0.08 (0.04)	0.02 (0.06)	0.39 (0.06)$_L$	0.07 (0.05)	0.14 (0.05)	0.99 (0.04)$_L$
Sound and Vision:$\sigma_{9.21}(\text{RP}_d)$	-0.37 (0.05)$_L$	0.31 (0.03)$_L$	0.83 (0.06)$_L$	-0.28 (0.06)$_L$	0.05 (0.06)	0.05 (0.05)
Sports and Activity:$\sigma_{9.21}(\text{RP}_d)$	0.31 (0.05)$_L$	-0.10 (0.07)	0.22 (0.07)	-0.19 (0.09)	-0.10 (0.09)	-0.46 (0.05)$_L$
Toys:$\sigma_{9.21}(\text{RP}_d)$	-0.03 (0.04)	0.19 (0.05)$_S$	0.51 (0.06)$_L$	-0.20 (0.03)$_L$	0.04 (0.05)	-3.31 (0.04)$_L$

	Cluster 7	Cluster 8	Cluster 9	Cluster 10	Cluster 11	Cluster 12
Intercept	-4.09 (0.09)$_L$	-2.47 (0.04)$_L$	-1.58 (0.05)$_L$	-0.59 (0.08)$_L$	-0.55 (0.09)$_L$	-0.41 (0.04)$_L$
Proportion of day for sale	3.34 (0.02)$_L$	3.19 (0.02)$_L$	2.90 (0.01)$_L$	3.12 (0.01)$_L$	2.46 (0.01)$_L$	2.77 (0.02)$_L$
Discount	-0.02 (0.08)	4.26 (0.04)$_L$	1.56 (0.04)$_L$	4.39 (0.02)$_L$	0.73 (0.02)$_L$	0.56 (0.05)$_L$
Monday	-0.09 (0.01)$_L$	-0.08 (0.01)$_L$	0.01 (0.01)	-0.03 (0.01)	-0.04 (0.01)$_S$	-0.07 (0.01)$_L$
Tuesday	-0.19 (0.01)$_L$	-0.13 (0.01)$_L$	-0.19 (0.01)$_L$	-0.16 (0.01)$_L$	-0.09 (0.01)$_L$	-0.16 (0.01)$_L$
Wednesday	-0.22 (0.01)$_L$	-0.12 (0.01)$_L$	-0.23 (0.01)$_L$	-0.14 (0.01)$_L$	-0.16 (0.01)$_L$	-0.28 (0.01)$_L$
Thursday	-0.33 (0.01)$_L$	-0.32 (0.01)$_L$	-0.36 (0.01)$_L$	-0.27 (0.01)$_L$	-0.32 (0.01)$_L$	-0.42 (0.01)$_L$
Friday	-0.49 (0.01)$_L$	-0.38 (0.01)$_L$	-0.47 (0.01)$_L$	-0.43 (0.01)$_L$	-0.41 (0.01)$_L$	-0.54 (0.01)$_L$
Saturday	-0.25 (0.01)$_L$	-0.21 (0.01)$_L$	-0.30 (0.01)$_L$	-0.15 (0.01)$_L$	-0.21 (0.01)$_L$	-0.27 (0.01)$_L$
Holiday	-0.64 (0.02)$_L$	-0.43 (0.01)$_L$	-0.47 (0.01)$_L$	-0.43 (0.01)$_L$	-0.51 (0.01)$_L$	-0.60 (0.01)$_L$
Black Friday	1.47 (0.01)$_L$	1.10 (0.01)$_L$	1.10 (0.01)$_L$	1.02 (0.01)$_L$	0.95 (0.01)$_L$	1.16 (0.02)$_L$
Lockdown	0.15 (0.01)$_L$	0.79 (0.00)$_L$	0.02 (0.01)	0.85 (0.01)$_L$	0.44 (0.00)$_L$	0.86 (0.01)$_L$
Drugs and Baby	-0.81 (0.11)$_L$	-0.15 (0.05)	-1.42 (0.05)$_L$	-3.48 (0.08)$_L$	-0.44 (0.10)$_M$T	0.50 (0.06)$_L$
Entertainment	2.61 (0.10)$_L$	-0.06 (0.05)	3.38 (0.06)$_L$	1.67 (0.08)$_L$	0.27 (0.09)	2.61 (0.06)$_L$
Hardware	2.57 (0.13)$_L$	0.66 (0.06)$_L$	-1.50 (0.06)$_L$	-1.08 (0.09)$_L$	0.05 (0.10)	-2.36 (0.05)$_L$
Kitchen and Household	1.34 (0.12)$_L$	1.22 (0.05)$_L$	0.00 (0.07)	-0.25 (0.09)	1.80 (0.16)$_L$	-1.81 (0.05)$_L$
other	1.57 (0.10)$_L$	2.61 (0.05)$_L$	0.03 (0.06)	-3.23 (0.08)$_L$	0.84 (0.10)$_L$	-0.77 (0.06)$_L$
Personal Care	2.79 (0.09)$_L$	1.56 (0.05)$_L$	-2.72 (0.06)$_L$	-2.03 (0.08)$_L$	-2.71 (0.09)$_L$	0.03 (0.05)
Domestic Appliances	5.28 (0.11)$_L$	2.79 (0.05)$_L$	-1.38 (0.06)$_L$	-1.26 (0.08)$_L$	-0.03 (0.09)	-0.21 (0.05)$_M$T
Sound and Vision	4.23 (0.10)$_L$	-0.07 (0.06)	2.17 (0.07)$_L$	0.23 (0.10)	-0.70 (0.09)$_L$	-0.05 (0.07)
Sports and Activity	3.57 (0.13)$_L$	2.39 (0.07)$_L$	-1.33 (0.06)$_L$	-1.37 (0.08)$_L$	0.60 (0.14)$_M$T	-0.34 (0.07)$_L$
Toys	3.83 (0.08)$_L$	-2.18 (0.12)$_L$	0.31 (0.05)$_L$	-2.66 (0.08)$_L$	1.54 (0.09)$_L$	-0.84 (0.05)$_L$
$\sigma_{9.21}(\text{RP}_p)$	4.39 (0.11)$_L$	0.52 (0.06)$_L$	0.57 (0.07)$_L$	0.23 (0.13)	-2.41 (0.14)$_L$	-1.35 (0.05)$_L$
$\sigma_{9.21}(\text{RP}_d)$	1.88 (0.05)$_L$	0.08 (0.03)	0.63 (0.03)$_L$	0.30 (0.05)$_L$	0.85 (0.06)$_L$	0.50 (0.03)$_L$
Drugs and Baby:$\sigma_{9.21}(\text{RP}_p)$	-0.95 (0.14)$_L$	2.61 (0.06)$_L$	2.41 (0.08)$_L$	3.19 (0.13)$_L$	3.05 (0.15)$_L$	1.27 (0.08)$_L$
Entertainment:$\sigma_{9.21}(\text{RP}_p)$	-4.57 (0.13)$_L$	1.90 (0.07)$_L$	1.17 (0.10)$_L$	-0.34 (0.13)	2.99 (0.14)$_L$	-1.23 (0.08)$_L$
Hardware:$\sigma_{9.21}(\text{RP}_p)$	-4.59 (0.17)$_L$	-0.70 (0.08)$_L$	2.76 (0.08)$_L$	0.80 (0.14)$_L$	3.20 (0.15)$_L$	3.01 (0.08)$_L$
Kitchen and Household:$\sigma_{9.21}(\text{RP}_p)$	-2.09 (0.16)$_L$	-0.83 (0.07)$_L$	-0.12 (0.10)	-0.38 (0.14)	2.35 (0.22)$_L$	2.88 (0.07)$_L$
other:$\sigma_{9.21}(\text{RP}_p)$	-2.23 (0.14)$_L$	-0.67 (0.08)$_L$	1.37 (0.09)$_L$	1.70 (0.13)$_L$	2.47 (0.15)$_L$	2.46 (0.08)$_L$
Personal Care:$\sigma_{9.21}(\text{RP}_p)$	-4.40 (0.12)$_L$	-1.83 (0.06)$_L$	3.57 (0.09)$_L$	0.67 (0.13)$_L$	9.05 (0.14)$_L$	2.77 (0.06)$_L$
Domestic Appliances:$\sigma_{9.21}(\text{RP}_p)$	-2.19 (0.14)$_L$	-1.04 (0.07)$_L$	3.61 (0.09)$_L$	-0.87 (0.14)$_L$	2.24 (0.14)$_L$	2.31 (0.08)$_L$
Sound and Vision:$\sigma_{9.21}(\text{RP}_p)$	-3.79 (0.13)$_L$	1.67 (0.09)$_L$	-0.96 (0.10)$_L$	-2.21 (0.16)$_L$	2.52 (0.14)$_L$	2.52 (0.12)$_L$
Sports and Activity:$\sigma_{9.21}(\text{RP}_p)$	-4.70 (0.19)$_L$	-2.09 (0.09)$_L$	1.87 (0.10)$_L$	0.77 (0.13)$_L$	-0.28 (0.21)	-0.33 (0.10)
Toys:$\sigma_{9.21}(\text{RP}_p)$	-3.64 (0.11)$_L$	3.52 (0.15)$_L$	1.44 (0.08)$_L$	4.73 (0.13)$_L$	2.15 (0.14)$_L$	2.89 (0.07)$_L$
Drugs and Baby:$\sigma_{9.21}(\text{RP}_d)$	-2.10 (0.07)$_L$	0.57 (0.04)$_L$	-0.53 (0.04)$_L$	0.28 (0.05)$_L$	-0.65 (0.06)$_L$	-0.46 (0.05)$_L$
Entertainment:$\sigma_{9.21}(\text{RP}_d)$	-1.94 (0.07)$_L$	-0.77 (0.04)$_L$	-0.52 (0.04)$_L$	-0.79 (0.06)$_L$	-0.67 (0.06)$_L$	-0.78 (0.05)$_L$
Hardware:$\sigma_{9.21}(\text{RP}_d)$	-1.46 (0.08)$_L$	0.37 (0.04)$_L$	-0.02 (0.04)	-0.03 (0.06)	-0.19 (0.06)	-0.66 (0.04)$_L$
Kitchen and Household:$\sigma_{9.21}(\text{RP}_d)$	-1.55 (0.09)$_L$	-0.18 (0.04)$_M$T	-1.13 (0.04)$_L$	-0.11 (0.06)	-0.45 (0.09)$_L$	-0.85 (0.04)$_L$
other:$\sigma_{9.21}(\text{RP}_d)$	-1.98 (0.08)$_L$	-0.40 (0.04)$_L$	-0.42 (0.04)$_L$	1.08 (0.05)$_L$	-0.92 (0.07)$_L$	-0.54 (0.05)$_L$
Personal Care:$\sigma_{9.21}(\text{RP}_d)$	-1.77 (0.06)$_L$	-0.90 (0.04)$_L$	-0.85 (0.04)$_L$	-0.08 (0.05)	-1.98 (0.06)$_L$	-1.02 (0.04)$_L$
Domestic Appliances:$\sigma_{9.21}(\text{RP}_d)$	-2.12 (0.07)$_L$	0.09 (0.04)	-0.62 (0.04)$_L$	0.07 (0.05)	-0.85 (0.06)$_L$	-0.30 (0.04)$_L$
Sound and Vision:$\sigma_{9.21}(\text{RP}_d)$	-2.03 (0.07)$_L$	-0.41 (0.04)$_L$	-0.49 (0.05)$_L$	0.12 (0.06)	-0.17 (0.06)	-0.47 (0.06)$_L$
Sports and Activity:$\sigma_{9.21}(\text{RP}_d)$	-1.80 (0.09)$_L$	-0.46 (0.05)$_L$	-1.38 (0.05)$_L$	-0.15 (0.05)	0.08 (0.09)	-0.85 (0.05)$_L$
Toys:$\sigma_{9.21}(\text{RP}_d)$	-1.64 (0.05)$_L$	0.72 (0.06)$_L$	-0.66 (0.04)$_L$	-0.20 (0.05)$_S$	-1.40 (0.06)$_L$	-0.24 (0.04)$_L$

	Cluster 13	Cluster 14	Cluster 15	Cluster 16	Cluster 17	Cluster 18
Intercept	-2.26 (0.09)$_L$	-3.69 (0.10)$_L$	-2.07 (0.07)$_L$	-3.23 (0.14)$_L$	-3.97 (0.08)$_L$	0.18 (0.07)
Proportion of day for sale	2.98 (0.02)$_L$	3.62 (0.01)$_L$	3.46 (0.02)$_L$	3.29 (0.02)$_L$	2.64 (0.01)$_L$	3.04 (0.02)$_L$
Discount	0.09 (0.04)	2.48 (0.02)$_L$	1.26 (0.09)$_L$	0.54 (0.05)$_L$	2.65 (0.07)$_L$	0.85 (0.11)$_L$
Monday	-0.06 (0.01)$_L$	-0.14 (0.01)$_L$	0.04 (0.01)$_S$	-0.18 (0.01)$_L$	0.12 (0.01)$_L$	-0.13 (0.01)$_L$
Tuesday	-0.21 (0.01)$_L$	-0.29 (0.01)$_L$	-0.12 (0.01)$_L$	-0.25 (0.01)$_L$	-0.16 (0.01)$_L$	-0.23 (0.01)$_L$
Wednesday	-0.24 (0.01)$_L$	-0.29 (0.01)$_L$	-0.14 (0.01)$_L$	-0.22 (0.01)$_L$	-0.23 (0.01)$_L$	-0.24 (0.01)$_L$
Thursday	-0.38 (0.01)$_L$	-0.34 (0.01)$_L$	-0.28 (0.01)$_L$	-0.38 (0.01)$_L$	-0.36 (0.01)$_L$	-0.27 (0.01)$_L$
Friday	-0.29 (0.01)$_L$	-0.51 (0.01)$_L$	-0.42 (0.01)$_L$	-0.65 (0.01)$_L$	-0.58 (0.01)$_L$	-0.46 (0.01)$_L$
Saturday	-0.15 (0.01)$_L$	-0.17 (0.01)$_L$	-0.19 (0.01)$_L$	-0.14 (0.01)$_L$	-0.28 (0.01)$_L$	-0.06 (0.01)$_L$
Holiday	-0.71 (0.01)$_L$	-0.71 (0.01)$_L$	-0.49 (0.01)$_L$	-0.93 (0.01)$_L$	-0.59 (0.01)$_L$	-0.42 (0.01)$_L$
Black Friday	0.77 (0.01)$_L$	1.27 (0.01)$_L$	1.24 (0.02)$_L$	1.41 (0.01)$_L$	1.26 (0.01)$_L$	1.88 (0.02)$_L$
Lockdown	1.01 (0.00)$_L$	0.07 (0.01)$_L$	0.69 (0.01)$_L$	-0.59 (0.01)$_L$	0.09 (0.00)$_L$	0.50 (0.01)$_L$
Drugs and Baby	-1.07 (0.12)$_L$	-0.87 (0.11)$_L$	-0.86 (0.07)$_L$	-1.73 (0.14)$_L$	4.30 (0.08)$_L$	-0.91 (0.08)$_L$
Entertainment	-0.84 (0.09)$_L$	3.78 (0.10)$_L$	-0.75 (0.13)$_L$	-0.27 (0.14)	6.95 (0.08)$_L$	-2.27 (0.09)$_L$
Hardware	-1.29 (0.09)$_L$	2.06 (0.10)$_L$	1.64 (0.09)$_L$	-3.68 (0.16)$_L$	3.73 (0.08)$_L$	-1.83 (0.08)$_L$
Kitchen and Household	-1.22 (0.11)$_L$	1.68 (0.12)$_L$	1.49 (0.08)$_L$	0.98 (0.14)$_L$	3.17 (0.08)$_L$	-2.27 (0.09)$_L$
other	-1.13 (0.10)$_L$	-0.40 (0.11)$_S$	-0.05 (0.08)	0.46 (0.15)	4.19 (0.08)$_L$	-1.80 (0.09)$_L$
Personal Care	0.77 (0.09)$_L$	2.62 (0.10)$_L$	0.09 (0.07)	2.10 (0.17)$_L$	2.45 (0.09)$_L$	-2.42 (0.07)$_L$
Domestic Appliances	2.48 (0.09)$_L$	0.24 (0.10)	0.82 (0.07)$_L$	0.87 (0.16)$_L$	1.89 (0.08)$_L$	-6.20 (0.08)$_L$
Sound and Vision	-1.41 (0.09)$_L$	0.98 (0.10)$_L$	0.33 (0.08)$_M$T	-0.07 (0.15)	0.83 (0.09)$_L$	-0.27 (0.12)
Sports and Activity	-1.01 (0.10)$_L$	2.41 (0.12)$_L$	-1.90 (0.10)$_L$	0.46 (0.17)	4.17 (0.12)$_L$	-1.85 (0.09)$_L$
Toys	2.53 (0.09)$_L$	2.97 (0.10)$_L$	1.18 (0.08)$_L$	1.16 (0.13)$_L$	3.36 (0.08)$_L$	-2.77 (0.08)$_L$
$\sigma_{9.21}(\text{RP}_p)$	1.46 (0.12)$_L$	7.46 (0.13)$_L$	0.25 (0.12)	4.90 (0.16)$_L$	3.02 (0.12)$_L$	0.97 (0.10)$_L$
$\sigma_{9.21}(\text{RP}_d)$	0.09 (0.06)	0.98 (0.06)$_L$	-0.04 (0.05)	-0.04 (0.10)	0.16 (0.05)	0.30 (0.05)$_L$
Drugs and Baby:$\sigma_{9.21}(\text{RP}_p)$	0.47 (0.15)	-2.63 (0.15)$_L$	2.70 (0.12)$_L$	-0.60 (0.17)	-1.39 (0.13)$_L$	0.97 (0.12)$_L$
Entertainment:$\sigma_{9.21}(\text{RP}_p)$	3.20 (0.12)$_L$	-7.05 (0.14)$_L$	4.93 (0.17)$_L$	-0.10 (0.17)	-1.86 (0.13)$_L$	1.37 (0.12)$_L$
Hardware:$\sigma_{9.21}(\text{RP}_p)$	5.14 (0.12)$_L$	-7.04 (0.14)$_L$	0.29 (0.13)	4.00 (0.19)$_L$	-4.75 (0.13)$_L$	-1.73 (0.11)$_L$
Kitchen and Household:$\sigma_{9.21}(\text{RP}_p)$	1.49 (0.14)$_L$	-8.84 (0.18)$_L$	0.04 (0.14)	-2.91 (0.16)$_L$	-0.06 (0.13)	-1.78 (0.12)$_L$
other:$\sigma_{9.21}(\text{RP}_p)$	2.55 (0.13)$_L$	-2.44 (0.15)$_L$	-0.52 (0.13)$_S$	-5.09 (0.18)$_L$	-1.02 (0.13)$_L$	-2.39 (0.14)$_L$
Personal Care:$\sigma_{9.21}(\text{RP}_p)$	-0.57 (0.12)$_L$	-4.88 (0.14)$_L$	5.91 (0.12)$_L$	-4.38 (0.19)$_L$	-1.16 (0.13)$_L$	2.30 (0.10)$_L$
Domestic Appliances:$\sigma_{9.21}(\text{RP}_p)$	-3.26 (0.12)$_L$	-4.99 (0.14)$_L$	1.66 (0.13)$_L$	-2.45 (0.19)$_L$	3.10 (0.13)$_L$	8.68 (0.12)$_L$
Sound and Vision:$\sigma_{9.21}(\text{RP}_p)$	2.84 (0.13)$_L$	-3.15 (0.15)$_L$	-0.22 (0.13)	-1.27 (0.18)$_L$	0.34 (0.14)	0.58 (0.15)$_S$
Sports and Activity:$\sigma_{9.21}(\text{RP}_p)$	-0.05 (0.14)	-5.91 (0.16)$_L$	3.98 (0.18)$_L$	-2.70 (0.21)$_L$	-1.44 (0.20)$_L$	-0.94 (0.14)$_L$
Toys:$\sigma_{9.21}(\text{RP}_p)$	-1.07 (0.12)$_L$	-7.53 (0.13)$_L$	-1.64 (0.12)$_L$	-1.86 (0.16)$_L$	-1.18 (0.13)$_L$	0.84 (0.11)$_L$
Drugs and Baby:$\sigma_{9.21}(\text{RP}_d)$	-0.18 (0.08)	-0.55 (0.07)$_L$	0.32 (0.06)$_L$	0.24 (0.10)	0.29 (0.06)$_L$	-2.65 (0.06)$_L$
Entertainment:$\sigma_{9.21}(\text{RP}_d)$	-0.82 (0.07)$_L$	-0.24 (0.06)$_S$	-0.21 (0.10)	0.61 (0.10)$_L$	0.11 (0.06)	0.65 (0.06)$_L$
Hardware:$\sigma_{9.21}(\text{RP}_d)$	-0.33 (0.07)$_L$	-0.29 (0.06)$_L$	0.19 (0.06)	0.21 (0.11)	-0.66 (0.06)$_L$	0.27 (0.05)$_L$
Kitchen and Household:$\sigma_{9.21}(\text{RP}_d)$	0.62 (0.08)$_L$	-0.92 (0.08)$_L$	0.48 (0.06)$_L$	0.74 (0.10)$_L$	-0.16 (0.06)	0.74 (0.06)$_L$
other:$\sigma_{9.21}(\text{RP}_d)$	-1.09 (0.07)$_L$	-0.82 (0.07)$_L$	0.14 (0.06)	1.21 (0.11)$_L$	-0.21 (0.06)	0.11 (0.06)
Personal Care:$\sigma_{9.21}(\text{RP}_d)$	0.09 (0.07)	-0.76 (0.06)$_L$	-1.02 (0.06)$_L$	0.45 (0.10)$_M$T	-0.02 (0.06)	0.20 (0.05)$_S$
Domestic Appliances:$\sigma_{9.21}(\text{RP}_d)$	-0.15 (0.07)	-0.63 (0.06)$_L$	0.11 (0.06)	1.29 (0.12)$_L$	-0.48 (0.06)$_L$	0.44 (0.05)$_L$
Sound and Vision:$\sigma_{9.21}(\text{RP}_d)$	0.60 (0.07)$_L$	-0.67 (0.06)$_L$	0.98 (0.06)$_L$	1.19 (0.11)$_L$	-0.26 (0.07)$_S$	0.43 (0.08)$_L$
Sports and Activity:$\sigma_{9.21}(\text{RP}_d)$	0.70 (0.07)$_L$	-0.60 (0.07)$_L$	-0.08 (0.07)	-0.34 (0.13)	0.05 (0.09)	0.24 (0.07)
Toys:$\sigma_{9.21}(\text{RP}_d)$	0.25 (0.07)	-0.48 (0.06)$_L$	0.05 (0.06)	0.69 (0.10)$_L$	-0.01 (0.06)	1.30 (0.05)$_L$

	Cluster 19	Cluster 20	Cluster 21	Cluster 22	Cluster 23	Cluster 24
Intercept	-3.77 (0.21)$_L$	-0.57 (0.06)$_L$	-1.74 (0.10)$_L$	-0.56 (0.20)	-3.90 (0.08)$_L$	-7.05 (0.09)$_L$
Proportion of day for sale	4.07 (0.02)$_L$	3.88 (0.02)$_L$	2.86 (0.01)$_L$	3.12 (0.01)$_L$	3.38 (0.02)$_L$	3.90 (0.02)$_L$
Discount	0.13 (0.05)	-1.64 (0.02)$_L$	1.58 (0.33)$_L$	1.39 (0.01)$_L$	0.80 (0.08)$_L$	2.38 (0.71)
Monday	-0.16 (0.01)$_L$	-0.16 (0.01)$_L$	-0.12 (0.01)$_L$	-0.09 (0.00)$_L$	-0.17 (0.01)$_L$	-0.20 (0.01)$_L$
Tuesday	-0.25 (0.01)$_L$	-0.20 (0.01)$_L$	-0.23 (0.01)$_L$	-0.20 (0.00)$_L$	-0.25 (0.01)$_L$	-0.24 (0.01)$_L$
Wednesday	-0.23 (0.01)$_L$	-0.21 (0.01)$_L$	-0.26 (0.01)$_L$	-0.21 (0.01)$_L$	-0.13 (0.01)$_L$	-0.14 (0.01)$_L$
Thursday	-0.38 (0.01)$_L$	-0.37 (0.01)$_L$	-0.42 (0.01)$_L$	-0.39 (0.01)$_L$	-0.42 (0.01)$_L$	-0.42 (0.01)$_L$
Friday	-0.56 (0.01)$_L$	-0.61 (0.01)$_L$	-0.51 (0.01)$_L$	-0.56 (0.01)$_L$	-0.70 (0.01)$_L$	-0.65 (0.01)$_L$
Saturday	0.09 (0.01)$_L$	-0.34 (0.01)$_L$	-0.32 (0.01)$_L$	-0.28 (0.01)$_L$	-0.05 (0.01)$_L$	-0.17 (0.01)$_L$
Holiday	-0.71 (0.02)$_L$	-0.97 (0.01)$_L$	-0.62 (0.01)$_L$	-0.84 (0.01)$_L$	-1.06 (0.01)$_L$	-1.19 (0.02)$_L$
Black Friday	1.02 (0.01)$_L$	1.24 (0.01)$_L$	1.15 (0.01)$_L$	1.11 (0.01)$_L$	1.25 (0.01)$_L$	1.06 (0.01)$_L$
Lockdown	0.62 (0.01)$_L$	-0.75 (0.01)$_L$	0.22 (0.01)$_L$	-0.26 (0.00)$_L$	-0.16 (0.00)$_L$	-0.58 (0.01)$_L$
Drugs and Baby	1.01 (0.21)$_L$	-1.38 (0.07)$_L$	-1.23 (0.10)$_L$	0.98 (0.20)$_L$	1.99 (0.08)$_L$	4.76 (0.11)$_L$
Entertainment	-0.95 (0.21)$_M$T	0.79 (0.06)$_L$	3.60 (0.10)$_L$	-3.30 (0.20)$_L$	2.13 (0.10)$_L$	2.70 (0.11)$_L$
Hardware	1.10 (0.22)$_L$	-9.54 (0.07)$_L$	2.21 (0.11)$_L$	2.70 (0.21)$_L$	-2.97 (0.11)$_L$	3.24 (0.13)$_L$
Kitchen and Household	3.07 (0.25)$_L$	1.30 (0.07)$_L$	-2.55 (0.11)$_L$	0.86 (0.21)$_M$T	5.12 (0.10)$_L$	2.29 (0.13)$_L$
other	3.65 (0.21)$_L$	0.20 (0.06)	1.11 (0.11)$_L$	1.77 (0.20)$_L$	-0.11 (0.08)	5.71 (0.10)$_L$
Personal Care	-0.15 (0.23)	-4.73 (0.07)$_L$	4.85 (0.10)$_L$	1.37 (0.20)$_L$	-2.64 (0.09)$_L$	1.31 (0.15)$_L$
Domestic Appliances	0.46 (0.22)	0.48 (0.06)$_L$	2.72 (0.11)$_L$	-3.95 (0.20)$_L$	-1.30 (0.08)$_L$	4.55 (0.10)$_L$
Sound and Vision	2.19 (0.24)$_L$	-1.99 (0.08)$_L$	4.35 (0.15)$_L$	0.00 (0.21)	0.72 (0.09)$_L$	4.64 (0.12)$_L$
Sports and Activity	4.79 (0.22)$_L$	-0.17 (0.09)	-1.66 (0.11)$_L$	-3.43 (0.20)$_L$	1.16 (0.18)$_L$	5.35 (0.15)$_L$
Toys	2.36 (0.21)$_L$	-0.60 (0.07)$_L$	2.84 (0.10)$_L$	1.79 (0.20)$_L$	4.82 (0.08)$_L$	6.27 (0.09)$_L$
$\sigma_{9.21}(\text{RP}_p)$	-0.04 (0.25)	-0.52 (0.08)$_L$	1.67 (0.17)$_L$	0.57 (0.24)	3.12 (0.11)$_L$	6.29 (0.13)$_L$
$\sigma_{9.21}(\text{RP}_d)$	0.78 (0.13)$_L$	-0.57 (0.04)$_L$	-1.01 (0.06)$_L$	0.09 (0.13)	1.12 (0.05)$_L$	1.13 (0.06)$_L$
Drugs and Baby:$\sigma_{9.21}(\text{RP}_p)$	0.03 (0.26)	-0.43 (0.09)$_L$	3.69 (0.17)$_L$	1.71 (0.24)$_L$	-2.20 (0.12)$_L$	-4.77 (0.15)$_L$
Entertainment:$\sigma_{9.21}(\text{RP}_p)$	6.75 (0.26)$_L$	-1.08 (0.09)$_L$	-1.27 (0.17)$_L$	3.83 (0.24)$_L$	-2.37 (0.14)$_L$	0.13 (0.15)
Hardware:$\sigma_{9.21}(\text{RP}_p)$	2.65 (0.27)$_L$	16.11 (0.10)$_L$	0.97 (0.18)$_L$	-3.55 (0.25)$_L$	5.41 (0.15)$_L$	-1.09 (0.18)$_L$
Kitchen and Household:$\sigma_{9.21}(\text{RP}_p)$	-1.97 (0.30)$_L$	-1.29 (0.10)$_L$	2.11 (0.19)$_L$	-5.60 (0.25)$_L$	-3.95 (0.15)$_L$	-0.06 (0.19)
other:$\sigma_{9.21}(\text{RP}_p)$	0.31 (0.27)	1.03 (0.08)$_L$	-2.14 (0.18)$_L$	-5.54 (0.24)$_L$	-0.59 (0.11)$_L$	-6.48 (0.14)$_L$
Personal Care:$\sigma_{9.21}(\text{RP}_p)$	0.34 (0.27)	4.47 (0.10)$_L$	-2.29 (0.17)$_L$	-1.94 (0.24)$_L$	5.13 (0.12)$_L$	-1.22 (0.19)$_L$
Domestic Appliances:$\sigma_{9.21}(\text{RP}_p)$	4.77 (0.28)$_L$	1.34 (0.09)$_L$	-0.73 (0.18)$_M$T	6.55 (0.24)$_L$	2.02 (0.12)$_L$	-6.61 (0.14)$_L$
Sound and Vision:$\sigma_{9.21}(\text{RP}_p)$	0.93 (0.28)	0.67 (0.11)$_L$	-1.55 (0.22)$_L$	0.34 (0.26)	-0.67 (0.12)$_L$	-5.18 (0.16)$_L$
Sports and Activity:$\sigma_{9.21}(\text{RP}_p)$	-1.48 (0.29)$_L$	-2.31 (0.15)$_L$	3.28 (0.18)$_L$	1.92 (0.24)$_L$	-3.22 (0.27)$_L$	-6.42 (0.24)$_L$
Toys:$\sigma_{9.21}(\text{RP}_p)$	1.81 (0.25)$_L$	2.98 (0.09)$_L$	-1.50 (0.17)$_L$	-0.13 (0.24)	-1.71 (0.11)$_L$	-3.60 (0.13)$_L$
Drugs and Baby:$\sigma_{9.21}(\text{RP}_d)$	-0.21 (0.14)	0.91 (0.05)$_L$	0.76 (0.07)$_L$	0.62 (0.13)$_L$	-1.07 (0.06)$_L$	-0.62 (0.08)$_L$
Entertainment:$\sigma_{9.21}(\text{RP}_d)$	0.01 (0.14)	0.54 (0.05)$_L$	1.31 (0.07)$_L$	0.01 (0.13)	-0.17 (0.06)	-0.45 (0.07)$_L$
Hardware:$\sigma_{9.21}(\text{RP}_d)$	-2.05 (0.14)$_L$	2.78 (0.05)$_L$	0.96 (0.07)$_L$	-0.49 (0.13)$_S$	0.13 (0.07)	-0.41 (0.07)$_L$
Kitchen and Household:$\sigma_{9.21}(\text{RP}_d)$	0.26 (0.15)	0.15 (0.05)	0.82 (0.07)$_L$	1.32 (0.13)$_L$	-0.21 (0.07)	-1.40 (0.09)$_L$
other:$\sigma_{9.21}(\text{RP}_d)$	0.07 (0.14)	0.16 (0.05)	1.40 (0.07)$_L$	-0.29 (0.13)	0.48 (0.06)$_L$	-1.61 (0.07)$_L$
Personal Care:$\sigma_{9.21}(\text{RP}_d)$	-0.02 (0.14)	-0.13 (0.05)	0.60 (0.07)$_L$	-0.44 (0.13)	-1.94 (0.06)$_L$	-0.38 (0.08)$_L$
Domestic Appliances:$\sigma_{9.21}(\text{RP}_d)$	0.24 (0.15)	0.27 (0.04)$_L$	0.76 (0.07)$_L$	0.52 (0.13)$_S$	0.75 (0.06)$_L$	0.41 (0.06)$_L$
Sound and Vision:$\sigma_{9.21}(\text{RP}_d)$	0.40 (0.18)	0.85 (0.05)$_L$	0.90 (0.09)$_L$	-0.08 (0.14)	-0.55 (0.07)$_L$	-0.43 (0.08)$_L$
Sports and Activity:$\sigma_{9.21}(\text{RP}_d)$	-3.22 (0.15)$_L$	0.22 (0.07)	-0.21 (0.07)	0.59 (0.13)$_M$T	0.48 (0.12)$_S$	-1.22 (0.09)$_L$
Toys:$\sigma_{9.21}(\text{RP}_d)$	0.37 (0.13)	0.66 (0.05)$_L$	1.19 (0.06)$_L$	0.02 (0.13)	-0.40 (0.06)$_L$	-0.81 (0.06)$_L$

S: $p < 5\%$ α-level
M: $p < 1\%$ α-level
L: $p < 0.1\%$ α-level

Table D.19: Full model coefficient estimates for studying RC, WTP and UTP during the regular period

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
Intercept	-2.14 (0.02)$_L$	1.49 (0.02)$_L$	-0.40 (0.03)$_L$	-1.69 (0.03)$_L$	-0.89 (0.02)$_L$	-0.95 (0.03)$_L$
Proportion of day for sale	3.05 (0.01)$_L$	2.76 (0.01)$_L$	2.66 (0.01)$_L$	2.91 (0.02)$_L$	2.75 (0.01)$_L$	2.53 (0.01)$_L$
temp	-0.02 (0.00)$_L$	-0.05 (0.00)$_L$	0.00 (0.00)	-0.02 (0.00)$_L$	0.01 (0.00)$_L$	-0.01 (0.00)$_L$
Discount	1.05 (0.02)$_L$	3.12 (0.03)$_L$	1.11 (0.04)$_L$	1.65 (0.04)$_L$	0.48 (0.07)$_L$	2.24 (0.03)$_L$
Display	0.51 (0.00)$_L$	0.34 (0.01)$_L$	0.39 (0.01)$_L$	-0.03 (0.01)	0.10 (0.01)$_L$	0.12 (0.01)$_L$
Holiday	0.08 (0.01)$_L$	-0.03 (0.01)	0.10 (0.01)$_L$	0.01 (0.01)	0.03 (0.01)	0.14 (0.01)$_L$
Monday	0.07 (0.01)$_L$	0.02 (0.01)	0.09 (0.01)$_L$	0.09 (0.01)$_L$	0.08 (0.01)$_L$	0.12 (0.01)$_L$
Tuesday	-0.02 (0.01)	-0.03 (0.01)	0.00 (0.01)	-0.01 (0.01)	0.01 (0.01)	0.02 (0.01)
Wednesday	-0.05 (0.01)$_L$	-0.06 (0.01)$_L$	-0.02 (0.01)	-0.03 (0.01)	0.00 (0.01)	-0.02 (0.01)
Thursday	-0.11 (0.01)$_L$	-0.14 (0.01)$_L$	-0.08 (0.01)$_L$	-0.10 (0.01)$_L$	-0.10 (0.01)$_L$	-0.06 (0.01)$_L$
Friday	-0.18 (0.01)$_L$	-0.21 (0.01)$_L$	-0.16 (0.01)$_L$	-0.14 (0.01)$_L$	-0.19 (0.01)$_L$	-0.13 (0.01)$_L$
Saturday	-0.07 (0.01)$_L$	-0.25 (0.01)$_L$	-0.24 (0.01)$_L$	-0.29 (0.01)$_L$	-0.30 (0.01)$_L$	-0.32 (0.01)$_L$
Domestic Appliances	2.98 (0.02)$_L$	-0.99 (0.02)$_L$	-0.84 (0.03)$_L$	0.66 (0.03)$_L$	-0.16 (0.03)$_L$	-0.80 (0.03)$_L$
Drugs and Baby	1.10 (0.02)$_L$	-3.47 (0.02)$_L$	0.19 (0.03)$_L$	0.63 (0.02)$_L$	-1.19 (0.02)$_L$	0.66 (0.02)$_L$
Entertainment	0.32 (0.03)$_L$	-2.13 (0.04)$_L$	-1.00 (0.04)$_L$	-0.01 (0.03)	-1.40 (0.03)$_L$	0.45 (0.03)$_L$
Hardware	-0.74 (0.03)$_L$	-2.34 (0.03)$_L$	-1.30 (0.03)$_L$	-0.03 (0.03)	-0.35 (0.02)$_L$	0.55 (0.03)$_L$
Kitchen and Household	-0.05 (0.02)	-1.39 (0.02)$_L$	0.01 (0.03)	0.36 (0.03)$_L$	0.71 (0.02)$_L$	-0.51 (0.03)$_L$
other	-0.08 (0.02)$_S$	-1.62 (0.02)$_L$	0.32 (0.03)$_L$	3.10 (0.03)$_L$	-1.07 (0.02)$_L$	0.04 (0.02)
Personal Care	-0.14 (0.02)$_L$	-2.51 (0.02)$_L$	-1.47 (0.03)$_L$	-0.45 (0.03)$_L$	0.25 (0.02)$_L$	0.47 (0.02)$_L$
Sound and Vision	1.17 (0.03)$_L$	-2.33 (0.03)$_L$	-0.22 (0.03)$_L$	0.43 (0.03)$_L$	-0.82 (0.03)$_L$	0.58 (0.03)$_L$
Sports and Activity	1.20 (0.02)$_L$	-1.98 (0.02)$_L$	-1.84 (0.03)$_L$	0.56 (0.03)$_L$	1.71 (0.02)$_L$	0.49 (0.03)$_L$
Toys	0.74 (0.02)$_L$	-2.69 (0.02)$_L$	-0.94 (0.03)$_L$	1.89 (0.02)$_L$	1.06 (0.02)$_L$	0.23 (0.03)$_L$
UTP	-0.33 (0.05)$_L$	0.05 (0.04)	0.52 (0.07)$_L$	0.59 (0.06)$_L$	0.43 (0.05)$_L$	0.28 (0.05)$_L$
RC	0.16 (0.04)$_S$	0.33 (0.03)$_L$	0.96 (0.05)$_L$	0.39 (0.04)$_L$	0.58 (0.03)$_L$	0.49 (0.04)$_L$
WTP	0.57 (0.06)$_L$	-1.21 (0.18)$_L$	2.03 (0.14)$_L$	-0.77 (0.09)$_L$	0.19 (0.09)	-0.52 (0.09)$_L$
Domestic Appliances:UTP	0.54 (0.05)$_L$	0.06 (0.05)	-0.65 (0.07)$_L$	0.58 (0.08)$_L$	0.80 (0.07)$_L$	0.02 (0.05)
Drugs and Baby:UTP	0.75 (0.06)$_L$	1.34 (0.06)$_L$	-0.62 (0.07)$_L$	-0.56 (0.06)$_L$	-0.24 (0.05)$_L$	-0.33 (0.05)$_L$
Entertainment:UTP	0.53 (0.07)$_L$	0.27 (0.15)	0.46 (0.08)$_L$	-0.47 (0.06)$_L$	0.38 (0.06)$_L$	-0.03 (0.08)
Hardware:UTP	1.90 (0.07)$_L$	0.30 (0.07)$_M$	-0.29 (0.08)	-2.15 (0.08)$_L$	-0.57 (0.06)$_L$	0.29 (0.05)$_L$
Kitchen and Household:UTP	0.36 (0.06)$_L$	0.20 (0.05)$_S$	-0.35 (0.08)$_M$	-0.50 (0.06)$_L$	-0.26 (0.05)$_L$	-0.05 (0.06)
other:UTP	0.32 (0.06)$_L$	-0.37 (0.06)$_L$	-0.46 (0.07)$_L$	-0.58 (0.06)$_L$	-0.26 (0.06)$_M$	0.15 (0.05)
Personal Care:UTP	1.09 (0.06)$_L$	0.07 (0.05)	-0.65 (0.07)$_L$	-0.54 (0.06)$_L$	-0.15 (0.05)	-0.19 (0.05)$_S$
Sound and Vision:UTP	-0.08 (0.10)	-0.35 (0.07)$_L$	-0.32 (0.08)$_S$	-0.12 (0.07)	-0.28 (0.07)$_S$	-0.03 (0.06)
Sports and Activity:UTP	-0.04 (0.08)	0.12 (0.07)	-0.40 (0.08)$_L$	-0.59 (0.07)$_L$	-0.48 (0.06)$_L$	-0.56 (0.09)$_L$
Toys:UTP	0.43 (0.05)$_L$	0.35 (0.05)$_L$	-0.08 (0.08)	-0.76 (0.06)$_L$	-0.23 (0.05)$_M$	-0.23 (0.06)$_S$
Domestic Appliances:RC	0.89 (0.04)$_L$	0.19 (0.04)$_L$	-0.83 (0.06)$_L$	0.99 (0.06)$_L$	1.15 (0.06)$_L$	-0.30 (0.05)$_L$
Drugs and Baby:RC	0.95 (0.04)$_L$	1.93 (0.04)$_L$	-0.67 (0.05)$_L$	-0.19 (0.04)$_L$	-0.11 (0.04)	-0.33 (0.05)$_L$
Entertainment:RC	0.99 (0.05)$_L$	-0.80 (0.08)$_L$	0.81 (0.07)$_L$	-0.24 (0.05)$_L$	-0.36 (0.05)$_L$	-0.68 (0.06)$_L$
Hardware:RC	2.32 (0.06)$_L$	2.11 (0.06)$_L$	-0.10 (0.06)	-0.21 (0.06)	-0.51 (0.04)$_L$	0.70 (0.05)$_L$
Kitchen and Household:RC	0.04 (0.04)	0.05 (0.04)	-0.71 (0.06)$_L$	-0.23 (0.05)$_M$	-0.33 (0.04)$_L$	-0.37 (0.05)$_L$
other:RC	0.07 (0.04)	-0.55 (0.04)$_L$	-0.45 (0.06)$_L$	-0.16 (0.04)$_S$	-0.22 (0.04)$_L$	-0.19 (0.05)$_S$
Personal Care:RC	1.54 (0.04)$_L$	0.12 (0.03)$_S$	-0.83 (0.05)$_L$	-0.05 (0.04)	0.19 (0.04)$_L$	-0.18 (0.05)
Sound and Vision:RC	-0.44 (0.07)$_L$	-0.85 (0.06)$_L$	-0.07 (0.06)	0.28 (0.06)$_M$	-0.22 (0.05)$_M$	-0.18 (0.06)
Sports and Activity:RC	0.56 (0.05)$_L$	-0.27 (0.05)$_L$	-0.79 (0.06)$_L$	-0.52 (0.05)$_L$	-0.34 (0.04)$_L$	-1.19 (0.06)$_L$
Toys:RC	0.18 (0.04)$_M$	0.13 (0.03)$_M$	0.34 (0.06)$_L$	-0.33 (0.04)$_L$	-0.17 (0.04)$_M$	-0.45 (0.05)$_L$
Domestic Appliances:WTP	0.11 (0.07)	1.25 (0.19)$_L$	-2.38 (0.15)$_L$	1.13 (0.16)$_L$	-0.02 (0.18)	-0.03 (0.12)
Drugs and Baby:WTP	-0.71 (0.08)$_L$	2.37 (0.20)$_L$	-1.79 (0.14)$_L$	0.83 (0.09)$_L$	-0.68 (0.10)$_L$	0.47 (0.10)$_M$
Entertainment:WTP	-0.51 (0.14)	-360.92 (479.52)	-1.28 (0.21)$_L$	0.12 (0.11)	-0.12 (0.10)	0.29 (0.12)
Hardware:WTP	1.03 (0.14)$_L$	1.17 (0.27)$_M$	-2.09 (0.16)$_L$	0.45 (0.14)	-0.85 (0.11)$_L$	-0.08 (0.12)
Kitchen and Household:WTP	-0.97 (0.10)$_L$	0.40 (0.19)	-2.58 (0.15)$_L$	0.29 (0.11)	-0.21 (0.11)	-0.37 (0.12)
other:WTP	-0.88 (0.08)$_L$	2.02 (0.19)$_L$	-2.20 (0.15)$_L$	1.19 (0.10)$_L$	-1.11 (0.10)$_L$	0.30 (0.10)
Personal Care:WTP	-0.69 (0.10)$_L$	1.05 (0.19)$_L$	-2.44 (0.14)$_L$	0.80 (0.10)$_L$	-1.64 (0.11)$_L$	0.07 (0.10)
Sound and Vision:WTP	-0.07 (0.16)	0.35 (0.23)	-3.15 (0.17)$_L$	0.10 (0.17)	-0.50 (0.16)	0.21 (0.13)
Sports and Activity:WTP	1.06 (0.11)$_L$	1.75 (0.20)$_L$	-1.63 (0.15)$_L$	-1.91 (0.15)$_L$	-0.47 (0.10)$_M$	-1.44 (0.22)$_L$
Toys:WTP	-0.60 (0.07)$_L$	1.13 (0.19)$_L$	-2.01 (0.16)$_L$	0.34 (0.10)	-0.77 (0.10)$_L$	3.42 (0.12)$_L$

	Cluster 7	Cluster 8	Cluster 9	Cluster 10	Cluster 11	Cluster 12
Intercept	-1.53 (0.03)$_L$	-1.44 (0.03)$_L$	-2.40 (0.06)$_L$	-2.42 (0.04)$_L$	0.67 (0.12)$_L$	-2.61 (0.06)$_L$
Proportion of day for sale	2.69 (0.02)$_L$	2.71 (0.01)$_L$	2.79 (0.01)$_L$	2.67 (0.01)$_L$	2.74 (0.01)$_L$	2.65 (0.02)$_L$
temp	-0.02 (0.00)$_L$	-0.02 (0.00)$_L$	0.04 (0.00)$_L$	0.00 (0.00)	-0.01 (0.00)$_L$	0.00 (0.00)
Discount	1.32 (0.06)$_L$	0.79 (0.02)$_L$	3.39 (0.04)$_L$	1.82 (0.03)$_L$	1.14 (0.02)$_L$	1.39 (0.04)$_L$
Display	0.85 (0.01)$_L$	0.52 (0.00)$_L$	0.02 (0.01)	0.14 (0.01)$_L$	0.50 (0.00)$_L$	0.17 (0.01)$_L$
Holiday	-0.03 (0.01)	-0.04 (0.01)$_S$	0.04 (0.01)$_S$	0.10 (0.01)$_L$	0.06 (0.01)$_L$	0.11 (0.01)$_L$
Monday	0.06 (0.01)$_L$	0.15 (0.00)$_L$	0.09 (0.01)$_L$	0.06 (0.00)$_L$	0.08 (0.00)$_L$	0.11 (0.01)$_L$
Tuesday	-0.03 (0.01)	0.05 (0.00)$_L$	0.03 (0.01)	-0.02 (0.00)$_L$	-0.05 (0.00)$_L$	0.05 (0.01)$_L$
Wednesday	-0.04 (0.01)$_S$	-0.02 (0.00)$_L$	0.01 (0.01)	-0.06 (0.00)$_L$	-0.07 (0.00)$_L$	0.00 (0.01)
Thursday	-0.11 (0.01)$_L$	-0.11 (0.00)$_L$	-0.07 (0.01)$_L$	-0.10 (0.01)$_L$	-0.16 (0.00)$_L$	-0.04 (0.01)$_S$
Friday	-0.18 (0.01)$_L$	-0.16 (0.00)$_L$	-0.18 (0.01)$_L$	-0.20 (0.01)$_L$	-0.21 (0.00)$_L$	-0.11 (0.01)$_L$
Saturday	-0.21 (0.01)$_L$	-0.12 (0.01)$_L$	-0.39 (0.01)$_L$	-0.31 (0.01)$_L$	-0.21 (0.01)$_L$	-0.15 (0.01)$_L$
Domestic Appliances	1.32 (0.02)$_L$	1.75 (0.02)$_L$	-0.07 (0.06)	1.74 (0.04)$_L$	-0.14 (0.12)	-1.48 (0.11)$_L$
Drugs and Baby	-0.40 (0.02)$_L$	2.53 (0.02)$_L$	1.56 (0.06)$_L$	0.95 (0.03)$_L$	-0.38 (0.12)	1.49 (0.06)$_L$
Entertainment	1.17 (0.03)$_L$	-0.54 (0.03)$_L$	1.12 (0.06)$_L$	2.04 (0.05)$_L$	-0.01 (0.12)	0.98 (0.06)$_L$
Hardware	0.50 (0.02)$_L$	0.62 (0.03)$_L$	-0.34 (0.06)$_L$	3.44 (0.03)$_L$	-1.86 (0.12)$_L$	2.74 (0.06)$_L$
Kitchen and Household	0.17 (0.03)$_L$	1.98 (0.02)$_L$	1.53 (0.06)$_L$	3.08 (0.03)$_L$	-1.64 (0.12)$_L$	1.55 (0.06)$_L$
other	0.43 (0.03)$_L$	1.20 (0.03)$_L$	-0.21 (0.06)	1.54 (0.03)$_L$	-0.28 (0.12)	0.90 (0.06)$_L$
Personal Care	0.66 (0.02)$_L$	2.41 (0.02)$_L$	1.12 (0.06)$_L$	2.39 (0.03)$_L$	-1.91 (0.12)$_L$	-0.05 (0.06)
Sound and Vision	-0.68 (0.05)$_L$	-0.57 (0.03)$_L$	2.88 (0.06)$_L$	0.04 (0.04)	-1.48 (0.12)$_L$	0.91 (0.06)$_L$
Sports and Activity	-0.21 (0.02)$_L$	1.74 (0.03)$_L$	0.77 (0.06)$_L$	0.74 (0.04)$_L$	-1.20 (0.12)$_L$	1.01 (0.06)$_L$
Toys	0.91 (0.02)$_L$	-0.77 (0.03)$_L$	0.01 (0.06)	2.20 (0.04)$_L$	-0.79 (0.12)$_L$	1.87 (0.06)$_L$
UTP	0.02 (0.05)	-0.28 (0.07)$_S$	0.98 (0.13)$_L$	0.85 (0.08)$_L$	-4.48 (1.15)$_S$	2.47 (0.11)$_L$
RC	0.04 (0.04)	0.85 (0.04)$_L$	0.90 (0.10)$_L$	0.73 (0.06)$_L$	-4.21 (0.26)$_L$	1.46 (0.09)$_L$
WTP	-0.34 (0.06)$_L$	0.02 (0.09)	-0.46 (0.22)	-1.34 (0.19)$_L$	-7.99 (0.78)$_L$	-1.52 (0.28)$_L$
Domestic Appliances:UTP	0.18 (0.05)	0.38 (0.07)$_L$	-0.87 (0.14)$_L$	-0.78 (0.08)$_L$	5.02 (1.15)$_M$	0.71 (0.28)
Drugs and Baby:UTP	0.07 (0.05)	0.70 (0.07)$_L$	-0.55 (0.13)$_M$	-0.58 (0.08)$_L$	4.53 (1.15)$_S$	-2.36 (0.12)$_L$
Entertainment:UTP	-0.22 (0.08)	0.20 (0.08)	-0.93 (0.14)$_L$	-0.35 (0.11)	4.56 (1.15)$_S$	-2.20 (0.12)$_L$
Hardware:UTP	0.39 (0.06)$_L$	0.61 (0.08)$_L$	-0.66 (0.13)$_L$	-0.49 (0.08)$_L$	3.74 (1.15)	-2.53 (0.12)$_L$
Kitchen and Household:UTP	0.46 (0.07)$_L$	0.20 (0.07)	-1.02 (0.14)$_L$	-0.52 (0.08)$_L$	4.75 (1.15)$_S$	-2.49 (0.13)$_L$
other:UTP	-0.62 (0.11)$_L$	-0.29 (0.09)	-0.47 (0.13)	-0.73 (0.09)$_L$	4.77 (1.15)$_S$	-2.28 (0.13)$_L$
Personal Care:UTP	0.15 (0.05)	0.12 (0.07)	-0.72 (0.13)$_L$	-0.58 (0.08)$_L$	4.45 (1.15)$_S$	-1.66 (0.12)$_L$
Sound and Vision:UTP	1.19 (0.10)$_L$	-0.01 (0.09)	-1.19 (0.13)$_L$	0.01 (0.10)	4.74 (1.15)$_S$	-2.06 (0.14)$_L$
Sports and Activity:UTP	0.42 (0.06)$_L$	0.13 (0.07)	-0.77 (0.13)$_L$	-0.77 (0.09)$_L$	4.45 (1.15)$_S$	-2.40 (0.12)$_L$
Toys:UTP	0.32 (0.05)$_L$	0.71 (0.07)$_L$	-0.53 (0.13)$_S$	-0.68 (0.09)$_L$	4.81 (1.15)$_S$	-2.38 (0.12)$_L$
Domestic Appliances:RC	0.74 (0.04)$_L$	-0.19 (0.05)$_S$	-0.51 (0.10)$_L$	-0.62 (0.06)$_L$	5.31 (0.26)$_L$	4.98 (0.18)$_L$
Drugs and Baby:RC	0.31 (0.04)$_L$	0.72 (0.04)$_L$	-0.31 (0.10)	-0.35 (0.06)$_L$	4.97 (0.26)$_L$	-0.89 (0.09)$_L$
Entertainment:RC	-0.07 (0.06)	-0.50 (0.05)$_L$	-0.87 (0.11)$_L$	0.08 (0.09)	4.75 (0.27)$_L$	-1.28 (0.10)$_L$
Hardware:RC	0.97 (0.05)$_L$	0.33 (0.05)$_L$	-0.77 (0.10)$_L$	0.03 (0.06)	4.06 (0.27)$_L$	-0.66 (0.09)$_L$
Kitchen and Household:RC	1.28 (0.05)$_L$	-0.42 (0.05)$_L$	-0.69 (0.10)$_L$	0.08 (0.06)	5.00 (0.27)$_L$	0.17 (0.10)
other:RC	-0.01 (0.07)	-0.95 (0.05)$_L$	-1.08 (0.10)$_L$	-0.19 (0.06)	5.06 (0.26)$_L$	0.04 (0.10)
Personal Care:RC	0.68 (0.04)$_L$	-0.12 (0.05)	-0.56 (0.10)$_L$	-0.05 (0.06)	4.42 (0.26)$_L$	-0.06 (0.09)
Sound and Vision:RC	2.51 (0.08)$_L$	0.14 (0.07)	-1.62 (0.10)$_L$	0.03 (0.08)	4.72 (0.27)$_L$	0.44 (0.11)$_S$
Sports and Activity:RC	0.05 (0.05)	-0.59 (0.05)$_L$	-0.76 (0.10)$_L$	-0.71 (0.06)$_L$	4.24 (0.27)$_L$	-0.86 (0.10)$_L$
Toys:RC	0.58 (0.04)$_L$	-0.11 (0.05)	-0.71 (0.10)$_L$	-0.51 (0.06)$_L$	5.11 (0.26)$_L$	-0.78 (0.09)$_L$
Domestic Appliances:WTP	0.32 (0.09)	-0.24 (0.09)	0.45 (0.23)	0.92 (0.20)$_M$	7.81 (0.78)$_L$	5.68 (0.36)$_L$
Drugs and Baby:WTP	0.19 (0.07)	-0.47 (0.09)$_L$	-0.21 (0.22)	1.17 (0.19)$_L$	7.54 (0.78)$_L$	0.94 (0.29)
Entertainment:WTP	-0.23 (0.17)	-1.13 (0.13)$_L$	-1.37 (0.28)$_L$	1.36 (0.25)$_L$	8.28 (0.79)$_L$	1.53 (0.30)$_L$
Hardware:WTP	0.18 (0.12)	-0.36 (0.12)	0.04 (0.23)	-0.02 (0.20)	7.33 (0.79)$_L$	0.16 (0.29)
Kitchen and Household:WTP	1.64 (0.12)$_L$	-0.21 (0.10)	2.22 (0.22)$_L$	2.09 (0.20)$_L$	9.90 (0.79)$_L$	-0.25 (0.36)
other:WTP	3.73 (0.12)$_L$	0.55 (0.09)$_L$	0.24 (0.22)	0.93 (0.20)$_M$	8.37 (0.78)$_L$	1.53 (0.29)$_L$
Personal Care:WTP	-0.04 (0.08)	0.03 (0.10)	0.40 (0.22)	1.32 (0.19)$_L$	7.65 (0.78)$_L$	0.92 (0.29)
Sound and Vision:WTP	2.53 (0.26)$_L$	-0.89 (0.17)$_L$	0.14 (0.25)	1.16 (0.23)$_L$	7.09 (0.79)$_L$	1.82 (0.33)$_L$
Sports and Activity:WTP	-2.23 (0.13)$_L$	-0.01 (0.10)	0.04 (0.22)	1.05 (0.20)$_L$	7.96 (0.79)$_L$	1.89 (0.29)$_L$
Toys:WTP	-0.03 (0.08)	-0.52 (0.10)$_L$	-0.22 (0.22)	1.23 (0.20)$_L$	7.04 (0.78)$_L$	1.16 (0.29)$_S$

	Cluster 13	Cluster 14	Cluster 15	Cluster 16	Cluster 17	Cluster 18
Intercept	-1.03 (0.04)$_L$	0.45 (0.03)$_L$	-0.97 (0.04)$_L$	0.25 (0.03)$_L$	-1.90 (0.03)$_L$	-0.76 (0.04)$_L$
Proportion of day for sale	2.82 (0.02)$_L$	2.66 (0.02)$_L$	2.51 (0.02)$_L$	2.54 (0.01)$_L$	2.73 (0.02)$_L$	2.43 (0.02)$_L$
temp	0.00 (0.00)	-0.06 (0.00)$_L$	0.03 (0.00)$_L$	-0.07 (0.00)$_L$	0.02 (0.00)$_L$	-0.08 (0.00)$_L$
Discount	1.28 (0.02)$_L$	2.25 (0.03)$_L$	0.51 (0.05)$_L$	0.45 (0.10)$_M$	4.10 (0.01)$_L$	3.81 (0.01)$_L$
Display	0.44 (0.00)$_L$	0.68 (0.01)$_L$	0.47 (0.01)$_L$	0.29 (0.01)$_L$	0.32 (0.01)$_L$	1.39 (0.01)$_L$
Holiday	-0.02 (0.01)	-0.17 (0.01)$_L$	0.08 (0.01)$_L$	-0.10 (0.01)$_L$	-0.01 (0.02)	-0.54 (0.02)$_L$
Monday	0.08 (0.01)$_L$	0.02 (0.01)	0.05 (0.01)$_L$	0.06 (0.01)$_L$	0.13 (0.01)$_L$	0.02 (0.01)
Tuesday	0.00 (0.01)	-0.08 (0.01)$_L$	-0.01 (0.01)	0.01 (0.01)	0.05 (0.01)$_L$	-0.07 (0.01)$_L$
Wednesday	-0.03 (0.01)	-0.09 (0.01)$_L$	-0.04 (0.01)$_S$	0.00 (0.01)	0.01 (0.01)	0.06 (0.01)$_L$
Thursday	-0.12 (0.01)$_L$	-0.15 (0.01)$_L$	-0.13 (0.01)$_L$	-0.08 (0.01)$_L$	-0.05 (0.01)$_L$	-0.13 (0.01)$_L$
Friday	-0.21 (0.01)$_L$	-0.25 (0.01)$_L$	-0.22 (0.01)$_L$	-0.18 (0.01)$_L$	-0.10 (0.01)$_L$	-0.26 (0.01)$_L$
Saturday	-0.20 (0.01)$_L$	-0.02 (0.01)	-0.26 (0.01)$_L$	-0.28 (0.01)$_L$	-0.26 (0.01)$_L$	-0.21 (0.01)$_L$
Domestic Appliances	-0.36 (0.03)$_L$	-1.26 (0.03)$_L$	0.18 (0.04)$_M$	-0.47 (0.02)$_L$	2.79 (0.03)$_L$	2.40 (0.03)$_L$
Drugs and Baby	1.50 (0.03)$_L$	-1.02 (0.03)$_L$	-2.09 (0.04)$_L$	0.02 (0.02)	0.44 (0.03)$_L$	1.97 (0.03)$_L$
Entertainment	-0.49 (0.04)$_L$	-0.34 (0.03)$_L$	0.41 (0.04)$_L$	0.96 (0.02)$_L$	0.37 (0.03)$_L$	0.60 (0.04)$_L$
Hardware	0.41 (0.03)$_L$	-1.71 (0.03)$_L$	-0.22 (0.04)$_L$	0.75 (0.02)$_L$	1.25 (0.03)$_L$	1.10 (0.04)$_L$
Kitchen and Household	-0.18 (0.04)$_M$	-0.71 (0.03)$_L$	0.01 (0.04)	-0.99 (0.03)$_L$	0.60 (0.03)$_L$	2.58 (0.03)$_L$
other	-1.26 (0.04)$_L$	-0.36 (0.03)$_L$	-1.48 (0.04)$_L$	0.29 (0.02)$_L$	0.14 (0.03)$_M$	1.02 (0.04)$_L$
Personal Care	-0.18 (0.03)$_L$	-0.98 (0.03)$_L$	1.23 (0.04)$_L$	1.03 (0.02)$_L$	-1.42 (0.04)$_L$	0.86 (0.04)$_L$
Sound and Vision	0.08 (0.05)	-0.96 (0.07)$_L$	0.74 (0.04)$_L$	-0.89 (0.04)$_L$	-0.25 (0.03)$_L$	1.00 (0.08)$_L$
Sports and Activity	-0.90 (0.05)$_L$	-1.09 (0.04)$_L$	0.37 (0.04)$_L$	-2.65 (0.06)$_L$	-0.74 (0.03)$_L$	2.74 (0.05)$_L$
Toys	-1.19 (0.03)$_L$	-1.45 (0.03)$_L$	-0.32 (0.04)$_L$	-0.02 (0.02)	0.48 (0.03)$_L$	0.68 (0.03)$_L$
UTP	0.50 (0.07)$_L$	-0.09 (0.06)	-0.60 (0.12)$_L$	-0.05 (0.05)	0.16 (0.07)	-0.04 (0.08)
RC	0.60 (0.05)$_L$	0.70 (0.04)$_L$	-0.79 (0.08)$_L$	0.11 (0.04)	0.27 (0.04)$_L$	0.19 (0.06)
WTP	-0.13 (0.12)	0.47 (0.11)$_M$	-0.84 (0.15)$_L$	0.60 (0.09)$_L$	-0.84 (0.11)$_L$	0.14 (0.14)
Domestic Appliances:UTP	0.01 (0.08)	-0.27 (0.06)$_M$	0.77 (0.12)$_L$	0.28 (0.06)$_M$	-0.42 (0.08)$_L$	-0.65 (0.10)$_L$
Drugs and Baby:UTP	-0.45 (0.07)$_L$	0.34 (0.07)$_L$	1.76 (0.12)$_L$	-0.07 (0.06)	0.85 (0.08)$_L$	0.73 (0.08)$_L$
Entertainment:UTP	-0.12 (0.10)	0.31 (0.08)$_S$	1.34 (0.13)$_L$	-0.02 (0.07)	0.19 (0.09)	0.34 (0.09)$_S$
Hardware:UTP	-0.79 (0.08)$_L$	-0.20 (0.08)	0.69 (0.13)$_L$	0.16 (0.06)	-0.26 (0.09)	-0.16 (0.11)
Kitchen and Household:UTP	0.01 (0.09)	-0.26 (0.07)	0.66 (0.12)$_L$	0.68 (0.07)$_L$	0.01 (0.09)	0.35 (0.11)
other:UTP	0.06 (0.11)	0.12 (0.08)	0.72 (0.12)$_L$	0.44 (0.07)$_L$	-0.23 (0.08)	-0.08 (0.10)
Personal Care:UTP	-0.41 (0.07)$_L$	0.36 (0.06)$_L$	1.32 (0.12)$_L$	0.30 (0.06)$_L$	1.34 (0.10)$_L$	-0.14 (0.09)
Sound and Vision:UTP	-0.24 (0.12)	0.59 (0.18)	0.82 (0.12)$_L$	-0.39 (0.09)$_M$	-0.16 (0.09)	0.92 (0.18)$_L$
Sports and Activity:UTP	0.69 (0.11)$_L$	1.30 (0.08)$_L$	0.57 (0.12)$_L$	2.44 (0.11)$_L$	0.13 (0.09)	-0.65 (0.10)$_L$
Toys:UTP	0.03 (0.08)	0.83 (0.06)$_L$	0.08 (0.12)	0.22 (0.06)	0.17 (0.08)	0.42 (0.08)$_L$
Domestic Appliances:RC	0.36 (0.06)$_L$	-0.25 (0.05)$_L$	1.22 (0.09)$_L$	0.49 (0.05)$_L$	-0.41 (0.05)$_L$	-2.22 (0.11)$_L$
Drugs and Baby:RC	0.21 (0.06)	0.90 (0.05)$_L$	2.23 (0.09)$_L$	0.00 (0.05)	1.07 (0.05)$_L$	1.53 (0.06)$_L$
Entertainment:RC	0.41 (0.08)$_L$	0.70 (0.06)$_L$	2.26 (0.09)$_L$	0.30 (0.05)$_L$	0.05 (0.05)	0.13 (0.07)
Hardware:RC	-0.11 (0.06)	-0.24 (0.06)$_S$	1.39 (0.09)$_L$	0.49 (0.05)$_L$	0.49 (0.05)$_L$	0.34 (0.11)
Kitchen and Household:RC	-0.45 (0.06)$_L$	-0.50 (0.05)$_L$	1.07 (0.09)$_L$	0.52 (0.06)$_L$	-0.22 (0.05)$_M$	0.33 (0.07)$_L$
other:RC	2.39 (0.07)$_L$	0.13 (0.05)	1.63 (0.09)$_L$	0.74 (0.05)$_L$	-0.38 (0.04)$_L$	-0.13 (0.08)
Personal Care:RC	-0.31 (0.06)$_L$	0.26 (0.05)$_L$	2.84 (0.08)$_L$	0.59 (0.04)$_L$	4.91 (0.07)$_L$	0.31 (0.07)$_M$
Sound and Vision:RC	-0.82 (0.11)$_L$	1.07 (0.12)$_L$	1.46 (0.08)$_L$	0.79 (0.07)$_L$	-0.06 (0.06)	1.95 (0.15)$_L$
Sports and Activity:RC	1.14 (0.08)$_L$	1.87 (0.06)$_L$	1.19 (0.08)$_L$	2.58 (0.10)$_L$	0.93 (0.06)$_L$	-1.74 (0.09)$_L$
Toys:RC	0.64 (0.06)$_L$	1.34 (0.04)$_L$	0.77 (0.08)$_L$	0.17 (0.04)$_M$	0.11 (0.05)	0.51 (0.06)$_L$
Domestic Appliances:WTP	0.24 (0.14)	-0.58 (0.12)$_L$	1.18 (0.17)$_L$	-0.93 (0.11)$_L$	0.01 (0.12)	-10.26 (1.35)$_L$
Drugs and Baby:WTP	-0.49 (0.12)$_S$	-0.19 (0.13)	-2.03 (0.22)$_L$	-0.58 (0.09)$_L$	-0.03 (0.14)	-0.81 (0.15)$_L$
Entertainment:WTP	0.99 (0.20)$_L$	-0.47 (0.17)	2.11 (0.19)$_L$	-4.49 (0.16)$_L$	-0.47 (0.19)	-0.55 (0.15)
Hardware:WTP	-0.06 (0.14)	-0.13 (0.17)	0.94 (0.17)$_L$	-0.61 (0.10)$_L$	0.26 (0.15)	-2.59 (0.37)$_L$
Kitchen and Household:WTP	-0.01 (0.14)	-1.77 (0.17)$_L$	0.41 (0.16)	-1.52 (0.15)$_L$	-0.89 (0.19)$_M$	-0.84 (0.14)$_L$
other:WTP	1.89 (0.17)$_L$	-0.43 (0.13)	-1.81 (0.19)$_L$	-0.54 (0.10)$_L$	0.87 (0.12)$_L$	2.07 (0.17)$_L$
Personal Care:WTP	-0.07 (0.12)	0.18 (0.13)	0.58 (0.16)	-1.28 (0.09)$_L$	5.58 (0.21)$_L$	-1.52 (0.17)$_L$
Sound and Vision:WTP	-3.83 (0.34)$_L$	0.95 (0.28)	-0.05 (0.16)	-0.24 (0.16)	0.94 (0.14)$_L$	-0.50 (0.51)
Sports and Activity:WTP	-0.81 (0.20)$_S$	1.01 (0.18)$_L$	0.40 (0.15)	-0.32 (0.30)	-0.45 (0.16)	-4.08 (0.37)$_L$
Toys:WTP	0.39 (0.13)	0.32 (0.13)	-0.82 (0.16)$_L$	-1.56 (0.10)$_L$	0.70 (0.13)$_L$	-0.31 (0.14)

	Cluster 19	Cluster 20	Cluster 21	Cluster 22	Cluster 23	Cluster 24
Intercept	0.13 (0.03)$_M$	-1.71 (0.14)$_L$	-0.54 (0.03)$_L$	-3.80 (0.08)$_L$	-3.41 (0.04)$_L$	-0.04 (0.03)
Proportion of day for sale	2.18 (0.02)$_L$	3.29 (0.02)$_L$	2.31 (0.02)$_L$	2.62 (0.02)$_L$	2.66 (0.02)$_L$	2.71 (0.02)$_L$
temp	-0.07 (0.00)$_L$	-0.06 (0.00)$_L$	-0.03 (0.00)$_L$	0.10 (0.00)$_L$	0.12 (0.00)$_L$	-0.10 (0.00)$_L$
Discount	4.28 (0.01)$_L$	0.59 (0.12)$_L$	1.48 (0.04)$_L$	0.61 (0.06)$_L$	1.35 (0.03)$_L$	1.93 (0.05)$_L$
Display	0.41 (0.01)$_L$	-0.14 (0.01)$_L$	1.06 (0.01)$_L$	0.13 (0.01)$_L$	0.99 (0.01)$_L$	1.35 (0.01)$_L$
Holiday	0.06 (0.01)$_L$	-0.10 (0.01)$_L$	-0.23 (0.01)$_L$	0.26 (0.02)$_L$	0.14 (0.03)$_M$	-0.34 (0.02)$_L$
Monday	0.03 (0.01)	0.06 (0.01)$_L$	0.11 (0.01)$_L$	0.11 (0.01)$_L$	0.02 (0.01)	-0.03 (0.01)
Tuesday	-0.04 (0.01)$_S$	-0.03 (0.01)	-0.04 (0.01)$_S$	0.01 (0.01)	0.01 (0.01)	-0.09 (0.01)$_L$
Wednesday	-0.03 (0.01)	0.00 (0.01)	0.02 (0.01)	-0.05 (0.01)$_L$	-0.14 (0.01)$_L$	0.05 (0.01)$_L$
Thursday	-0.10 (0.01)$_L$	-0.14 (0.01)$_L$	-0.13 (0.01)$_L$	-0.14 (0.01)$_L$	-0.27 (0.01)$_L$	-0.13 (0.01)$_L$
Friday	-0.20 (0.01)$_L$	-0.22 (0.01)$_L$	-0.24 (0.01)$_L$	-0.28 (0.01)$_L$	-0.34 (0.01)$_L$	-0.28 (0.01)$_L$
Saturday	-0.13 (0.01)$_L$	-0.30 (0.01)$_L$	-0.09 (0.01)$_L$	-0.38 (0.01)$_L$	-0.29 (0.01)$_L$	-0.24 (0.01)$_L$
Domestic Appliances	0.32 (0.03)$_L$	1.63 (0.14)$_L$	0.43 (0.02)$_L$	2.98 (0.08)$_L$	0.51 (0.04)$_L$	0.95 (0.04)$_L$
Drugs and Baby	1.05 (0.03)$_L$	0.43 (0.14)	0.59 (0.02)$_L$	0.58 (0.08)$_L$	0.77 (0.03)$_L$	-2.12 (0.04)$_L$
Entertainment	2.32 (0.03)$_L$	0.78 (0.14)$_L$	-1.04 (0.04)$_L$	0.49 (0.08)$_L$	1.31 (0.05)$_L$	-0.53 (0.03)$_L$
Hardware	0.78 (0.03)$_L$	0.34 (0.14)	-0.59 (0.04)$_L$	1.07 (0.09)$_L$	0.64 (0.06)$_L$	-0.49 (0.05)$_L$
Kitchen and Household	0.69 (0.03)$_L$	1.86 (0.14)$_L$	0.07 (0.03)	1.52 (0.09)$_L$	0.64 (0.12)$_L$	0.90 (0.03)$_L$
other	-0.41 (0.03)$_L$	0.63 (0.14)$_M$	-0.24 (0.02)$_L$	1.68 (0.08)$_L$	0.18 (0.03)$_L$	0.27 (0.03)$_L$
Personal Care	0.46 (0.03)$_L$	3.43 (0.14)$_L$	0.64 (0.02)$_L$	0.18 (0.08)	0.19 (0.04)$_L$	1.02 (0.03)$_L$
Sound and Vision	0.24 (0.10)	1.70 (0.15)$_L$	0.15 (0.04)	2.97 (0.08)$_L$	-0.15 (0.08)	0.37 (0.05)$_L$
Sports and Activity	0.25 (0.05)$_L$	0.95 (0.14)$_L$	-0.30 (0.03)$_L$	0.81 (0.08)$_L$	-0.27 (0.04)$_L$	0.56 (0.05)$_L$
Toys	0.69 (0.03)$_L$	2.42 (0.14)$_L$	2.37 (0.02)$_L$	2.41 (0.08)$_L$	-3.00 (0.09)$_L$	1.29 (0.03)$_L$
UTP	0.01 (0.07)	1.58 (0.28)$_L$	-0.06 (0.05)	0.51 (0.22)	-0.75 (0.12)$_L$	-0.96 (0.08)$_L$
RC	0.56 (0.05)$_L$	2.15 (0.26)$_L$	-0.13 (0.05)	0.29 (0.14)	-0.37 (0.07)$_L$	-0.49 (0.06)$_L$
WTP	0.69 (0.09)$_L$	1.80 (0.59)	1.03 (0.12)$_L$	-12.37 (2.10)$_L$	0.05 (0.19)	0.10 (0.12)
Domestic Appliances:UTP	0.35 (0.08)$_M$	-1.59 (0.28)$_L$	-0.10 (0.06)	-0.72 (0.22)	0.02 (0.14)	1.91 (0.11)$_L$
Drugs and Baby:UTP	-0.07 (0.08)	-1.50 (0.28)$_L$	0.45 (0.05)$_L$	0.21 (0.22)	0.44 (0.13)	3.75 (0.11)$_L$
Entertainment:UTP	0.53 (0.07)$_L$	-1.22 (0.29)$_M$	-0.26 (0.09)	-0.04 (0.23)	0.81 (0.17)$_L$	0.66 (0.11)$_L$
Hardware:UTP	0.11 (0.09)	-0.78 (0.29)	0.42 (0.08)$_L$	-0.10 (0.24)	1.40 (0.16)$_L$	1.33 (0.12)$_L$
Kitchen and Household:UTP	-0.56 (0.11)$_L$	-1.47 (0.28)$_L$	0.01 (0.07)	-1.07 (0.24)$_M$	0.59 (0.37)	0.24 (0.13)
other:UTP	0.08 (0.08)	-2.66 (0.29)$_L$	0.31 (0.07)$_M$	-0.14 (0.22)	1.12 (0.13)$_L$	0.90 (0.11)$_L$
Personal Care:UTP	0.48 (0.07)$_L$	-2.05 (0.28)$_L$	0.27 (0.05)$_L$	0.50 (0.22)	1.60 (0.13)$_L$	0.44 (0.09)$_L$
Sound and Vision:UTP	0.89 (0.20)$_M$	-1.49 (0.32)$_M$	-0.29 (0.09)	0.27 (0.22)	1.48 (0.17)$_L$	0.93 (0.14)$_L$
Sports and Activity:UTP	-0.04 (0.15)	-2.07 (0.35)$_L$	-0.19 (0.09)	-0.27 (0.22)	0.57 (0.14)$_S$	0.07 (0.16)
Toys:UTP	0.33 (0.07)$_L$	-1.07 (0.28)$_S$	0.13 (0.05)	-0.64 (0.22)	6.85 (0.25)$_L$	1.44 (0.09)$_L$
Domestic Appliances:RC	0.80 (0.06)$_L$	-1.86 (0.26)$_L$	0.81 (0.06)$_L$	-0.45 (0.14)	0.36 (0.08)$_M$	1.07 (0.09)$_L$
Drugs and Baby:RC	-0.14 (0.05)	-2.11 (0.26)$_L$	1.56 (0.06)$_L$	0.84 (0.14)$_L$	0.43 (0.08)$_L$	5.45 (0.08)$_L$
Entertainment:RC	0.89 (0.06)$_L$	-1.18 (0.26)$_M$	1.61 (0.08)$_L$	-0.58 (0.15)$_S$	-0.20 (0.14)	0.35 (0.07)$_L$
Hardware:RC	-0.28 (0.07)$_S$	-2.11 (0.27)$_L$	2.34 (0.08)$_L$	0.31 (0.16)	1.96 (0.12)$_L$	1.32 (0.09)$_L$
Kitchen and Household:RC	-0.68 (0.06)$_L$	-1.80 (0.26)$_L$	0.00 (0.07)	-0.45 (0.31)	0.59 (0.18)	0.88 (0.07)$_L$
other:RC	-0.58 (0.06)$_L$	-2.08 (0.26)$_L$	0.66 (0.06)$_L$	0.31 (0.14)	0.80 (0.07)$_L$	1.19 (0.07)$_L$
Personal Care:RC	0.74 (0.05)$_L$	-2.06 (0.26)$_L$	1.69 (0.06)$_L$	0.85 (0.14)$_L$	1.81 (0.08)$_L$	0.72 (0.06)$_L$
Sound and Vision:RC	0.66 (0.19)	-2.75 (0.30)$_L$	0.25 (0.07)	0.82 (0.14)$_L$	2.03 (0.18)$_L$	1.34 (0.10)$_L$
Sports and Activity:RC	0.36 (0.08)$_M$	-2.04 (0.27)$_L$	0.56 (0.08)$_L$	-0.03 (0.14)	0.31 (0.08)$_S$	-0.38 (0.10)$_S$
Toys:RC	0.47 (0.05)$_L$	-1.27 (0.26)$_L$	0.99 (0.05)$_L$	-1.01 (0.14)$_L$	5.22 (0.13)$_L$	1.32 (0.06)$_L$
Domestic Appliances:WTP	-0.48 (0.13)	-1.09 (0.59)	-1.69 (0.14)$_L$	11.67 (2.11)$_L$	-1.06 (0.27)$_S$	-0.32 (0.23)
Drugs and Baby:WTP	-0.27 (0.11)	-1.92 (0.59)	-2.01 (0.13)$_L$	10.83 (2.10)$_L$	-2.53 (0.25)$_L$	3.47 (0.17)$_L$
Entertainment:WTP	-0.32 (0.12)	-2.03 (0.61)	-0.61 (0.21)	10.44 (2.11)$_L$	-950.13 (121.29)$_L$	-0.60 (0.16)
Hardware:WTP	0.14 (0.26)	0.09 (0.60)	-1.44 (0.23)$_L$	12.13 (2.11)$_L$	-0.12 (0.28)	-1.53 (0.31)$_L$
Kitchen and Household:WTP	-1.32 (0.14)$_L$	-2.64 (0.59)$_M$	-0.01 (0.15)	8.46 (2.22)$_S$	1.00 (0.43)	0.74 (0.15)$_L$
other:WTP	-0.35 (0.12)	-2.68 (0.59)$_M$	-1.33 (0.14)$_L$	11.61 (2.10)$_L$	-0.97 (0.20)$_L$	0.14 (0.15)
Personal Care:WTP	-1.02 (0.11)$_L$	-3.50 (0.59)$_L$	-0.58 (0.13)$_M$	11.92 (2.10)$_L$	-0.87 (0.22)$_S$	-1.35 (0.15)$_L$
Sound and Vision:WTP	-6.02 (0.73)$_L$	-5.86 (0.73)$_L$	-3.24 (0.28)$_L$	12.47 (2.10)$_L$	0.55 (1.27)	1.50 (0.86)
Sports and Activity:WTP	-0.79 (0.23)	-5.10 (0.68)$_L$	-0.85 (0.15)$_L$	11.49 (2.10)$_L$	-0.74 (0.21)	-0.31 (0.34)
Toys:WTP	-1.02 (0.10)$_L$	-2.53 (0.59)$_M$	-0.10 (0.12)	11.19 (2.10)$_L$	3.97 (0.35)$_L$	-0.20 (0.13)

S: $p < 5\%$ α-level
M: $p < 1\%$ α-level
L: $p < 0.1\%$ α-level

Table D.20: Full model coefficient estimates for studying RC, WTP and UTP during the holiday period

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Intercept	-2.15 (0.04)$_L$	-1.31 (0.02)$_L$	-2.13 (0.02)$_L$	-1.00 (0.02)$_L$	-1.41 (0.02)$_L$
Proportion of day for sale	3.03 (0.02)$_L$	2.94 (0.02)$_L$	3.34 (0.01)$_L$	2.81 (0.01)$_L$	2.90 (0.01)$_L$
Discount	4.46 (0.05)$_L$	2.04 (0.05)$_L$	1.12 (0.04)$_L$	1.04 (0.08)$_L$	1.18 (0.03)$_L$
Monday	-0.15 (0.01)$_L$	-0.09 (0.01)$_L$	-0.06 (0.01)$_L$	-0.07 (0.01)$_L$	-0.05 (0.01)$_L$
Tuesday	-0.26 (0.01)$_L$	-0.13 (0.01)$_L$	-0.15 (0.01)$_L$	-0.14 (0.01)$_L$	-0.11 (0.01)$_L$
Wednesday	-0.29 (0.01)$_L$	-0.12 (0.01)$_L$	-0.19 (0.01)$_L$	-0.16 (0.01)$_L$	-0.12 (0.01)$_L$
Thursday	-0.37 (0.01)$_L$	-0.24 (0.01)$_L$	-0.30 (0.01)$_L$	-0.28 (0.01)$_L$	-0.31 (0.01)$_L$
Friday	-0.45 (0.01)$_L$	-0.40 (0.01)$_L$	-0.41 (0.01)$_L$	-0.35 (0.01)$_L$	-0.45 (0.01)$_L$
Saturday	-0.23 (0.01)$_L$	-0.28 (0.01)$_L$	-0.16 (0.01)$_L$	-0.20 (0.01)$_L$	-0.11 (0.01)$_L$
Holiday	-0.59 (0.01)$_L$	-0.41 (0.01)$_L$	-0.39 (0.01)$_L$	-0.52 (0.01)$_L$	-0.47 (0.01)$_L$
Black Friday	0.94 (0.01)$_L$	0.92 (0.01)$_L$	0.68 (0.01)$_L$	0.68 (0.01)$_L$	1.13 (0.01)$_L$
Lockdown	0.19 (0.01)$_L$	-0.12 (0.00)$_L$	0.65 (0.00)$_L$	0.66 (0.00)$_L$	0.30 (0.01)$_L$
Drugs and Baby	0.66 (0.13)$_L$	0.91 (0.02)$_L$	1.24 (0.01)$_L$	-1.06 (0.02)$_L$	2.34 (0.02)$_L$
Entertainment	1.90 (0.04)$_L$	0.45 (0.02)$_L$	-0.28 (0.02)$_L$	-0.23 (0.02)$_L$	1.11 (0.02)$_L$
Hardware	1.12 (0.04)$_L$	1.63 (0.02)$_L$	-0.26 (0.02)$_L$	0.86 (0.02)$_L$	-0.13 (0.02)$_L$
Kitchen and Household	0.30 (0.04)$_L$	1.30 (0.02)$_L$	0.24 (0.02)$_L$	1.79 (0.02)$_L$	1.23 (0.02)$_L$
other	0.91 (0.04)$_L$	0.46 (0.02)$_L$	1.87 (0.01)$_L$	0.46 (0.02)$_L$	0.41 (0.02)$_L$
Personal Care	3.03 (0.05)$_L$	0.32 (0.03)$_L$	0.91 (0.02)$_L$	1.06 (0.02)$_L$	-0.22 (0.02)$_L$
Domestic Appliances	1.72 (0.04)$_L$	-0.05 (0.01)$_L$	-0.13 (0.01)$_L$	0.34 (0.02)$_L$	0.32 (0.02)$_L$
Sound and Vision	0.60 (0.04)$_L$	0.48 (0.02)$_L$	0.47 (0.01)$_L$	0.10 (0.02)$_L$	1.55 (0.02)$_L$
Sports and Activity	1.30 (0.05)$_L$	-0.37 (0.02)$_L$	0.68 (0.02)$_L$	0.80 (0.02)$_L$	-0.74 (0.02)$_L$
Toys	0.23 (0.04)$_L$	0.06 (0.01)$_L$	1.37 (0.01)$_L$	-0.01 (0.02)	0.94 (0.02)$_L$
WTP	0.42 (0.32)	-0.20 (0.07)	0.37 (0.07)$_L$	-0.55 (0.07)$_L$	0.12 (0.07)
UTP	-0.41 (0.15)	0.04 (0.04)	-0.18 (0.04)$_M$	-0.50 (0.06)$_L$	0.42 (0.06)$_L$
RC	0.21 (0.08)	-0.04 (0.02)	0.34 (0.02)$_L$	0.07 (0.03)	0.97 (0.03)$_L$
Drugs and Baby:WTP	1.37 (2.77)	0.57 (0.08)$_L$	-0.59 (0.08)$_L$	0.51 (0.09)$_L$	-1.06 (0.09)$_L$
Entertainment:WTP	-1.05 (0.33)	0.14 (0.11)	-0.64 (0.11)$_L$	0.31 (0.07)$_M$	0.59 (0.08)$_L$
Hardware:WTP	-0.57 (0.33)	1.04 (0.11)$_L$	-0.56 (0.11)$_L$	0.49 (0.09)$_L$	0.30 (0.09)
Kitchen and Household:WTP	2.65 (0.36)$_L$	0.83 (0.10)$_L$	-0.53 (0.12)$_M$	1.00 (0.08)$_L$	-0.72 (0.11)$_L$
other:WTP	-0.95 (0.34)	-0.36 (0.08)$_M$	-0.97 (0.08)$_L$	-0.10 (0.08)	-0.04 (0.09)
Personal Care:WTP	-1.21 (0.33)	-0.11 (0.23)	-0.91 (0.09)$_L$	0.14 (0.08)	-0.90 (0.08)$_L$
Domestic Appliances:WTP	-0.98 (0.33)	0.36 (0.07)$_L$	-0.48 (0.08)$_L$	-0.17 (0.08)	2.71 (0.09)$_L$
Sound and Vision:WTP	-0.79 (0.33)	-0.62 (0.11)$_L$	-0.14 (0.08)	0.24 (0.09)	1.05 (0.11)$_L$
Sports and Activity:WTP	-0.75 (0.45)	0.05 (0.46)	-1.51 (0.13)$_L$	-0.04 (0.11)	0.30 (0.11)
Toys:WTP	-0.54 (0.33)	-0.15 (0.07)	-2.27 (0.08)$_L$	0.47 (0.09)$_L$	0.98 (0.07)$_L$
Drugs and Baby:UTP	2.96 (0.26)$_L$	-0.06 (0.05)	0.58 (0.05)$_L$	0.63 (0.07)$_L$	-0.09 (0.06)
Entertainment:UTP	0.90 (0.15)$_L$	0.24 (0.05)$_L$	0.23 (0.07)	0.46 (0.07)$_L$	-1.25 (0.06)$_L$
Hardware:UTP	0.15 (0.16)	-0.97 (0.09)$_L$	-0.93 (0.06)$_L$	0.55 (0.08)$_L$	-0.55 (0.08)$_L$
Kitchen and Household:UTP	3.59 (0.18)$_L$	-0.47 (0.07)$_L$	-0.04 (0.06)	0.02 (0.07)	-0.49 (0.08)$_L$
other:UTP	-0.27 (0.15)	0.08 (0.07)	-0.05 (0.05)	0.38 (0.06)$_L$	-0.56 (0.06)$_L$
Personal Care:UTP	0.71 (0.16)$_M$	-0.44 (0.06)$_L$	0.25 (0.05)$_L$	1.03 (0.06)$_L$	-0.38 (0.06)$_L$
Domestic Appliances:UTP	0.50 (0.16)	-0.11 (0.05)	-0.24 (0.05)$_L$	0.24 (0.07)	-0.49 (0.07)$_L$
Sound and Vision:UTP	-0.26 (0.15)	-0.08 (0.05)	0.10 (0.05)	1.32 (0.07)$_L$	0.78 (0.07)$_L$
Sports and Activity:UTP	0.10 (0.22)	-1.46 (0.08)$_L$	0.34 (0.06)$_L$	0.57 (0.08)$_L$	-0.39 (0.10)$_S$
Toys:UTP	0.55 (0.15)	0.11 (0.04)	0.10 (0.04)	0.87 (0.06)$_L$	-0.18 (0.06)
Drugs and Baby:RC	2.22 (0.23)$_L$	0.65 (0.03)$_L$	1.08 (0.03)$_L$	0.13 (0.04)	0.22 (0.04)$_L$
Entertainment:RC	-0.07 (0.09)	0.09 (0.04)	-0.31 (0.04)$_L$	-0.14 (0.04)	-1.01 (0.04)$_L$
Hardware:RC	-0.08 (0.09)	0.40 (0.05)$_L$	-0.10 (0.04)	0.32 (0.04)$_L$	-0.73 (0.04)$_L$
Kitchen and Household:RC	2.66 (0.10)$_L$	-0.12 (0.04)	-0.17 (0.04)$_M$	0.37 (0.04)$_L$	-0.69 (0.05)$_L$
other:RC	0.03 (0.09)	0.43 (0.03)$_L$	-0.61 (0.03)$_L$	-0.30 (0.04)$_L$	-1.53 (0.04)$_L$
Personal Care:RC	0.83 (0.09)$_L$	0.02 (0.06)	0.32 (0.03)$_L$	0.64 (0.04)$_L$	-0.74 (0.04)$_L$
Domestic Appliances:RC	-0.05 (0.09)	-0.21 (0.03)$_L$	-0.51 (0.03)$_L$	-0.31 (0.04)$_L$	1.29 (0.04)$_L$
Sound and Vision:RC	-0.10 (0.08)	-0.25 (0.04)$_L$	-0.03 (0.03)	1.36 (0.04)$_L$	0.67 (0.05)$_L$
Sports and Activity:RC	-0.44 (0.10)$_M$	-0.09 (0.05)	-0.16 (0.04)$_S$	0.31 (0.04)$_L$	-0.97 (0.05)$_L$
Toys:RC	0.11 (0.08)	0.26 (0.03)$_L$	-0.24 (0.03)$_L$	1.82 (0.04)$_L$	0.75 (0.03)$_L$

	Cluster 6	Cluster 7	Cluster 8	Cluster 9	Cluster 10
Intercept	-2.06 (0.03)$_L$	-0.45 (0.02)$_L$	0.42 (0.04)$_L$	-0.46 (0.04)$_L$	-0.69 (0.06)$_L$
Proportion of day for sale	3.15 (0.01)$_L$	3.50 (0.01)$_L$	2.39 (0.01)$_L$	2.75 (0.01)$_L$	3.46 (0.02)$_L$
Discount	0.44 (0.06)$_L$	1.12 (0.09)$_L$	4.41 (0.01)$_L$	2.53 (0.04)$_L$	1.39 (0.02)$_L$
Monday	-0.06 (0.01)$_L$	-0.14 (0.01)$_L$	-0.16 (0.00)$_L$	0.19 (0.01)$_L$	-0.19 (0.01)$_L$
Tuesday	-0.16 (0.01)$_L$	-0.25 (0.01)$_L$	-0.23 (0.00)$_L$	-0.15 (0.01)$_L$	-0.25 (0.01)$_L$
Wednesday	-0.22 (0.01)$_L$	-0.25 (0.01)$_L$	-0.27 (0.00)$_L$	-0.23 (0.01)$_L$	-0.23 (0.01)$_L$
Thursday	-0.35 (0.01)$_L$	-0.39 (0.01)$_L$	-0.35 (0.00)$_L$	-0.35 (0.01)$_L$	-0.40 (0.01)$_L$
Friday	-0.46 (0.01)$_L$	-0.50 (0.01)$_L$	-0.52 (0.01)$_L$	-0.54 (0.01)$_L$	-0.60 (0.01)$_L$
Saturday	-0.17 (0.01)$_L$	-0.20 (0.01)$_L$	-0.16 (0.01)$_L$	-0.27 (0.01)$_L$	-0.34 (0.01)$_L$
Holiday	-0.55 (0.01)$_L$	-0.71 (0.01)$_L$	-0.67 (0.01)$_L$	-0.47 (0.01)$_L$	-0.83 (0.01)$_L$
Black Friday	1.09 (0.01)$_L$	0.96 (0.01)$_L$	1.13 (0.01)$_L$	1.10 (0.01)$_L$	1.09 (0.01)$_L$
Lockdown	0.57 (0.00)$_L$	0.39 (0.00)$_L$	-0.21 (0.00)$_L$	0.05 (0.01)$_L$	-0.51 (0.00)$_L$
Drugs and Baby	0.68 (0.02)$_L$	-1.60 (0.02)$_L$	-1.22 (0.03)$_L$	-0.08 (0.04)	-0.77 (0.06)$_L$
Entertainment	2.04 (0.02)$_L$	0.41 (0.03)$_L$	-0.46 (0.03)$_L$	3.98 (0.04)$_L$	-1.06 (0.05)$_L$
Hardware	1.12 (0.02)$_L$	-1.22 (0.02)$_L$	-0.16 (0.04)$_S$	-1.21 (0.05)$_L$	0.04 (0.06)
Kitchen and Household	1.92 (0.03)$_L$	-0.54 (0.02)$_L$	1.82 (0.04)$_L$	-1.23 (0.05)$_L$	-1.31 (0.07)$_L$
other	0.06 (0.03)	-1.94 (0.02)$_L$	-1.28 (0.04)$_L$	-1.43 (0.05)$_L$	-1.60 (0.06)$_L$
Personal Care	2.88 (0.02)$_L$	-0.68 (0.02)$_L$	-0.43 (0.04)$_L$	-0.59 (0.05)$_L$	0.75 (0.06)$_L$
Domestic Appliances	2.94 (0.02)$_L$	2.23 (0.02)$_L$	0.15 (0.04)$_S$	0.81 (0.04)$_L$	1.65 (0.06)$_L$
Sound and Vision	-0.21 (0.05)$_M$	-0.19 (0.02)$_L$	-0.45 (0.04)$_L$	3.15 (0.05)$_L$	0.50 (0.06)$_L$
Sports and Activity	2.67 (0.03)$_L$	-2.00 (0.02)$_L$	-1.86 (0.04)$_L$	0.03 (0.05)	0.80 (0.06)$_L$
Toys	0.92 (0.03)$_L$	1.13 (0.02)$_L$	-0.39 (0.03)$_L$	0.52 (0.04)$_L$	0.52 (0.05)$_L$
WTP	-0.54 (0.27)	-0.10 (0.09)	-1.26 (0.13)$_L$	-0.33 (0.22)	-1.89 (0.20)$_L$
UTP	0.16 (0.06)	-0.21 (0.05)$_M$	-0.21 (0.06)	-0.26 (0.24)	-1.91 (0.12)$_L$
RC	-0.25 (0.04)$_L$	0.32 (0.04)$_L$	0.38 (0.07)$_L$	0.06 (0.07)	-0.16 (0.10)
Drugs and Baby:WTP	0.28 (0.27)	-0.32 (0.10)	1.42 (0.14)$_L$	0.45 (0.23)	0.76 (0.28)
Entertainment:WTP	-0.95 (0.27)	-0.14 (0.16)	2.38 (0.14)$_L$	0.60 (0.22)	1.46 (0.21)$_L$
Hardware:WTP	0.99 (0.27)	-0.43 (0.10)$_M$	1.16 (0.15)$_L$	0.24 (0.26)	0.19 (0.21)
Kitchen and Household:WTP	0.59 (0.27)	0.24 (0.10)	1.97 (0.17)$_L$	0.62 (0.24)	1.46 (0.29)$_L$
other:WTP	1.02 (0.27)$_S$	0.12 (0.12)	0.62 (0.16)$_S$	0.55 (0.32)	2.50 (0.23)$_L$
Personal Care:WTP	-0.58 (0.27)	0.05 (0.11)	0.81 (0.16)$_L$	-0.32 (0.22)	4.15 (0.21)$_L$
Domestic Appliances:WTP	-0.01 (0.27)	-0.44 (0.10)$_M$	2.19 (0.14)$_L$	0.51 (0.23)	0.24 (0.23)
Sound and Vision:WTP	0.72 (0.30)	-0.87 (0.11)$_L$	1.82 (0.20)$_L$	-0.39 (0.24)	2.09 (0.24)$_L$
Sports and Activity:WTP	0.45 (0.29)	-5.76 (0.11)$_L$	1.48 (0.29)$_L$	-0.70 (0.23)	2.03 (0.25)$_L$
Toys:WTP	0.98 (0.28)	-1.23 (0.10)$_L$	1.04 (0.14)$_L$	-0.17 (0.22)	1.58 (0.21)$_L$
Drugs and Baby:UTP	-0.29 (0.07)$_M$	0.39 (0.06)$_L$	0.30 (0.07)$_M$	0.42 (0.24)	1.99 (0.13)$_L$
Entertainment:UTP	1.11 (0.07)$_L$	0.35 (0.07)$_L$	0.55 (0.06)$_L$	0.27 (0.24)	2.15 (0.12)$_L$
Hardware:UTP	-0.41 (0.07)$_L$	-0.14 (0.07)	0.30 (0.08)$_S$	0.41 (0.24)	2.75 (0.13)$_L$
Kitchen and Household:UTP	-0.06 (0.07)	0.09 (0.06)	-0.27 (0.08)	-0.99 (0.24)$_M$	2.50 (0.18)$_L$
other:UTP	0.19 (0.07)	-1.20 (0.07)$_L$	0.44 (0.08)$_L$	4.20 (0.25)$_L$	2.40 (0.14)$_L$
Personal Care:UTP	3.41 (0.07)$_L$	3.40 (0.06)$_L$	0.45 (0.07)$_L$	1.24 (0.24)$_L$	3.26 (0.12)$_L$
Domestic Appliances:UTP	0.47 (0.08)$_L$	-0.51 (0.06)$_L$	0.72 (0.07)$_L$	0.68 (0.24)	0.68 (0.13)$_L$
Sound and Vision:UTP	0.24 (0.09)	0.13 (0.07)	-0.07 (0.17)	0.38 (0.25)	2.97 (0.29)$_L$
Sports and Activity:UTP	-0.18 (0.10)	0.22 (0.07)	1.95 (0.08)$_L$	0.58 (0.24)	2.13 (0.15)$_L$
Toys:UTP	-0.50 (0.07)$_L$	-0.07 (0.06)	0.35 (0.06)$_L$	0.42 (0.24)	2.20 (0.12)$_L$
Drugs and Baby:RC	0.52 (0.05)$_L$	-0.12 (0.04)	0.23 (0.07)	0.29 (0.07)$_M$	0.97 (0.10)$_L$
Entertainment:RC	2.54 (0.05)$_L$	0.94 (0.05)$_L$	1.27 (0.07)$_L$	0.54 (0.07)$_L$	0.05 (0.10)
Hardware:RC	0.43 (0.05)$_L$	1.36 (0.05)$_L$	0.30 (0.07)$_M$	-0.47 (0.08)$_L$	1.40 (0.10)$_L$
Kitchen and Household:RC	0.78 (0.05)$_L$	-0.35 (0.04)$_L$	-0.07 (0.08)	-0.61 (0.08)$_L$	0.30 (0.13)
other:RC	1.86 (0.05)$_L$	-0.52 (0.05)$_L$	-0.38 (0.08)$_L$	0.32 (0.09)	3.46 (0.11)$_L$
Personal Care:RC	-0.18 (0.05)	0.34 (0.05)$_L$	0.58 (0.07)$_L$	0.27 (0.08)	0.84 (0.10)$_L$
Domestic Appliances:RC	0.55 (0.05)$_L$	-1.37 (0.04)$_L$	1.08 (0.07)$_L$	0.03 (0.07)	-1.03 (0.10)$_L$
Sound and Vision:RC	0.31 (0.08)$_S$	-0.52 (0.05)$_L$	0.17 (0.09)	-0.35 (0.08)$_M$	1.20 (0.11)$_L$
Sports and Activity:RC	0.69 (0.06)$_L$	-0.09 (0.04)	0.65 (0.10)$_L$	0.37 (0.08)$_L$	0.68 (0.11)$_L$
Toys:RC	0.22 (0.06)	-0.33 (0.04)$_L$	0.19 (0.07)	0.33 (0.07)$_L$	0.77 (0.10)$_L$

	Cluster 11	Cluster 12	Cluster 13	Cluster 14	Cluster 15
Intercept	-1.18 (0.03)$_L$	1.21 (0.02)$_L$	-1.15 (0.05)$_L$	-0.99 (0.02)$_L$	-2.19 (0.03)$_L$
Proportion of day for sale	3.23 (0.01)$_L$	2.86 (0.01)$_L$	3.48 (0.01)$_L$	3.18 (0.01)$_L$	3.30 (0.02)$_L$
Discount	1.03 (0.03)$_L$	3.43 (0.06)$_L$	2.58 (0.08)$_L$	0.90 (0.02)$_L$	2.73 (0.04)$_L$
Monday	0.01 (0.01)	-0.13 (0.01)$_L$	-0.11 (0.01)$_L$	-0.03 (0.01)	-0.18 (0.01)$_L$
Tuesday	-0.20 (0.01)$_L$	-0.24 (0.01)$_L$	-0.18 (0.01)$_L$	-0.12 (0.01)$_L$	-0.21 (0.01)$_L$
Wednesday	-0.19 (0.01)$_L$	-0.24 (0.01)$_L$	-0.10 (0.01)$_L$	-0.14 (0.01)$_L$	-0.23 (0.01)$_L$
Thursday	-0.33 (0.01)$_L$	-0.43 (0.01)$_L$	-0.37 (0.01)$_L$	-0.28 (0.01)$_L$	-0.34 (0.01)$_L$
Friday	-0.53 (0.01)$_L$	-0.52 (0.01)$_L$	-0.60 (0.01)$_L$	-0.40 (0.01)$_L$	-0.63 (0.01)$_L$
Saturday	-0.04 (0.01)$_S$	-0.14 (0.01)$_L$	-0.16 (0.01)$_L$	-0.15 (0.01)$_L$	-0.35 (0.01)$_L$
Holiday	-0.64 (0.01)$_L$	-0.67 (0.01)$_L$	-0.88 (0.01)$_L$	-0.53 (0.01)$_L$	-0.97 (0.01)$_L$
Black Friday	1.32 (0.01)$_L$	1.13 (0.01)$_L$	1.16 (0.01)$_L$	1.07 (0.01)$_L$	1.13 (0.01)$_L$
Lockdown	0.30 (0.00)$_L$	0.53 (0.00)$_L$	-0.24 (0.01)$_L$	0.78 (0.01)$_L$	-0.64 (0.00)$_L$
Drugs and Baby	1.12 (0.03)$_L$	-1.32 (0.02)$_L$	-1.42 (0.05)$_L$	-0.55 (0.02)$_L$	-1.25 (0.02)$_L$
Entertainment	0.74 (0.03)$_L$	-0.18 (0.02)$_L$	2.02 (0.05)$_L$	0.96 (0.03)$_L$	2.56 (0.03)$_L$
Hardware	0.31 (0.03)$_L$	-1.77 (0.02)$_L$	-0.08 (0.05)	1.30 (0.02)$_L$	-0.53 (0.03)$_L$
Kitchen and Household	-0.06 (0.03)	-2.99 (0.02)$_L$	-0.58 (0.06)$_L$	-0.25 (0.02)$_L$	0.88 (0.03)$_L$
other	1.65 (0.03)$_L$	0.44 (0.02)$_L$	-1.44 (0.05)$_L$	-0.99 (0.02)$_L$	0.20 (0.02)$_L$
Personal Care	2.46 (0.03)$_L$	-2.53 (0.02)$_L$	-1.36 (0.06)$_L$	0.42 (0.02)$_L$	4.60 (0.03)$_L$
Domestic Appliances	-0.42 (0.04)$_L$	-0.55 (0.02)$_L$	-0.34 (0.05)$_L$	0.95 (0.02)$_L$	0.65 (0.02)$_L$
Sound and Vision	0.30 (0.04)$_L$	-0.71 (0.04)$_L$	1.64 (0.06)$_L$	1.98 (0.03)$_L$	1.76 (0.03)$_L$
Sports and Activity	1.03 (0.04)$_L$	-2.64 (0.02)$_L$	-0.94 (0.05)$_L$	0.25 (0.05)$_L$	1.88 (0.03)$_L$
Toys	-0.70 (0.03)$_L$	-0.11 (0.02)$_L$	3.02 (0.05)$_L$	0.79 (0.02)$_L$	2.65 (0.02)$_L$
WTP	1.20 (0.14)$_L$	-0.47 (0.08)$_L$	-0.61 (0.24)	-0.53 (0.11)$_L$	-0.89 (0.08)$_L$
UTP	-0.09 (0.09)	-0.04 (0.06)	1.73 (0.19)$_L$	0.07 (0.06)	0.83 (0.08)$_L$
RC	-0.44 (0.06)$_L$	0.44 (0.03)$_L$	2.91 (0.09)$_L$	0.31 (0.03)$_L$	0.54 (0.04)$_L$
Drugs and Baby:WTP	-1.83 (0.15)$_L$	0.60 (0.10)$_L$	-2.72 (0.26)$_L$	0.18 (0.12)	2.90 (0.09)$_L$
Entertainment:WTP	-1.34 (0.15)$_L$	0.96 (0.09)$_L$	1.33 (0.26)$_L$	0.56 (0.13)$_M$	-0.14 (0.10)
Hardware:WTP	-5.18 (0.15)$_L$	-0.85 (0.09)$_L$	1.17 (0.30)$_S$	0.31 (0.12)	3.78 (0.14)$_L$
Kitchen and Household:WTP	-0.27 (0.16)	-0.48 (0.09)$_L$	-0.22 (0.29)	0.15 (0.11)	1.62 (0.12)$_L$
other:WTP	-1.70 (0.15)$_L$	1.02 (0.10)$_L$	1.06 (0.25)$_M$	0.11 (0.13)	0.07 (0.09)
Personal Care:WTP	-6.63 (0.15)$_L$	0.36 (0.09)$_S$	-0.01 (0.28)	-0.12 (0.12)	0.22 (1.15)
Domestic Appliances:WTP	-1.48 (0.17)$_L$	0.63 (0.09)$_L$	0.42 (0.26)	-0.68 (0.12)$_L$	0.65 (0.10)$_L$
Sound and Vision:WTP	0.00 (0.15)	-0.03 (0.16)	-0.34 (0.28)	0.63 (0.14)$_M$	0.96 (0.11)$_L$
Sports and Activity:WTP	-1.58 (0.17)$_L$	-0.69 (0.11)$_L$	1.50 (0.30)$_L$	-1.36 (0.24)$_L$	0.75 (0.11)$_L$
Toys:WTP	-0.75 (0.15)$_L$	0.44 (0.10)$_M$	1.07 (0.25)$_M$	-0.71 (0.11)$_L$	0.78 (0.09)$_L$
Drugs and Baby:UTP	0.33 (0.09)	-0.15 (0.07)	-1.32 (0.20)$_L$	0.18 (0.07)	0.93 (0.08)$_L$
Entertainment:UTP	0.60 (0.10)$_L$	-0.87 (0.07)$_L$	-2.29 (0.19)$_L$	-0.10 (0.08)	-0.59 (0.09)$_L$
Hardware:UTP	-1.81 (0.09)$_L$	0.85 (0.07)$_L$	-1.90 (0.22)$_L$	-0.08 (0.08)	1.32 (0.11)$_L$
Kitchen and Household:UTP	-0.52 (0.09)$_L$	0.07 (0.07)	-2.51 (0.26)$_L$	0.12 (0.07)	-0.24 (0.11)
other:UTP	0.09 (0.09)	0.25 (0.07)	-2.10 (0.20)$_L$	-0.13 (0.07)	-0.60 (0.08)$_L$
Personal Care:UTP	1.64 (0.09)$_L$	0.14 (0.06)	-1.59 (0.19)$_L$	-0.68 (0.07)$_L$	-1.35 (0.08)$_L$
Domestic Appliances:UTP	0.28 (0.13)	0.31 (0.07)$_M$	-0.89 (0.19)$_L$	-0.26 (0.08)	-1.41 (0.08)$_L$
Sound and Vision:UTP	0.41 (0.10)$_M$	-0.16 (0.12)	-4.54 (0.20)$_L$	-0.17 (0.11)	-0.22 (0.09)
Sports and Activity:UTP	0.34 (0.10)	0.27 (0.08)	-1.94 (0.20)$_L$	-1.48 (0.12)$_L$	-0.80 (0.09)$_L$
Toys:UTP	0.86 (0.09)$_L$	0.44 (0.07)$_L$	-1.43 (0.19)$_L$	0.56 (0.06)$_L$	-0.49 (0.08)$_L$
Drugs and Baby:RC	1.84 (0.06)$_L$	-0.34 (0.04)$_L$	-2.09 (0.10)$_L$	0.94 (0.04)$_L$	1.29 (0.05)$_L$
Entertainment:RC	2.15 (0.06)$_L$	-0.23 (0.04)$_L$	-2.44 (0.10)$_L$	-0.45 (0.05)$_L$	-0.61 (0.05)$_L$
Hardware:RC	-1.04 (0.06)$_L$	-0.02 (0.04)	-2.23 (0.11)$_L$	0.01 (0.04)	3.01 (0.06)$_L$
Kitchen and Household:RC	0.37 (0.06)$_L$	-0.34 (0.04)$_L$	-1.99 (0.12)$_L$	0.59 (0.04)$_L$	-0.37 (0.06)$_L$
other:RC	0.97 (0.06)$_L$	-0.01 (0.04)	-1.60 (0.11)$_L$	-0.20 (0.04)$_L$	-0.66 (0.05)$_L$
Personal Care:RC	2.85 (0.06)$_L$	0.54 (0.03)$_L$	-2.70 (0.10)$_L$	-0.90 (0.04)$_L$	-1.35 (0.05)$_L$
Domestic Appliances:RC	0.87 (0.08)$_L$	0.19 (0.04)$_L$	-2.10 (0.10)$_L$	-0.15 (0.04)$_S$	1.57 (0.05)$_L$
Sound and Vision:RC	0.43 (0.07)$_L$	-0.49 (0.06)$_L$	-4.20 (0.11)$_L$	0.00 (0.06)	0.19 (0.06)
Sports and Activity:RC	0.67 (0.07)$_L$	-0.95 (0.04)$_L$	-2.30 (0.11)$_L$	-1.50 (0.09)$_L$	-0.68 (0.06)$_L$
Toys:RC	2.02 (0.06)$_L$	0.90 (0.04)$_L$	-1.98 (0.09)$_L$	1.18 (0.03)$_L$	0.23 (0.05)$_M$

	Cluster 16	Cluster 17	Cluster 18	Cluster 19	Cluster 20
Intercept	-2.20 (0.02)$_L$	-1.63 (0.02)$_L$	-1.89 (0.05)$_L$	-0.52 (0.03)$_L$	-1.29 (0.02)$_L$
Proportion of day for sale	3.16 (0.01)$_L$	3.23 (0.01)$_L$	3.55 (0.01)$_L$	2.40 (0.02)$_L$	3.76 (0.02)$_L$
Discount	0.61 (0.01)$_L$	0.32 (0.02)$_L$	0.24 (0.06)$_S$	1.76 (0.04)$_L$	1.79 (0.04)$_L$
Monday	-0.24 (0.00)$_L$	-0.12 (0.01)$_L$	-0.16 (0.01)$_L$	0.02 (0.01)	-0.04 (0.01)$_S$
Tuesday	-0.31 (0.01)$_L$	-0.20 (0.01)$_L$	-0.25 (0.01)$_L$	-0.09 (0.01)$_L$	-0.22 (0.01)$_L$
Wednesday	-0.36 (0.01)$_L$	-0.16 (0.01)$_L$	-0.21 (0.01)$_L$	-0.17 (0.01)$_L$	-0.18 (0.01)$_L$
Thursday	-0.36 (0.01)$_L$	-0.26 (0.01)$_L$	-0.41 (0.01)$_L$	-0.29 (0.01)$_L$	-0.40 (0.01)$_L$
Friday	-0.46 (0.01)$_L$	-0.45 (0.01)$_L$	-0.62 (0.01)$_L$	-0.31 (0.01)$_L$	-0.55 (0.01)$_L$
Saturday	-0.06 (0.01)$_L$	0.16 (0.01)$_L$	-0.21 (0.01)$_L$	-0.13 (0.01)$_L$	-0.06 (0.01)$_L$
Holiday	-0.57 (0.01)$_L$	-0.62 (0.01)$_L$	-1.07 (0.01)$_L$	-0.50 (0.01)$_L$	-0.74 (0.01)$_L$
Black Friday	2.17 (0.01)$_L$	1.86 (0.01)$_L$	1.33 (0.01)$_L$	1.05 (0.01)$_L$	1.13 (0.01)$_L$
Lockdown	0.62 (0.00)$_L$	0.53 (0.00)$_L$	-0.74 (0.01)$_L$	0.31 (0.00)$_L$	-0.17 (0.00)$_L$
Drugs and Baby	2.46 (0.02)$_L$	0.97 (0.04)$_L$	-0.15 (0.07)	1.41 (0.03)$_L$	2.62 (0.03)$_L$
Entertainment	2.83 (0.02)$_L$	-0.19 (0.02)$_L$	1.37 (0.05)$_L$	3.08 (0.03)$_L$	3.21 (0.02)$_L$
Hardware	0.11 (0.03)	0.56 (0.02)$_L$	2.48 (0.06)$_L$	2.64 (0.03)$_L$	0.85 (0.02)$_L$
Kitchen and Household	1.68 (0.03)$_L$	0.00 (0.07)	-0.11 (0.06)	-0.10 (0.04)	-0.55 (0.03)$_L$
other	-0.25 (0.06)$_M$	1.33 (0.02)$_L$	1.32 (0.05)$_L$	0.35 (0.03)$_L$	0.26 (0.02)$_L$
Personal Care	-0.39 (0.03)$_L$	-0.21 (0.02)$_L$	0.32 (0.05)$_L$	1.48 (0.03)$_L$	0.26 (0.02)$_L$
Domestic Appliances	1.12 (0.02)$_L$	3.11 (0.02)$_L$	1.17 (0.06)$_L$	1.01 (0.03)$_L$	1.74 (0.02)$_L$
Sound and Vision	2.94 (0.02)$_L$	0.53 (0.03)$_L$	0.24 (0.06)$_S$	-0.60 (0.03)$_L$	-1.43 (0.02)$_L$
Sports and Activity	0.86 (0.03)$_L$	-0.58 (0.02)$_L$	0.39 (0.05)$_L$	-0.34 (0.04)$_L$	-1.28 (0.03)$_L$
Toys	1.42 (0.02)$_L$	1.67 (0.02)$_L$	2.77 (0.05)$_L$	0.72 (0.03)$_L$	2.11 (0.02)$_L$
WTP	-3.36 (0.07)$_L$	-1.50 (0.08)$_L$	-1.58 (0.22)$_L$	-2.42 (0.15)$_L$	0.34 (0.09)$_S$
UTP	-1.16 (0.07)$_L$	-1.98 (0.07)$_L$	0.64 (0.09)$_L$	0.23 (0.13)	0.74 (0.06)$_L$
RC	0.52 (0.04)$_L$	-1.06 (0.04)$_L$	1.83 (0.09)$_L$	0.00 (0.06)	0.24 (0.04)$_L$
Drugs and Baby:WTP	-6.77 (0.09)$_L$	-0.57 (0.13)$_M$	2.45 (0.26)$_L$	2.31 (0.20)$_L$	-0.84 (0.11)$_L$
Entertainment:WTP	2.34 (0.08)$_L$	2.35 (0.10)$_L$	0.44 (0.24)	2.41 (0.16)$_L$	-0.34 (0.11)
Hardware:WTP	3.52 (0.11)$_L$	2.31 (0.09)$_L$	0.21 (0.27)	0.90 (0.16)$_L$	-0.48 (0.09)$_L$
Kitchen and Household:WTP	1.46 (0.11)$_L$	1.71 (0.23)$_L$	5.62 (0.26)$_L$	2.48 (0.19)$_L$	-0.69 (0.12)$_L$
other:WTP	2.38 (0.23)$_L$	1.50 (0.09)$_L$	2.25 (0.25)$_L$	2.22 (0.15)$_L$	0.77 (0.11)$_L$
Personal Care:WTP	4.02 (0.10)$_L$	1.15 (0.09)$_L$	2.04 (0.22)$_L$	1.07 (0.16)$_L$	-1.74 (0.10)$_L$
Domestic Appliances:WTP	2.87 (0.09)$_L$	1.53 (0.10)$_L$	2.23 (0.27)$_L$	2.50 (0.15)$_L$	0.17 (0.10)
Sound and Vision:WTP	3.01 (0.10)$_L$	2.41 (0.10)$_L$	0.91 (0.28)	3.05 (0.16)$_L$	-0.68 (0.11)$_L$
Sports and Activity:WTP	1.58 (0.11)$_L$	1.70 (0.12)$_L$	-0.27 (0.24)	2.59 (0.19)$_L$	-2.18 (0.19)$_L$
Toys:WTP	3.43 (0.08)$_L$	0.46 (0.09)$_L$	1.70 (0.22)$_L$	1.78 (0.16)$_L$	-0.56 (0.10)$_L$
Drugs and Baby:UTP	1.93 (0.08)$_L$	1.62 (0.10)$_L$	-1.14 (0.13)$_L$	-0.29 (0.14)	-0.71 (0.07)$_L$
Entertainment:UTP	1.50 (0.07)$_L$	2.57 (0.07)$_L$	-1.03 (0.10)$_L$	-0.49 (0.14)	-0.96 (0.08)$_L$
Hardware:UTP	1.67 (0.08)$_L$	2.58 (0.08)$_L$	-2.49 (0.13)$_L$	-0.70 (0.14)$_L$	-0.66 (0.06)$_L$
Kitchen and Household:UTP	0.13 (0.13)	2.81 (0.18)$_L$	-2.34 (0.13)$_L$	0.17 (0.16)	-1.00 (0.08)$_L$
other:UTP	1.29 (0.12)$_L$	1.90 (0.08)$_L$	0.09 (0.10)	0.05 (0.13)	-0.08 (0.07)
Personal Care:UTP	1.29 (0.08)$_L$	-0.10 (0.07)	1.34 (0.09)$_L$	-1.01 (0.15)$_L$	-0.01 (0.07)
Domestic Appliances:UTP	0.80 (0.08)$_L$	1.91 (0.07)$_L$	0.56 (0.15)$_S$	-1.23 (0.13)$_L$	-0.19 (0.07)
Sound and Vision:UTP	1.91 (0.07)$_L$	1.47 (0.09)$_L$	-0.76 (0.12)$_L$	0.92 (0.16)$_L$	-2.48 (0.07)$_L$
Sports and Activity:UTP	-0.61 (0.09)$_L$	1.44 (0.09)$_L$	-0.79 (0.11)$_L$	-0.77 (0.16)$_L$	-0.23 (0.12)
Toys:UTP	2.58 (0.07)$_L$	1.63 (0.07)$_L$	-0.33 (0.09)	2.25 (0.14)$_L$	-0.10 (0.06)
Drugs and Baby:RC	-3.66 (0.04)$_L$	1.52 (0.06)$_L$	-1.88 (0.13)$_L$	0.20 (0.06)	0.92 (0.05)$_L$
Entertainment:RC	-0.37 (0.04)$_L$	2.74 (0.05)$_L$	-2.39 (0.10)$_L$	0.36 (0.07)$_L$	0.34 (0.05)$_L$
Hardware:RC	1.07 (0.06)$_L$	2.77 (0.05)$_L$	-3.51 (0.12)$_L$	0.40 (0.06)$_L$	0.96 (0.04)$_L$
Kitchen and Household:RC	-1.89 (0.06)$_L$	0.32 (0.11)	-2.14 (0.11)$_L$	0.49 (0.09)$_L$	-0.75 (0.05)$_L$
other:RC	0.09 (0.11)	1.86 (0.05)$_L$	-1.51 (0.10)$_L$	0.97 (0.06)$_L$	1.28 (0.04)$_L$
Personal Care:RC	0.79 (0.05)$_L$	0.69 (0.04)$_L$	-0.82 (0.09)$_L$	-0.82 (0.06)$_L$	1.23 (0.04)$_L$
Domestic Appliances:RC	0.81 (0.05)$_L$	2.44 (0.05)$_L$	1.08 (0.12)$_L$	-0.51 (0.06)$_L$	0.88 (0.04)$_L$
Sound and Vision:RC	1.36 (0.04)$_L$	2.76 (0.05)$_L$	-1.27 (0.12)$_L$	2.51 (0.07)$_L$	-0.20 (0.04)$_L$
Sports and Activity:RC	-0.25 (0.06)$_M$	1.92 (0.05)$_L$	-1.83 (0.10)$_L$	0.06 (0.08)	-0.78 (0.06)$_L$
Toys:RC	1.36 (0.04)$_L$	1.12 (0.04)$_L$	-1.24 (0.09)$_L$	-0.47 (0.06)$_L$	0.89 (0.04)$_L$

$_S$: $p < 5\%$ α-level
$_M$: $p < 1\%$ α-level
$_L$: $p < 0.1\%$ α-level

Appendix D.2. $\sigma_{9.21}(RP_p)$ and $\sigma_{9.21}(RP_d)$ during the Regular Period

Appendix D.2.1. Results Model Training

In Table D.21 we have presented the results of the model training for estimating the effects of $\sigma_{9.21}(\text{RP}_p)$ and $\sigma_{9.21}(\text{RP}_d)$ during the regular period. The first column shows the number of clusters we start the model training with, the second column the number of different clusters which have at least different 100 products per cluster. Here it should be noted that we remove all clusters during training which validate this criterion. Hence the results of the other columns correspond to the number of clusters indicated in the second column. The third column shows the log-likelihood of the best training session, and the other columns the results with respect to different selection criteria.

#S start	#S above threshold	log likelihood	AIC	CAIC	AWE	BIC	CLC	NEC	ICL-BIC
5	5	-5043682	10087773	20177860	20181194	10090291	10108802	0.002	10111728
10	10	-4856854	9714526	19433692	19440376	9719574	9857695	0.018	9863562
15	15	-4782881	9566990	19140945	19150980	9574569	9784789	0.027	9793596
20	20	-4755586	9512811	19034913	19048298	9522920	9805072	0.037	9816819
22	22	-4696042	9394062	18799342	18815506	9406269	9641548	0.029	9655734
23	23	-4687071	9376210	18764150	18781049	9388973	9611230	0.031	9626061
24	22	-4700503	9402984	18817186	18833350	9415191	9657000	0.032	9671186
25	23	-4690646	9383360	18778450	18795349	9396123	9621428	0.030	9636259

Table D.21: Results for modelling $\sigma_{9.21}(\text{RP}_p)$ and $\sigma_{9.21}(\text{RP}_d)$ during the regular period.
Gold: selected cluster size
Gray: best solution for selection criterion
Red: Contains segments below threshold of 100 products

Based on the results of Table D.21, we see that AIC, CAIC, AWE, BIC, CLC and ICL-BIC are decreasing as we increment the different number of clusters. For NEC on the other hand, we find that this criterion is minimised when we select only 5 different clusters. However, for the other clusters this selection criterion is still small. All-in-all, the different selection criteria lead us in the direction to increase the number of different clusters. For this reason, we include the posterior size of every cluster in our analysis. Based on the first two columns of Table D.21, we find that up to 23 different clusters, all clusters contain at least 100 products different products. However, once we increase to 24 and 25 different clusters, we observe that some clusters are below this threshold. Therefore, we decide to select 23 different clusters.

In Figure D.23 we can find the posterior size of the different clusters based on the results of Table D.21. Note that we have relabeled every cluster based on their posterior size. In this figure, we see that the cluster with the largest posterior size is a couple of percentage points larger than the second largest cluster. From the fourth cluster on wards, we observe that the posterior sizes are gradually decreasing with a couple of sudden jumps in between.

In Figure D.24 we present the distribution of over the different clusters per shop category. The first observation we want to highlight is that the distribution over the different shopping categories does not match the decreasing shape of Figure D.23. For instance, the shop category *Sound and Vision* does not have a decreasing tendency over the different clusters, but a much more bumpy shape. Secondly, we find that the representation for certain shopping categories is largest for clusters which are on the farther right of Figure D.23.

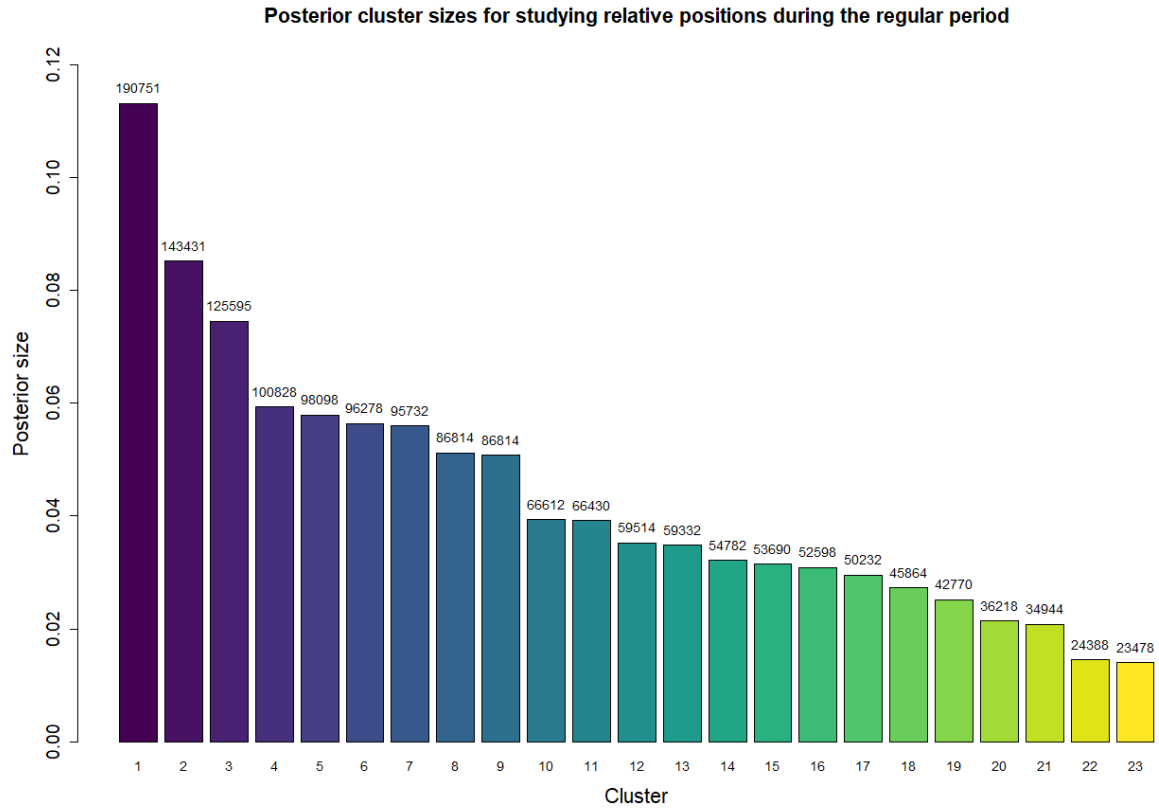

Figure D.23: Posterior cluster sizes for studying over all products. Number on the bars indicate number of observations per cluster

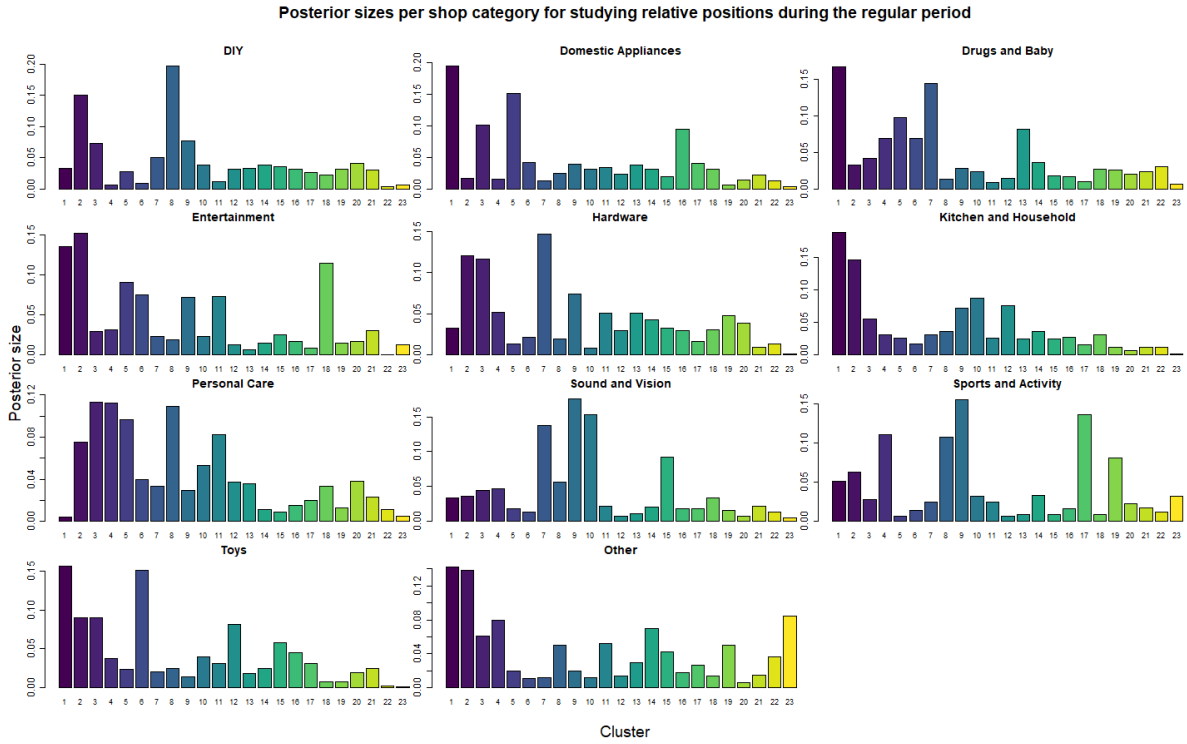

Figure D.24: Normalised posterior cluster sizes per shop category

Cluster Similarity. In Table D.22 and Figure D.25 we depict the cluster similarity based on KL-divergence. The larger the KL-divergence the more dissimilar clusters are. Based on these results, we can for example see that clusters 2 and 3 share relatively much similarity and that cluster 23 is most dissimilar from the other clusters.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1	0	77	73	102	76	74	129	128	98	124	195	154	106	67	136	120	61	185	96	140	76	80	893
2	68	0	25	50	91	68	88	85	68	126	132	66	97	32	145	113	62	172	73	116	93	68	922
3	47	24	0	60	51	60	88	77	48	122	138	78	65	31	148	79	33	146	70	116	77	60	924
4	173	72	111	0	191	99	49	86	143	128	199	97	159	109	210	163	175	233	157	126	141	172	916
5	90	117	86	143	0	87	128	140	79	178	196	148	52	68	186	92	95	118	94	118	99	61	923
6	115	148	118	141	81	0	167	195	152	170	234	165	137	158	217	162	121	217	189	157	152	121	1014
7	233	130	176	56	263	149	0	143	160	158	264	94	177	142	217	180	211	265	190	120	160	184	929
8	214	159	139	125	251	183	207	0	114	72	86	90	230	138	176	131	115	184	156	215	132	262	927
9	139	110	71	134	84	120	119	76	0	145	133	90	51	78	122	91	81	65	62	103	41	109	855
10	207	340	290	212	330	251	351	79	269	0	207	267	407	253	300	199	182	271	315	294	243	387	864
11	517	252	295	393	532	396	482	98	209	196	0	76	466	320	225	255	246	304	292	413	332	459	1115
12	285	104	141	148	300	185	165	58	107	117	77	0	232	146	174	155	150	206	170	178	178	235	1000
13	173	185	116	182	56	157	138	139	41	225	226	172	0	112	170	92	158	67	85	116	49	144	856
14	74	42	56	84	80	83	116	115	104	170	169	110	87	0	178	108	67	176	48	144	113	71	925
15	287	302	408	386	398	295	256	390	207	349	396	323	267	331	0	263	282	335	152	214	81	286	950
16	247	239	138	180	197	193	141	120	165	172	254	157	144	173	199	0	114	240	187	195	164	214	1002
17	94	97	48	107	114	90	115	80	72	100	168	93	124	65	167	72	0	171	112	129	106	91	942
18	425	468	313	429	174	354	335	228	94	353	318	305	112	295	327	206	330	0	229	222	140	365	863
19	158	119	136	167	158	147	150	166	108	236	208	149	112	73	156	170	163	190	0	165	101	147	924
20	290	270	246	241	171	117	187	232	137	215	337	186	163	230	291	211	172	149	242	0	157	200	1039
21	142	166	162	181	129	145	128	169	61	197	241	182	68	143	72	121	147	126	76	98	0	154	864
22	96	103	140	157	56	116	122	196	136	194	227	162	120	63	190	118	105	205	106	143	154	0	944
23	3961	6243	5518	4549	5167	5058	5647	3646	4290	2491	4264	5330	6558	4833	4226	3797	4086	2904	5080	5302	4881	5292	0

Table D.22: Values of KL-divergence of different clusters for modeling$\sigma_{9.21}(\text{RP}_p)$ and $\sigma_{9.21}(\text{RP}_d)$ during the regular period. Note that we have divided the numbers by 100,000 for readability

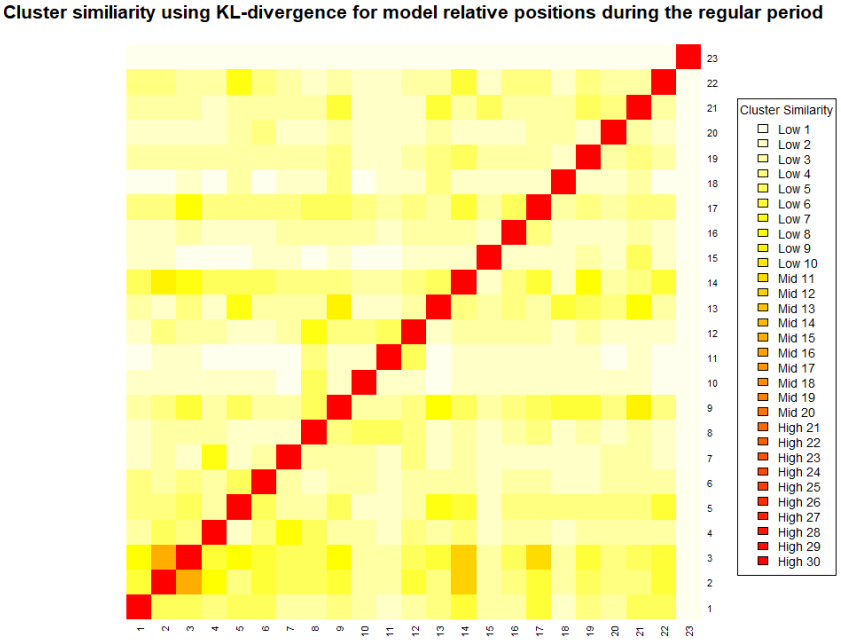

Figure D.25: Heatmap of cluster similarity based on KL-divergence values of Table D.22. The darker the color, the more clusters share similarity.

Appendix D.2.2. Parameter Estimates

In Table 8 we have presented the parameter estimates of $\sigma_{9.21}(\mathrm{RP}_p)$ and $\sigma_{9.21}(\mathrm{RP}_d)$ during the regular period over the different shop categories. We have taken the shop category *DIY* as a baseline. We complement this table by Figures D.26 and D.27 in which we respectively show barplots of the statistical power of the parameters of Table 8, and boxplots of significant marginal effects (in bi-symmetric log scale) at a 5% α-level per shop category over the different clusters. In Figure D.26, a value of minus one indicates that the parameter is insignificant at an α-level of 5%, while the numbers besides the variables indicate the average shop power of all significant parameters and the number of significant parameters.

In Figure D.26 can make the following observations. First, most of the parameter estimates for $\sigma_{9.21}(\mathrm{RP}_p)$ are significant at a 5% α-level, and furthermore exhibit high statistical power. None of the shopping categories has an average statistical power below 0.8, while for individual parameters we only incidentally observe powers below 0.8. For the parameter estimates of $\sigma_{9.21}(\mathrm{RP}_d)$ on the other hand, we observe much more insignificant parameter estimates and generally lower statistical power. At a first glance, we see that more parameter estimates are insignificant over all shop categories, and that the average statistical power is below 0.8 for multiple shopping categories. More specifically, for the shop categories *DIY* and *Sound and Vision*, we find that the average statistical power is far below 0.8. This can be explained by the fact that a number of clusters within these shopping categories have statistical power very close to 0. For example, for the shopping category *Sound and Vision* we find that clusters 12 and 14 have weak statistical power. We can partly explain these results by consulting Figure D.24, in which we see that the representation of for this shopping category in these clusters is low. Other factors which can explain why the statistical power for $\sigma_{9.21}(\mathrm{RP}_d)$ is lower are the size of the effects, and the amount of variability within $\sigma_{9.21}(\mathrm{RP}_d)$. For a discussion on this last topic, we refer to Appendix B.1

By considering Figure D.27 we can obtain an understanding of the magnitudes of the marginal effects with respect to $\sigma_{9.21}(\mathrm{RP}_p)$ and $\sigma_{9.21}(\mathrm{RP}_d)$ over the different clusters and shopping categories. We believe that the following observations are worthy to be mentioned. First, we see that for $\sigma_{9.21}(\mathrm{RP}_p)$ the boxplots are in many circumstances much more spread out than the boxplots of $\sigma_{9.21}(\mathrm{RP}_d)$, which indicates that $\sigma_{9.21}(\mathrm{RP}_p)$ has a wider range of marginal effects. Secondly, we find that if we condition on one percentile, say the median, the marginal effects for $\sigma_{9.21}(\mathrm{RP}_p)$ generally tend to be larger than the marginal effects of $\sigma_{9.21}(\mathrm{RP}_d)$. In the next part of this subsection, we elaborate on this in more detail. An observation related to the sign of the marginal effects of $\sigma_{9.21}(\mathrm{RP}_p)$ and $\sigma_{9.21}(\mathrm{RP}_d)$ is that we observe for every shopping category clusters with negative marginal effects for $\sigma_{9.21}(\mathrm{RP}_p)$ and $\sigma_{9.21}(\mathrm{RP}_d)$, possibly indicating that there is unawareness of relative price positions and relative delivery promise positions for a number of products.

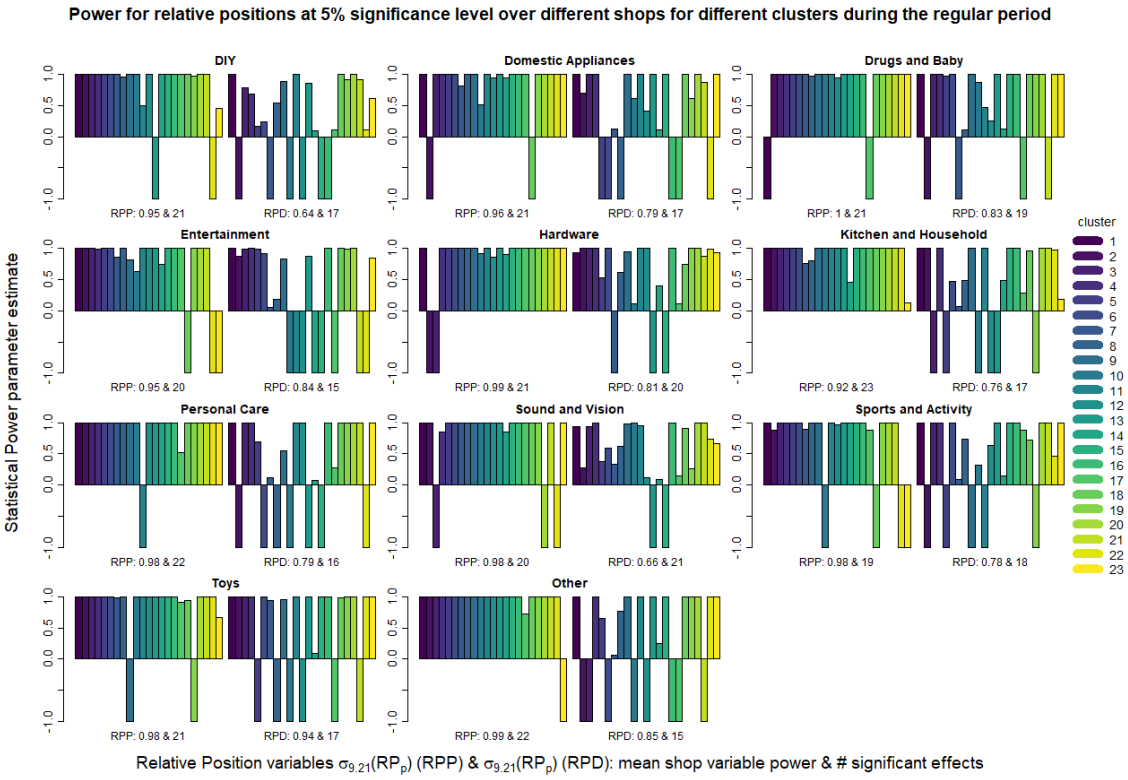

Figure D.26: Statistical power for the different parameter estimates of Table 8. A value of minus one indicates an insignificant effect at $\alpha = 0.05$. Values next to variables RPP and RPD indicate average cluster power, and the number of significant effects.

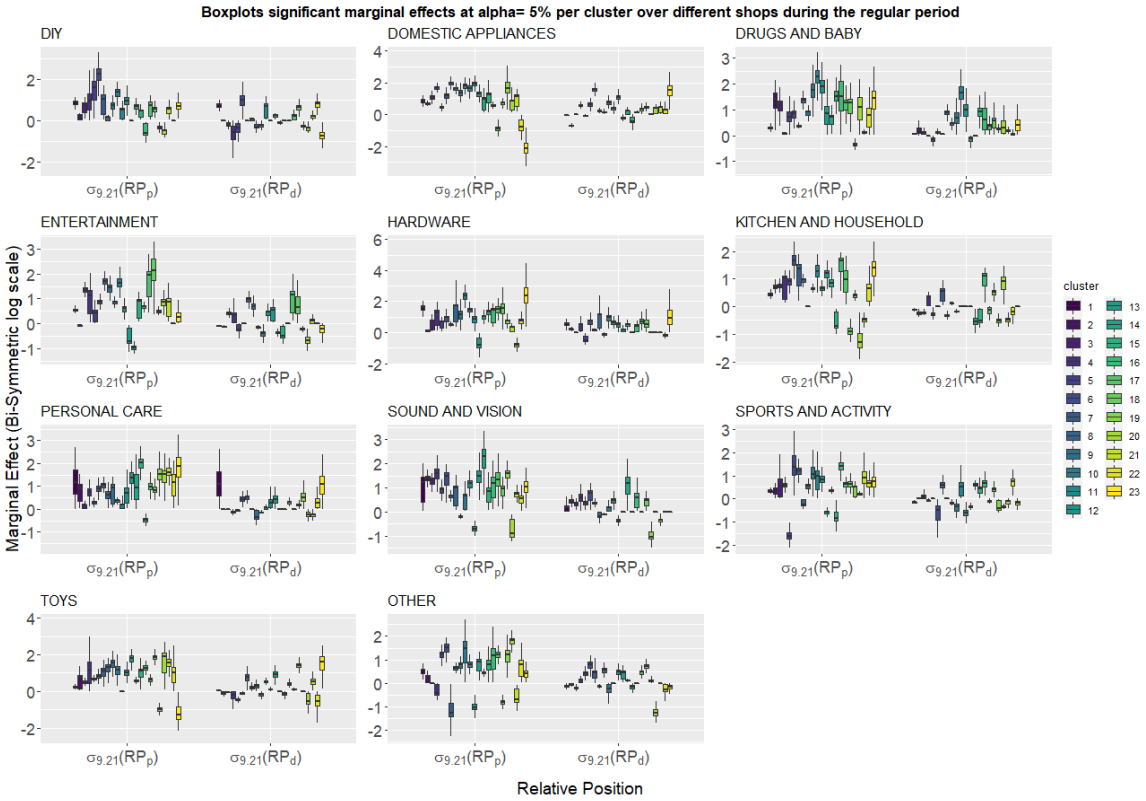

Figure D.27: Significant marginal effects using Equation C.49 in bi-symmetric log-scale (with base 10). Significance is determined at $\alpha = 0.05$.

Appendix D.2.3. Additional Plots Hypothesis Tests

Given the results of Figure 6, we now consider how the products with different effect types differ in terms of product popularity (number of daily sales), price proposition, and delivery promise proposition. In Figure D.28 we provide the results of the Lepage tests derived in Lepage (1971) of testing the location and scale between different samples. The set-up of our test is as follows. For every product, we take the median daily sales. Then we consider all products with the same effect type (conditioned on shop category) belonging to the same sample. Given such a sample we test whether the location and/or scale are/is significantly different compared to another the sample belonging to a different effect type using the Lepage test. Since we are considering the significance of multiple variables at the same time, we need to account FWER, which we do by using the procedure of Holm (1979).

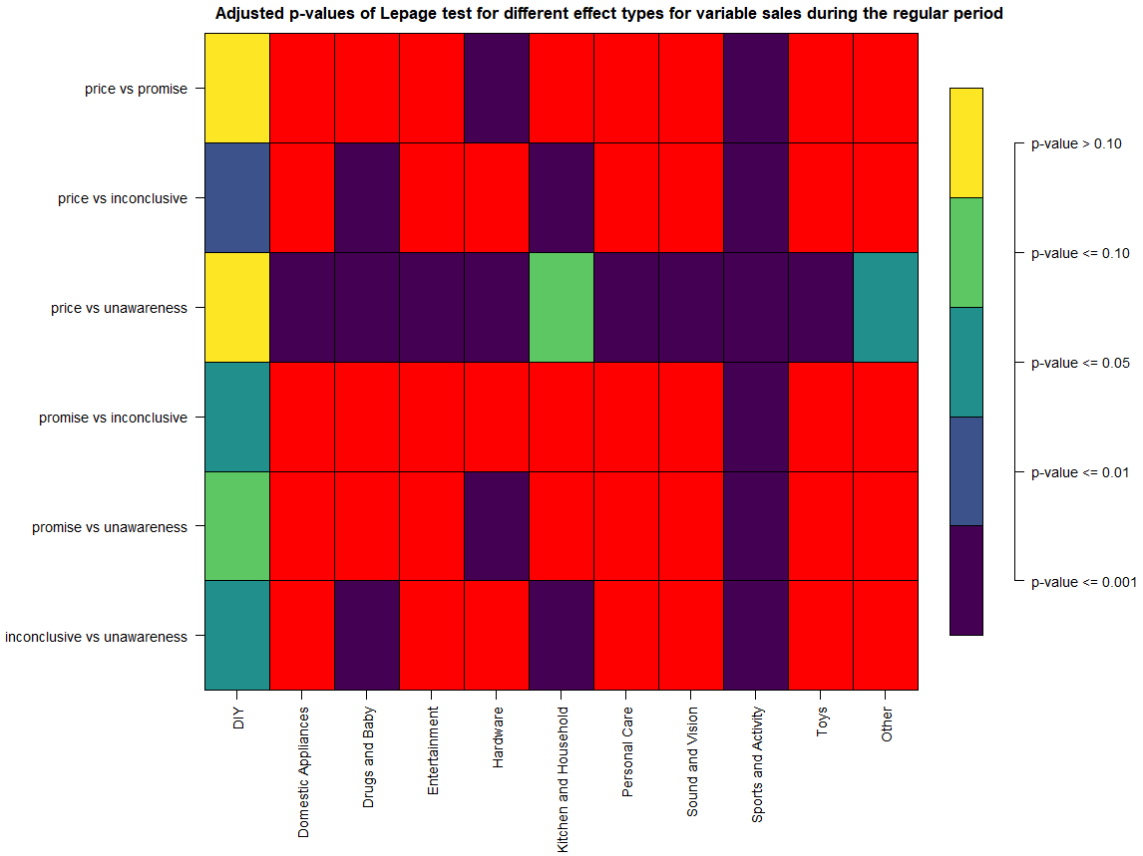

Figure D.28: Cells in red indicate that the combination does not exist for a given shop category. The shop effects are based on the results of Figure 6.

In Figure D.28, the cells colored in red indicate that the test is not applicable for two different effect types given a shop category, since at least one of the effect types does not exist. Based on the results of Figure D.28 we can see that most non-red cells are colored green-blue, dark blue or dark purple. This indicates that we reject the null hypothesis of the Lepage test for an α-level of at least 5%. As most of these cells are colored in dark purple, we in fact reject the null hypothesis at an α-level of at 0.01%. This provides evidence that the location and/or scale of median daily sales between different effect types is statistically significant at α levels of 5% and lower.

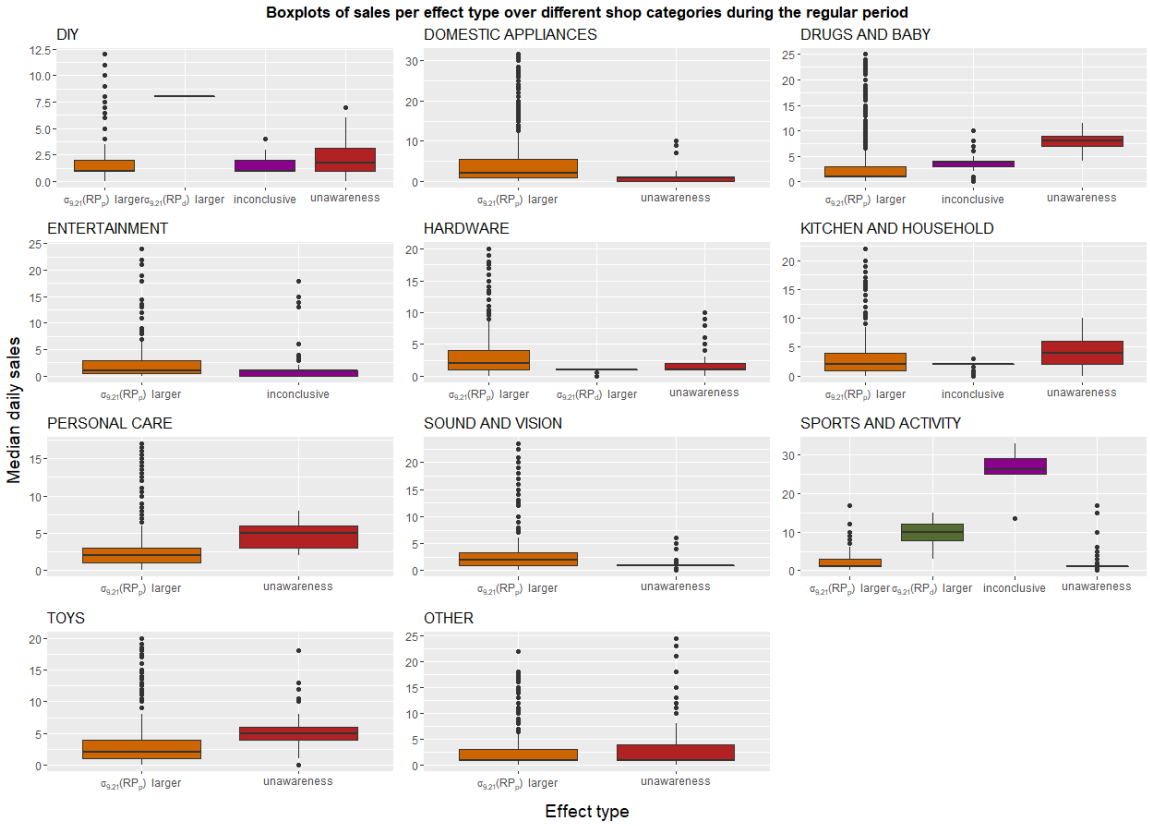

Figure D.29: The shop effects are based on the results of Figure 6.

In Figure D.29 we show the boxplots of the median daily sales of the different effect types over the different shop categories in order to determine how the effects might differ in terms of product popularity once we reject the null hypotheses of the Lepage test of Figure D.28. Based on the boxplots in this figure, we cannot draw any general conclusions about characterisation of the product popularity of one effect type for all shop categories, but rather that these are different from shop category to shop category. For instance, for the shop category *Drugs and Baby* the medium daily sales of the effect type *unawareness* seem to be clustered around slightly more popular products than the other two effect types (ignoring outliers), while for the shop category *Sound and Vision* the effect type *unawareness* seems to correspond to products which are relatively less popular. In terms of largest deviations, we see that for *Sports and Activity* the products corresponding to *inconclusive* are most popular, followed by products with the effect type $\sigma_{9.21}(RP_d)$ *larger*.

For prices and delivery promises we have done a similar analysis which we can see by considering Figures D.30, D.31, D.32, D.33. Compared to the results on sales, we find that for prices and delivery promises there are in general no significant changes for the different effect types.

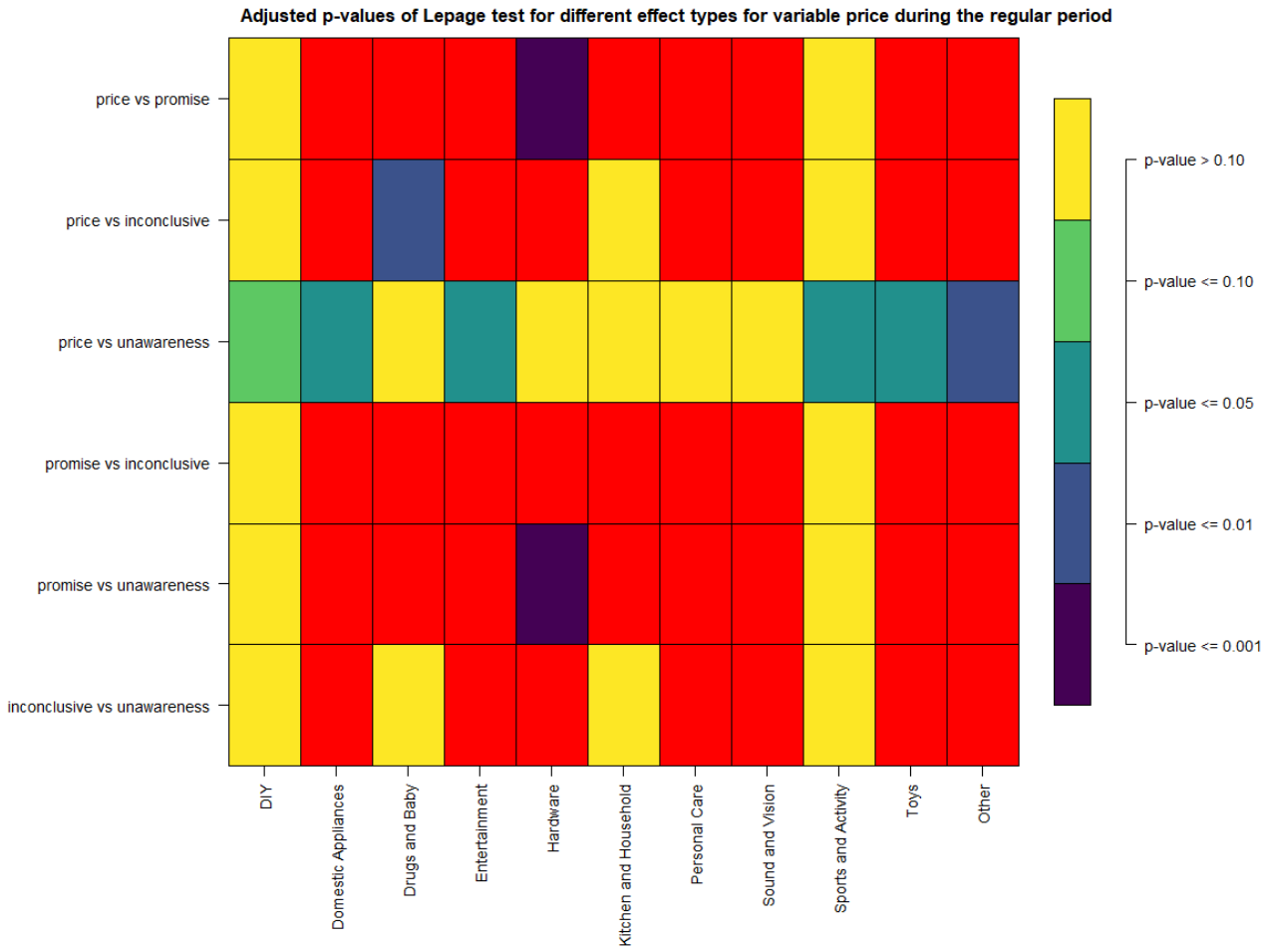

Figure D.30: Table of adjusted p-values based on Holm-procedure (Holm (1979)) for different effect type combinations. Cells in red indicate that the combination does not exist for a given shop category. The effect types are based on the results of Figure 6.

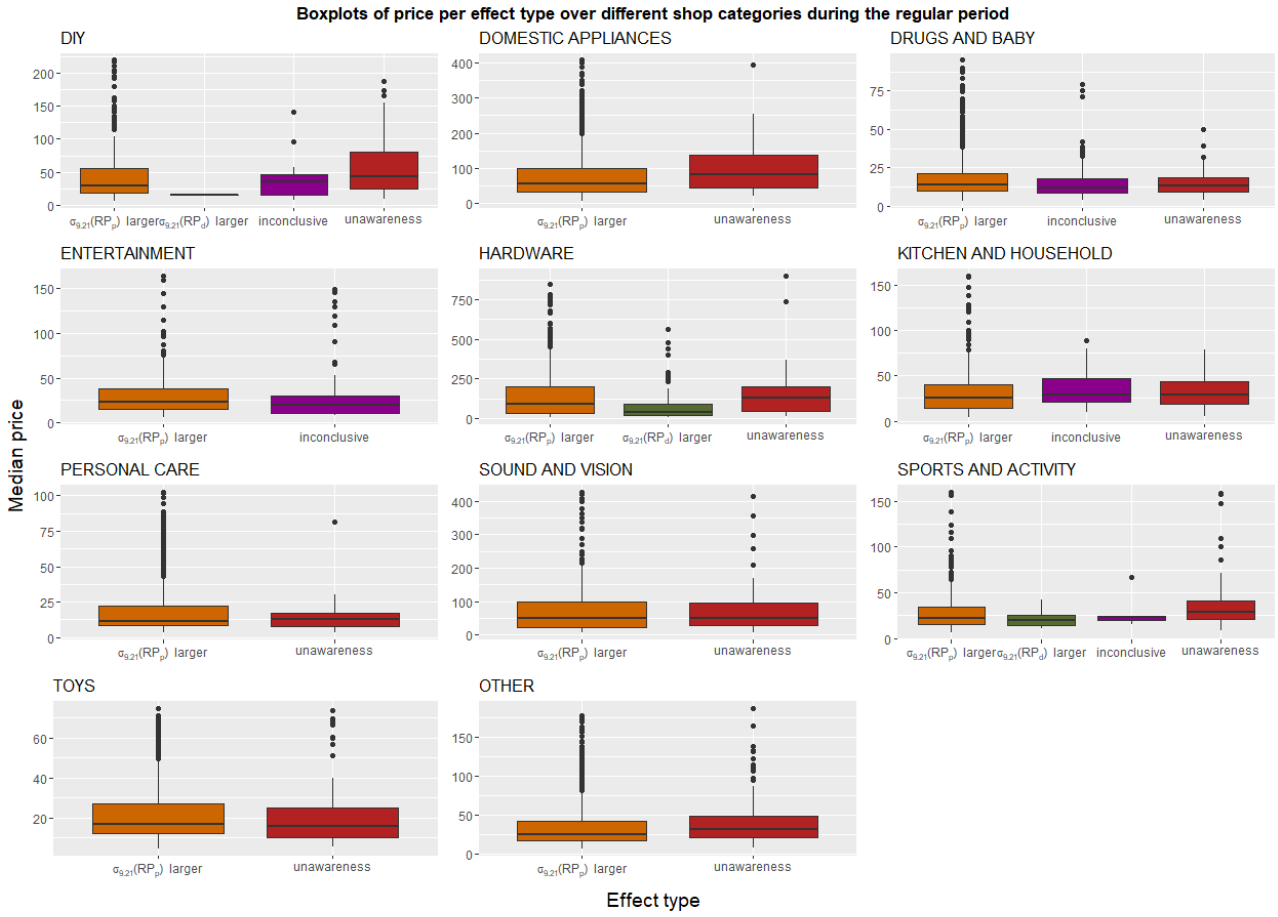

Figure D.31: The effect types are based on the results of Figure 6.

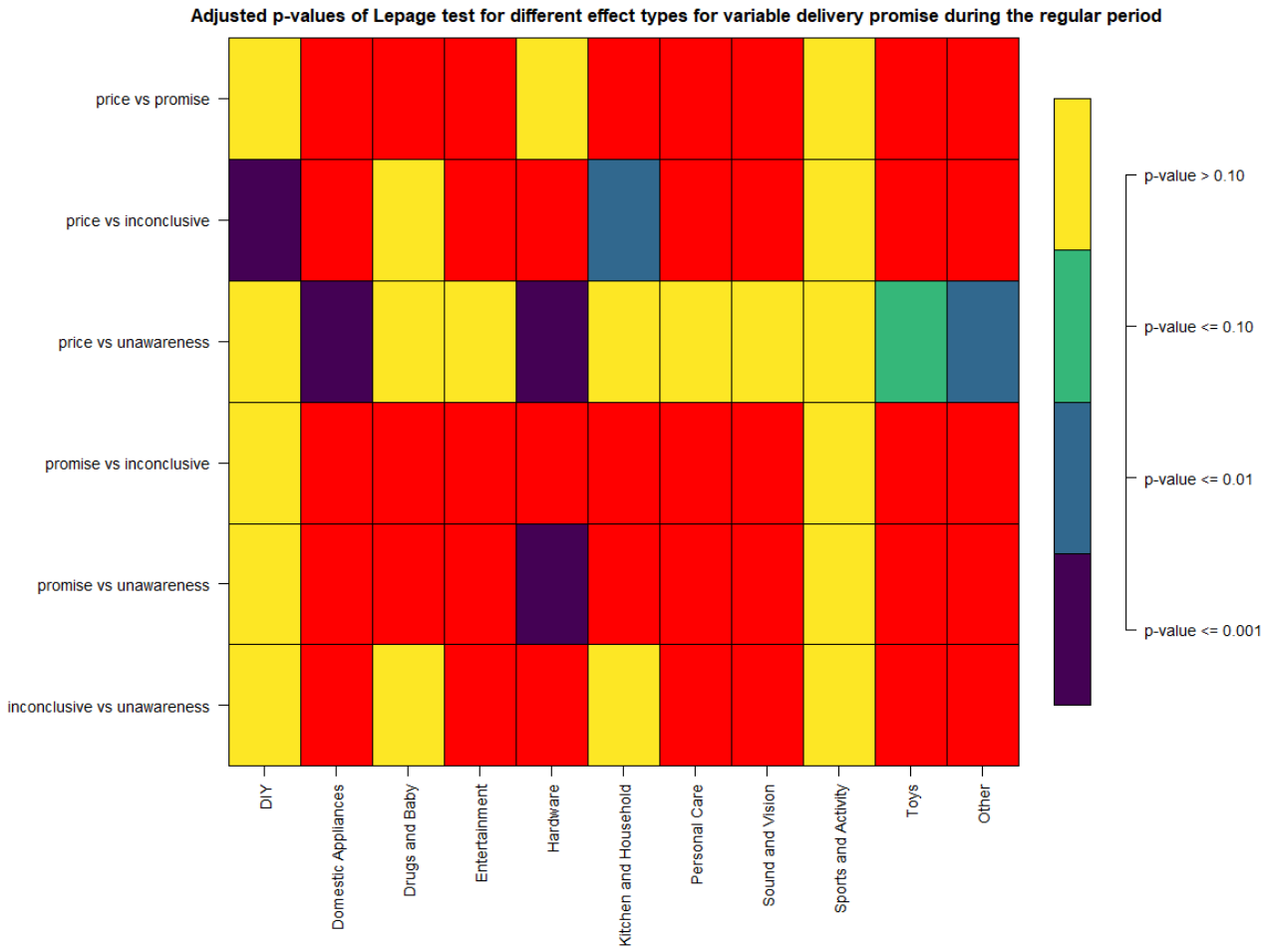

Figure D.32: Table of adjusted p-values based on Holm-procedure (Holm (1979)) for different effect type combinations. Cells in red indicate that the combination does not exist for a given shop category. The effect types are based on the results of Figure 6.

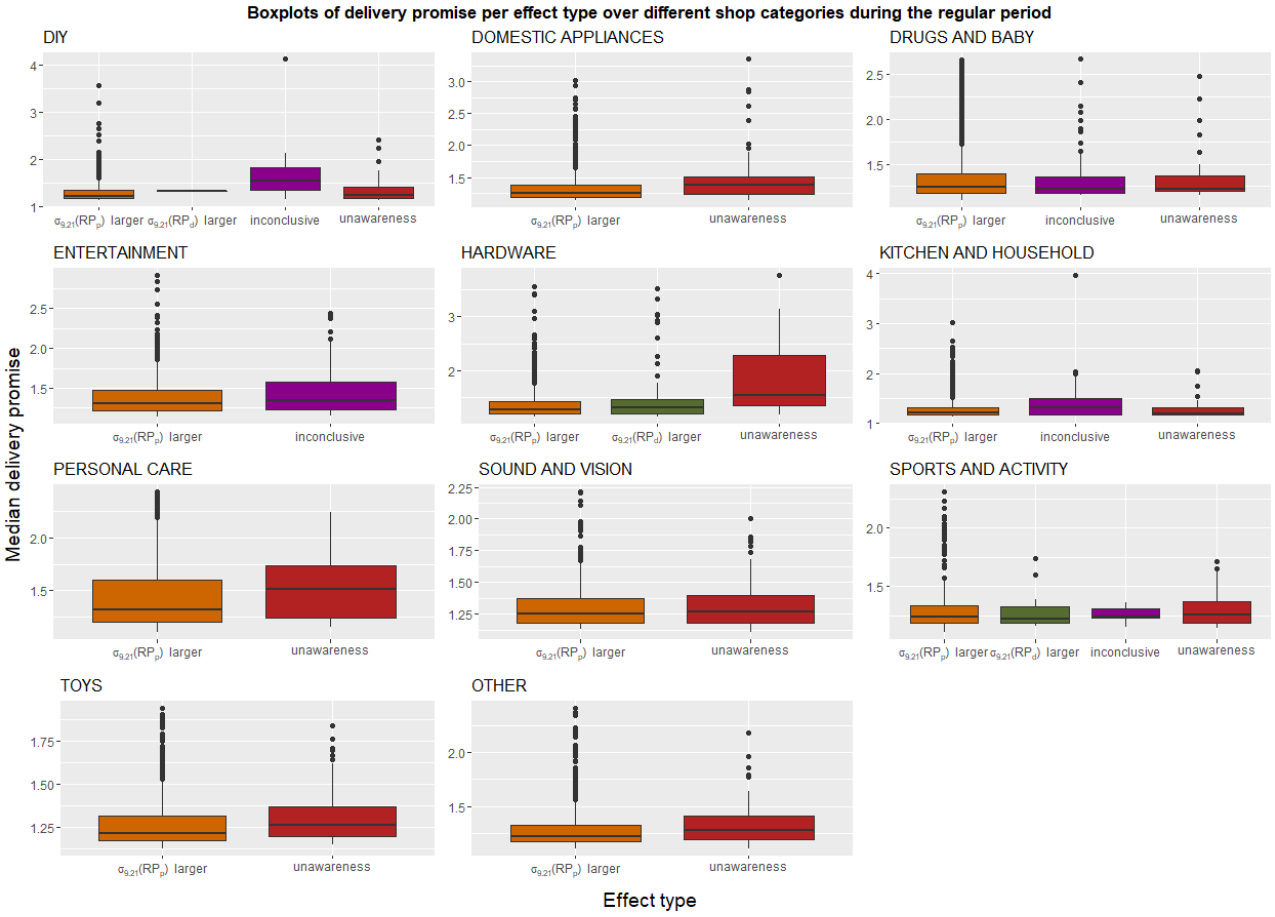

Figure D.33: The effect types are based on the results of Figure 6.

Appendix D.3. $\sigma_{9.21}(RP_p)$ and $\sigma_{9.21}(RP_d)$ during the Holiday Period

Appendix D.3.1. Results Model Training

In Table D.23 we provide the results of the model training for estimating the effects of $\sigma_{9.21}(\text{RP}_p)$ and $\sigma_{9.21}(\text{RP}_d)$ during the holiday period. Table D.23 follows a similar structure as Table D.21 with the slight difference that we require every cluster to have at least 1% of all observations, rather than having 100 different products. In practice this implies that we increase the threshold from 100 different products per cluster to 131 different products per cluster. Similar to Table D.21, the third column shows the log-likelihood of the best training session, while the columns 4 to 10 show the results under different selection criteria.

#S start	#S above threshold	log likelihood	AIC	CAIC	AWE	BIC	CLC	NEC	ICL-BIC
5	5	-3664156	7328760	14659890	14663381	7331354	7344014	0.001	7347056
10	10	-3414375	6829648	13664049	13671046	6834849	6913912	0.007	6920011
15	15	-3324220	6649788	13306709	13317212	6657595	6793890	0.013	6803045
19	19	-3282628	6566964	13142966	13156275	6576856	6728570	0.014	6740170
20	20	-3274318	6550435	13110385	13124394	6560849	6737386	0.017	6749598
22	21	-3255139	6512166	13034322	13049033	6523101	6699892	0.017	6712715
24	24	-3231170	6464497	12940414	12957229	6476996	6668048	0.018	6682705
25	24	-3237130	6476418	12964255	12981070	6488916	6673152	0.017	6687809

Table D.23: Results for modelling $\sigma_{9.21}(\text{RP}_p)$ and $\sigma_{9.21}(\text{RP}_d)$ during the holiday period.
Gold: selected cluster size
Gray: best solution for selection criterion
Red: Contains segments below threshold of 1%

Given the results of Table D.23, we find that the log-likelihood is increasing as we increase the number of clusters, while most of the selection criteria decrease. The only selection criterion which tends to increase as we add more clusters is NEC, although the increments are small. Based on the second column, we see that up to 20 different clusters, the posterior size of every cluster was at least 1%. However, for the configuration with 22 different clusters, one cluster did not satisfy this threshold. Given this result, we quite surprisingly find that for the model configuration with 24 different clusters, all 24 clusters have an posterior size of at least 1%. For the mixture with 25 clusters on the other hand, we observe one cluster violating the requirement of at least containing 131 products. Therefore, we select the model configuration with 24 different mixture components.

In Figure D.34 we have plotted the posterior size of the different mixture components (relabeled based on their posterior size). We see that the first three clusters stand out in terms of their size compared to the other clusters, and that the first two clusters are a little larger than the third cluster. From cluster 4 to cluster 19 we find the clusters which form the middle brackets in this mixture model. Clusters 21 to 24 can be considered as being the clusters with the overall smallest posterior size, while cluster 20 falls in between the middle brackets and the bottom 4 clusters. In Figure D.35 we see that the distribution of the different shopping categories over the different clusters generally deviates from the picture pf Figure D.34, an observation we also made when we compared the plots of Figure D.24 to that of Figure D.23.

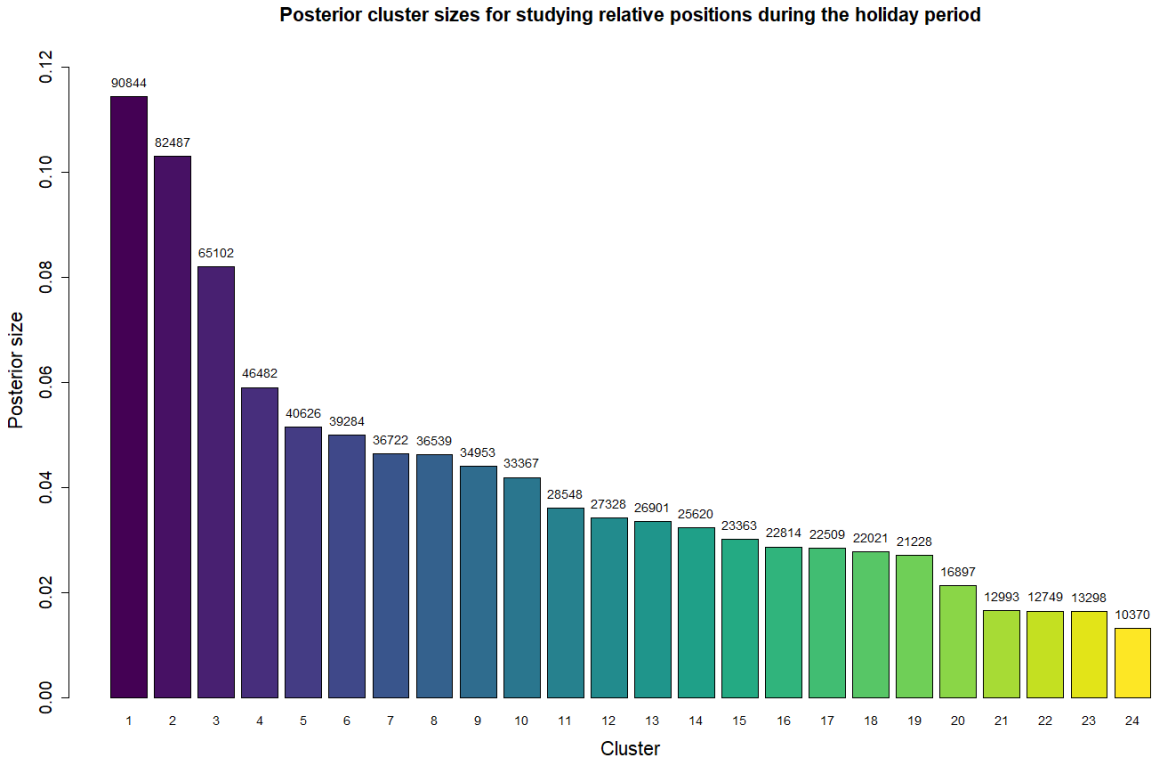

Figure D.34: Posterior cluster sizes for studying over all products. Number on the bars indicate number of observations per cluster

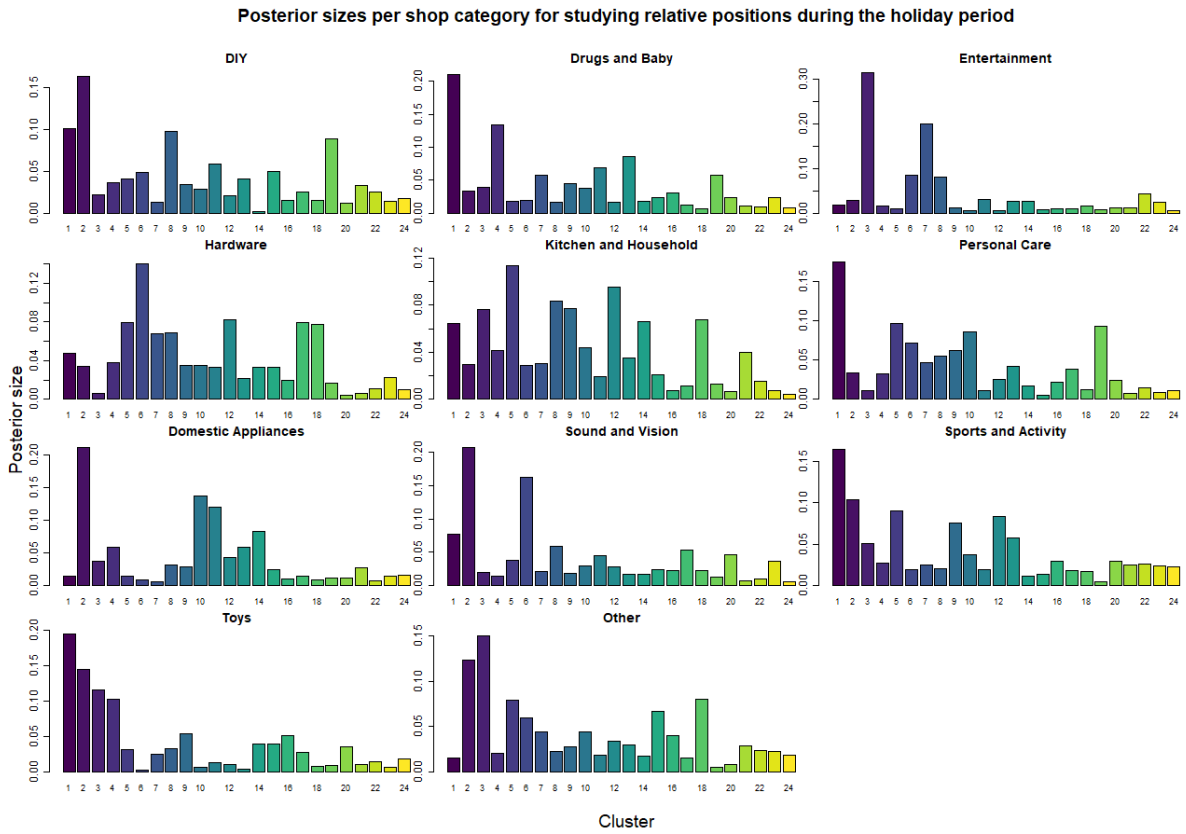

Figure D.35: Posterior cluster sizes per shop category

Cluster Similarity. In Table D.24 and Figure D.36 we depict the cluster similarity based on KL-divergence. The larger the KL-divergence the more dissimilar clusters are. Remarkable observations we can make are that clusters 1,2,3,4 have relatively much similarity with each other, while clusters 22,23 and 24 are most dissimilar from the other clusters.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	0	39	80	27	50	126	148	47	85	46	61	38	75	125	168	51	266	80	192	426	266	236	330	167
2	36	0	39	31	69	114	166	34	121	40	30	36	57	128	155	52	298	84	220	419	279	189	298	149
3	99	68	0	95	134	194	185	109	201	107	75	105	77	132	152	108	391	124	286	454	206	193	370	185
4	96	45	81	0	92	136	163	47	116	60	44	38	89	105	162	75	272	87	199	453	270	252	337	185
5	97	164	130	129	0	70	97	61	175	152	157	71	150	218	204	93	262	107	176	445	245	202	366	214
6	373	341	294	335	136	0	248	231	356	226	288	232	268	389	446	223	402	315	286	551	387	265	383	259
7	283	496	303	370	97	200	0	236	389	419	387	248	315	421	366	206	413	197	194	515	311	328	470	399
8	108	50	73	43	51	86	144	0	141	69	66	35	90	154	185	82	275	100	186	441	284	189	337	182
9	158	302	482	217	208	426	480	383	0	151	284	219	322	170	304	237	122	245	243	639	229	501	524	244
10	129	66	106	77	74	126	157	78	91	0	62	43	51	109	213	51	264	79	163	413	243	193	253	117
11	112	45	81	62	144	162	183	111	169	80	0	67	77	137	125	83	300	106	223	443	269	230	255	162
12	58	49	68	40	53	114	141	50	106	44	45	0	63	99	156	59	258	52	185	446	217	182	299	160
13	140	95	84	152	124	213	138	122	151	52	63	77	0	142	226	52	346	108	149	372	214	165	207	92
14	373	372	278	291	335	390	307	427	313	246	324	259	312	0	324	210	493	139	494	720	356	394	496	347
15	632	423	377	337	582	602	653	714	608	605	216	356	485	241	0	492	640	302	824	1051	280	654	642	564
16	86	79	75	92	64	129	106	84	115	44	68	51	39	112	202	0	288	57	144	382	227	158	222	91
17	664	884	1224	683	595	912	1119	968	202	586	795	664	975	497	683	790	0	742	531	1150	429	1023	1017	639
18	165	205	147	130	114	208	124	167	172	152	157	78	145	116	201	86	362	0	215	534	220	213	354	241
19	537	569	551	474	377	491	304	398	319	338	363	340	305	375	565	302	324	350	0	553	326	373	324	231
20	2209	1668	1498	2323	2050	2649	2243	2391	1873	1998	1798	2485	1170	2012	1834	1442	2960	2529	2056	0	1143	2204	1310	1133
21	751	748	501	606	601	835	600	816	559	615	555	484	515	318	400	527	681	415	594	990	0	542	801	545
22	687	429	407	646	317	366	577	384	520	425	430	345	474	413	547	455	389	455	449	771	365	0	444	272
23	1123	891	794	1134	779	876	504	946	750	522	589	707	388	685	1044	424	736	670	253	595	550	330	0	147
24	491	378	351	489	295	398	292	419	275	184	270	307	143	283	513	137	395	294	132	411	249	177	117	0

Table D.24: Values of KL-divergence of different clusters for modeling$\sigma_{9.21}(\mathrm{RP}_p)$ and $\sigma_{9.21}(\mathrm{RP}_d)$ during the holiday period. Note that we have divided the numbers by 100,000 for readability

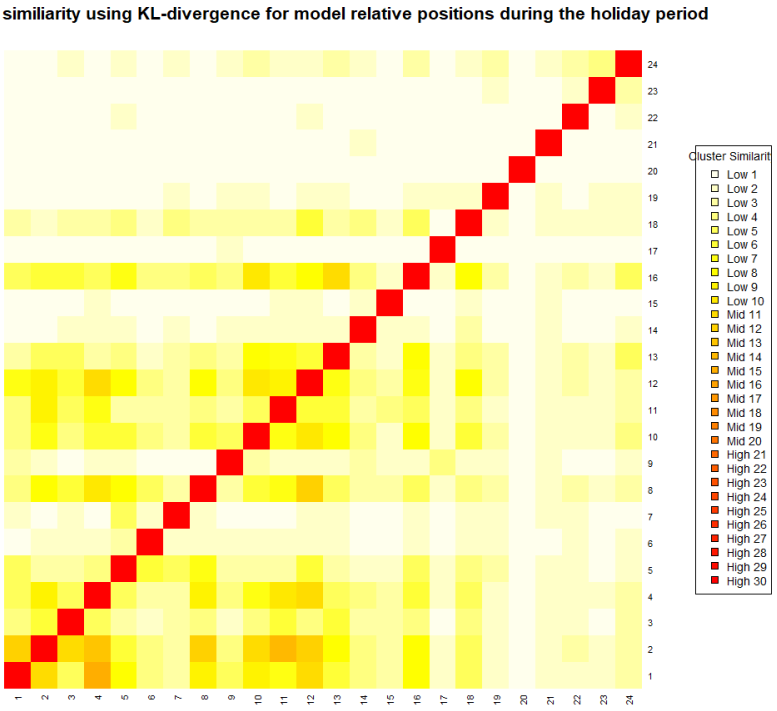

Figure D.36: Heatmap of cluster similarity based on KL-divergence values of Table D.24. The darker the color, the more clusters share similarity.

Appendix D.3.2. Parameter Estimates

In Table 9 we provide the coefficient estimates for the study variables $\sigma_{9.21}(\text{RP}_p)$ and $\sigma_{9.21}(\text{RP}_d)$ during the holiday period, while we provide in Table D.18 of Appendix D.1 the complete output tables of all coefficient estimates. We complement the results of Table 9 by means of Figures D.37 and D.38, which respectively show the statistical power of the parameter estimates, significant parameters, and marginal effects of significant parameters, all at an α-level of 5%.

Based on Figure D.37, we find that a far majority of all parameter estimates of the variable $\sigma_{9.21}(\text{RP}_p)$ are significant and contain strong statistical power. We made a similar observation when we studied the power for $\sigma_{9.21}(\text{RP}_p)$ during the regular period. Given that analysis, it is not surprising that the the statistical power of the parameter estimates for the variable $\sigma_{9.21}(\text{RP}_d)$ are much weaker, and that we find fewer parameters which are statistically significant at α-level of 5%. However, compared to the regular period, for the holiday period we observe a higher lower limit for the statistical power (compare the shop categories *DIY* and *Sound and Vision* over the two periods).

By consulting Figure D.38 and comparing these to the marginal effects of Figure D.27, we can carry over many of the observations we made in Figure D.27. For instance, for a given percentile (say the median), the marginal effects of $\sigma_{9.21}(\text{RP}_p)$ seem to be larger than those for $\sigma_{9.21}(\text{RP}_d)$ for a given cluster and shop category. Furthermore, we observe negative marginal effects for $\sigma_{9.21}(\text{RP}_p)$ over all shopping categories, which indicates unawareness for relative offer propositions. However, contrasted to Figure D.27, the boxplots of the marginal effects of $\sigma_{9.21}(\text{RP}_d)$ generally seem to be more spread out in the holiday period compared to the regular period, which indicates a wider range of effects for this variable during the holiday period.

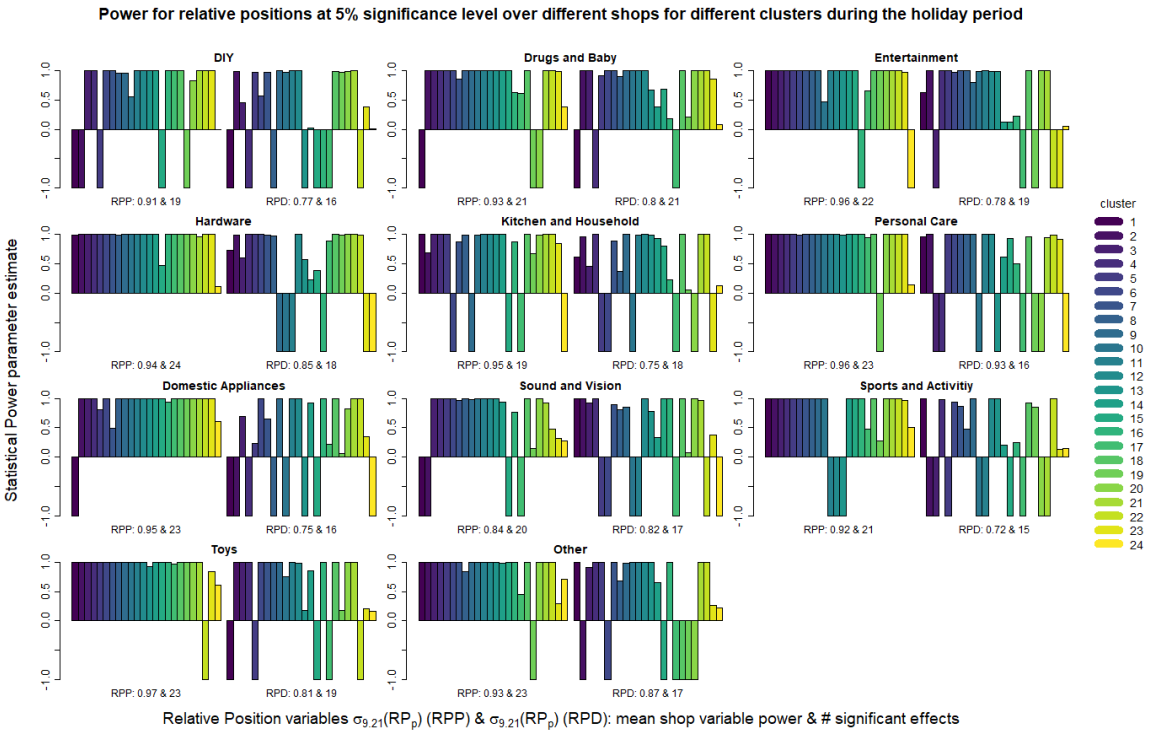

Figure D.37: Statistical power for the different parameter estimates of Table 9. A value of minus one indicates an insignificant effect at $\alpha = 0.05$. Values next to variables RPP and RPD indicate average cluster power, and the number of significant effects.

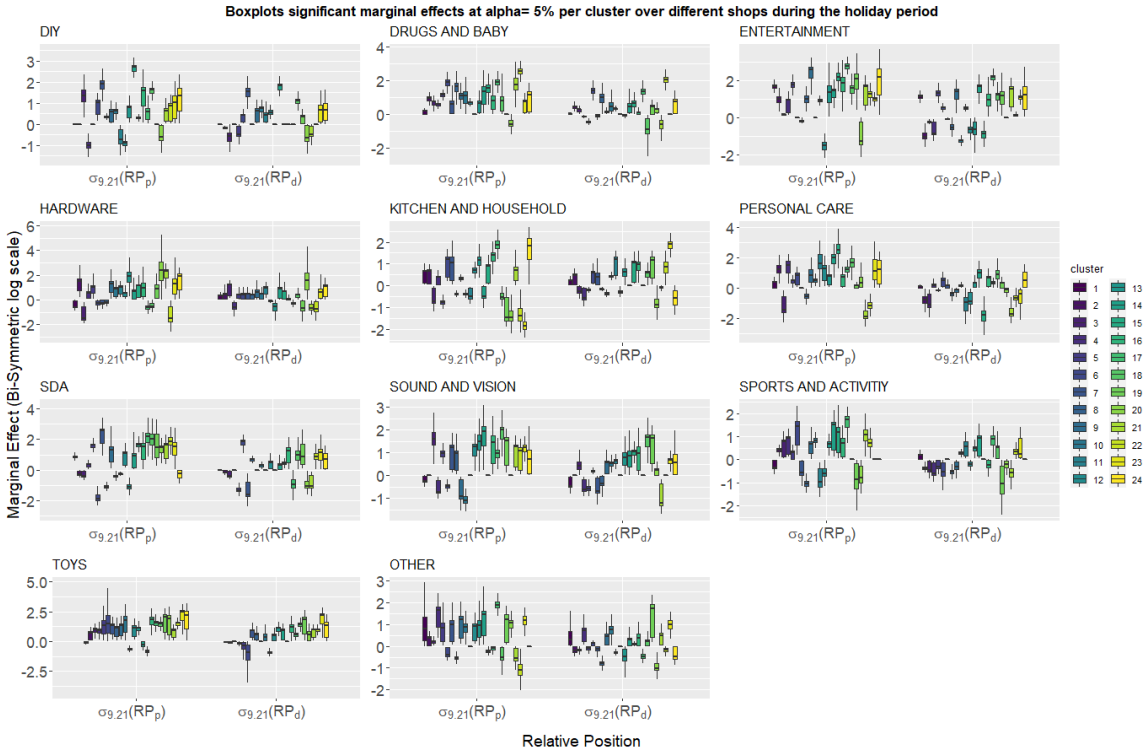

Figure D.38: Significant marginal effects using Equation C.49 in bi-symmetric log-scale (with base 10). Significance is determined at $\alpha = 0.05$.

Appendix D.3.3. Additional Plots Hypothesis Tests

Categorisation of Different Effect Types. In Figure D.39 we provide the results of the adjusted p-values of the Lepage tests for testing the location and scale between different samples for median daily product sales. Similar as for Figure D.28, we use the the median daily sales of every product. Based on this number, we consider all products with the same effect type (conditioned on shop category) belonging to the same sample.

In Figure D.39 the red colored cells indicate that at least one effect type does not exist for the shop category, which is why we cannot compute the Lepage test. Based on the results of Figure D.39. As most of the non-red colored cells are colored in dark purple, we fact reject the null hypothesis at an α-level of at 0.01%. This provides evidence that the location and/or scale of median daily sales between different effect types is statistically significant at α levels of 0.01%.

Given the results of Figure D.39, we can obtain an understanding of how the distributions of the different effect types over the different shop categories might differ by means of a consultation of Figure D.40. Considering the shown boxplots in this figure, we see that the differences between the effect types differ from shop category to shop category. For instance for the shop categories *Kitchen and Household* and *Other*, products within the effect type $\sigma_{9.21}(RP_d)$ *larger* seem to correspond to relatively more popular products, while for the shop category *Sound and Vision* it is much less clear whether this is the case.

For prices and delivery promises we have done a similar analysis which we can see by considering Figures D.41, D.42, D.43, D.44. Compared to the results on sales, we find that for prices and delivery promises there are in general no significant changes for the different effect types.

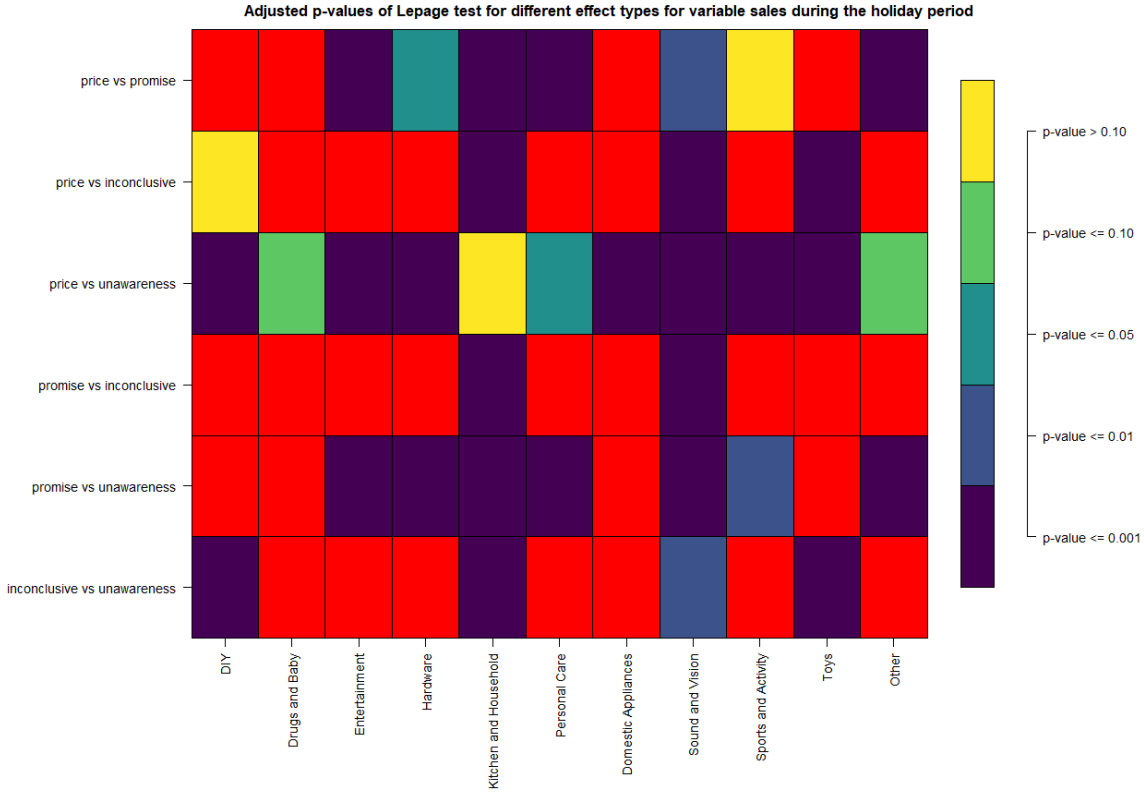

Figure D.39: Table of adjusted p-values based on Holm-procedure (Holm (1979)) for different effect type combinations. Cells in red indicate that the combination does not exist for a given shop category. The shop effects are based on the results of Figure 7.

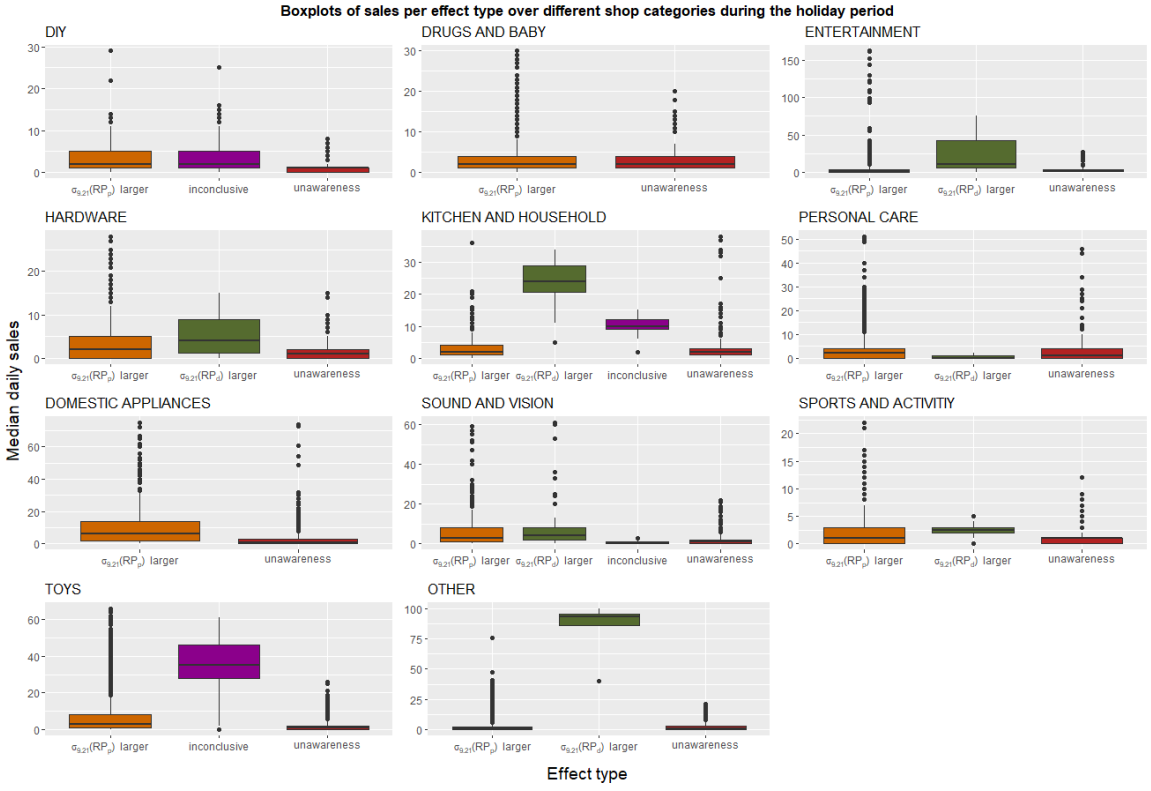

Figure D.40: Boxplots of median daily sales per product for different effect types during the holiday period

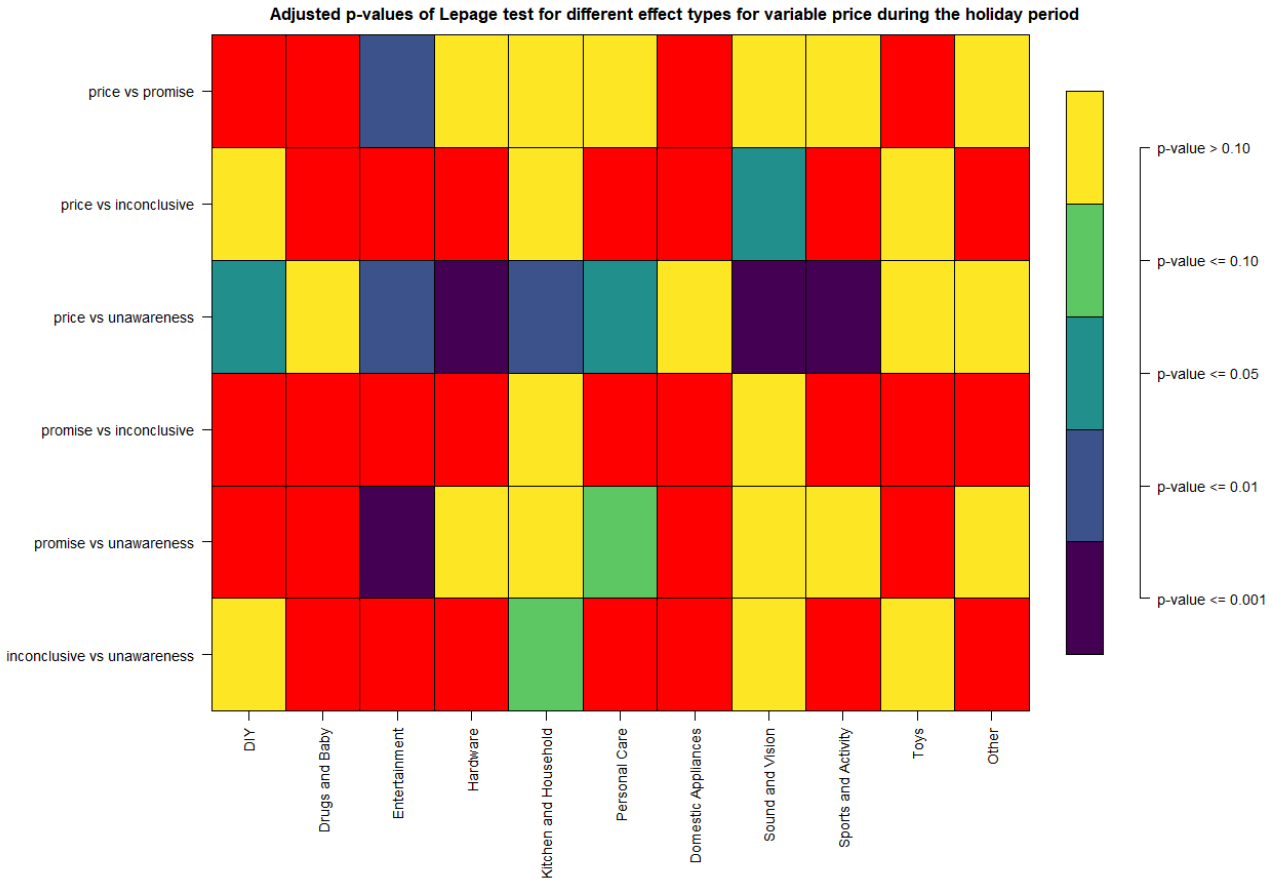

Figure D.41: Table of adjusted p-values based on Holm-procedure (Holm (1979)) for different effect type combinations. Cells in red indicate that the combination does not exist for a given shop category. The effect types are based on the results of Figure 7.

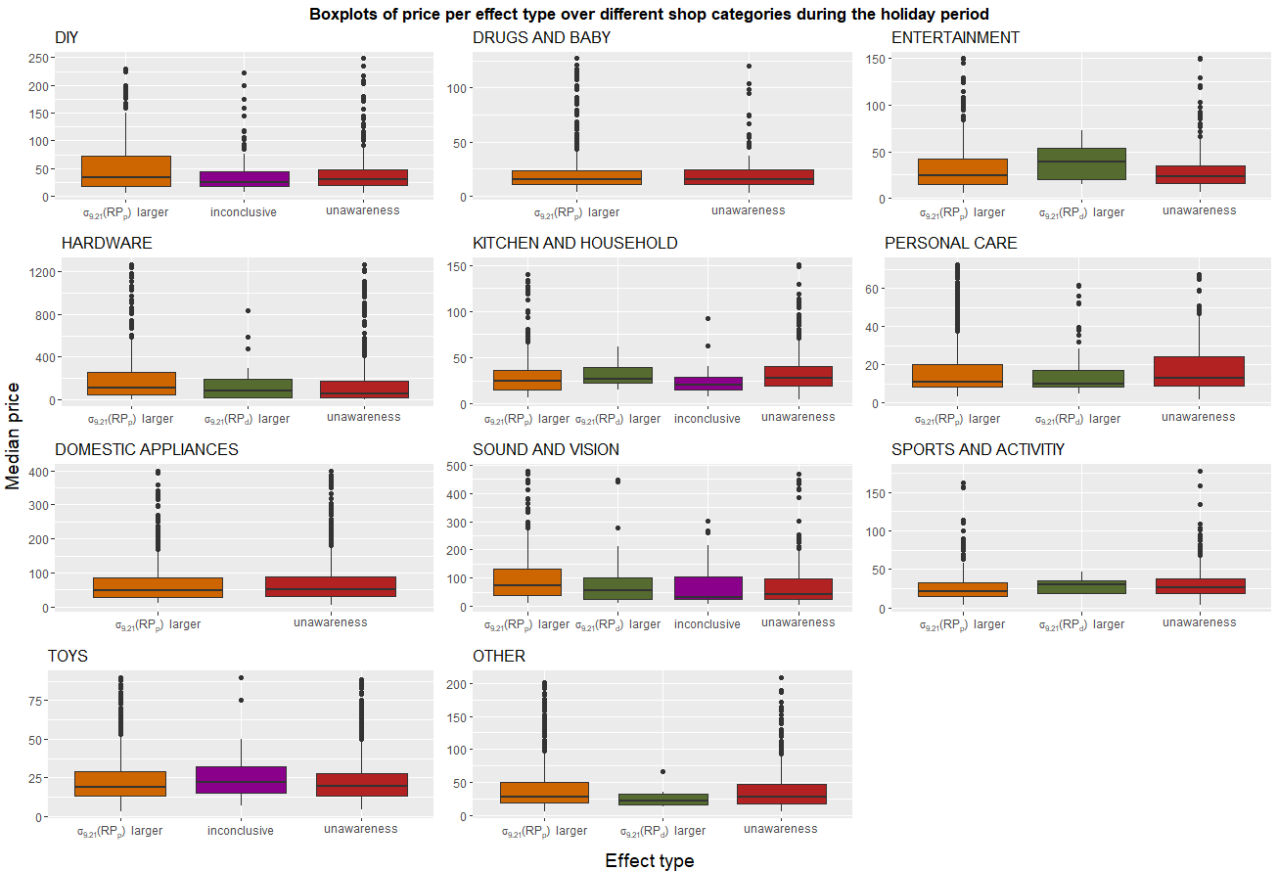
Boxplots of price per effect type over different shop categories during the holiday period
DIY
DRUGS AND BABY
ENTERTAINMENT
HARDWARE
KITCHEN AND HOUSEHOLD
PERSONAL CARE
DOMESTIC APPLIANCES
SOUND AND VISION
SPORTS AND ACTIVITIY
TOYS
OTHER
Median price
Effect type
inconclusive
unawareness
larger

Figure D.42

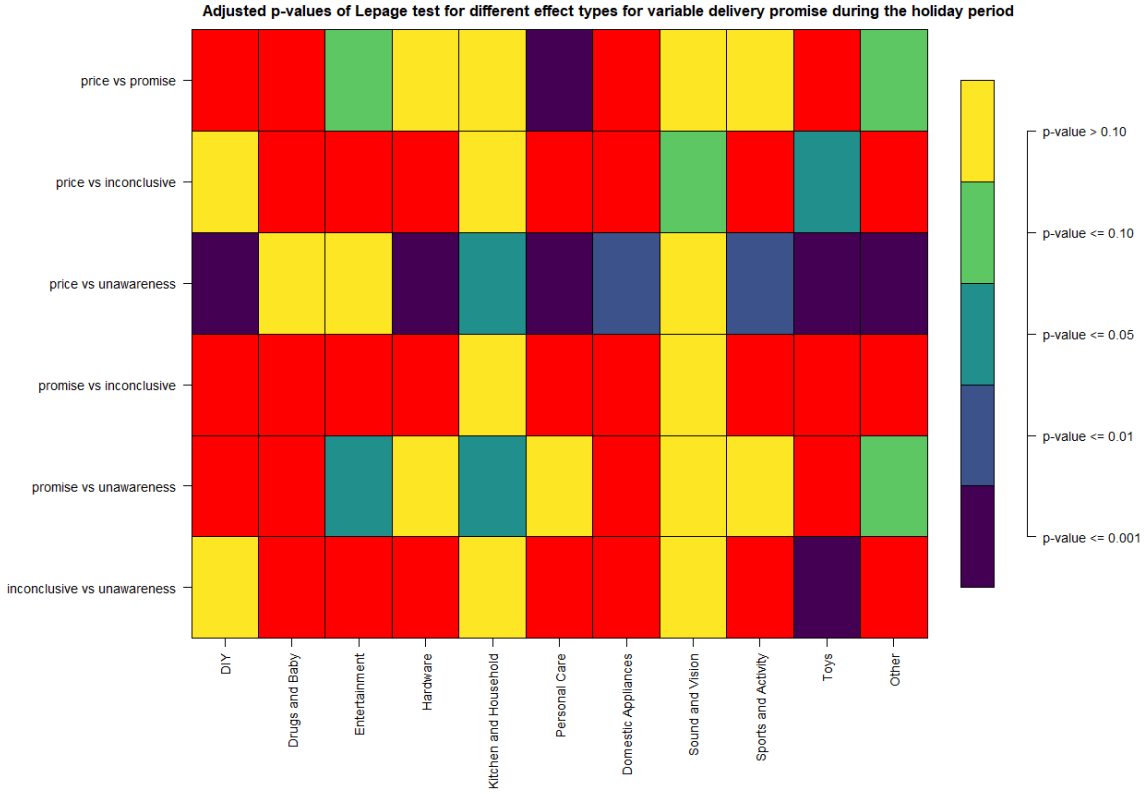

Figure D.43: Table of adjusted p-values based on Holm-procedure (Holm (1979)) for different effect type combinations. Cells in red indicate that the combination does not exist for a given shop category. The effect types are based on the results of Figure 7.

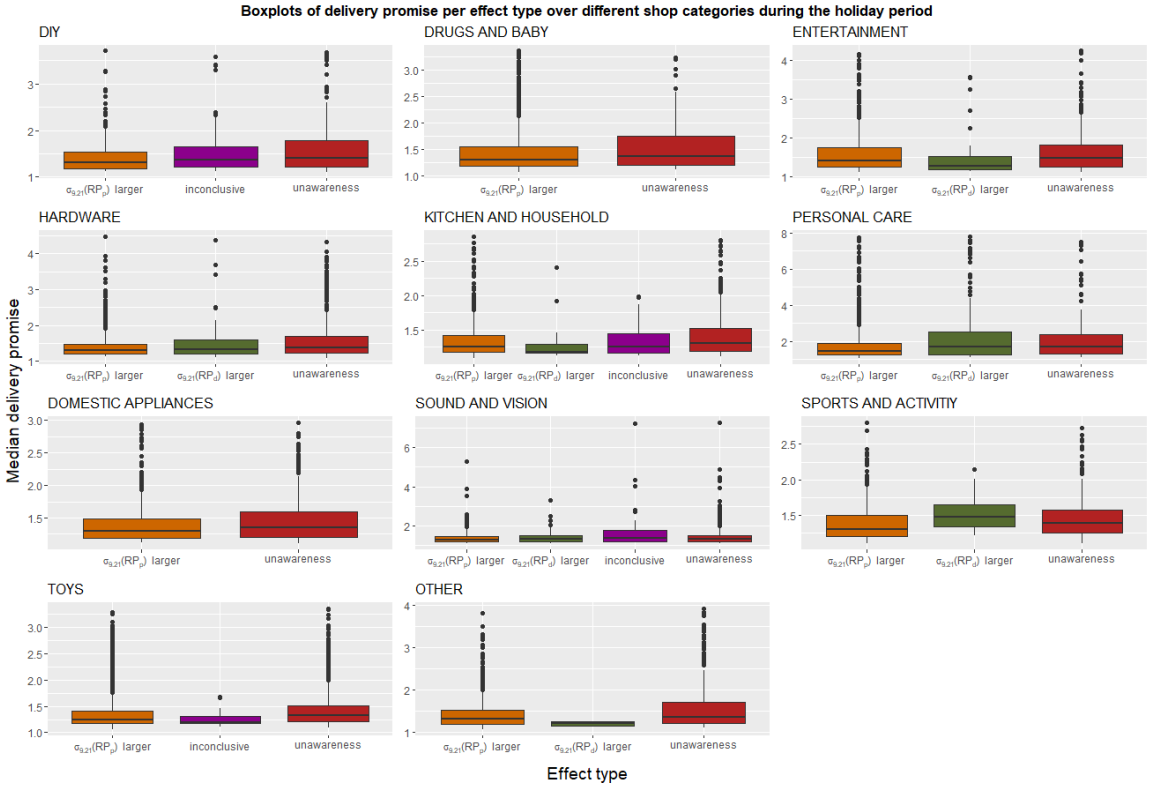

Figure D.44

Appendix D.4. RC, WTP, and UTP during Regular Period

Appendix D.4.1. Results Model Training

For training the mixture model of studying RC, WTP, and UTP during Regular Period we utilise a different strategy compared to the other model specifications. Chronologically, we have trained this model specification last. As a result, we already had some knowledge based on the other model specifications what number of mixture components could be very likely. As a result, we did not train the model with lower mixture components. In fact, we have only trained the model for 25 different components 10 times and selected verified how many clusters where above the threshold of at least 100 different products. By doing so we arrived at 24 different mixture components.

In Figures D.45 and D.46 we have plotted the posterior cluster sizes of the different cluster components. Based on Figure D.56, we see that the cluster sizes are gradually decreasing, with clusters 1 and 2 being the larges, although not by a large margin. In Figure D.46 we can see how the posterior sizes deviate from the general shape of Figure D.56. Compared to the posterior sizes of Figure D.45, we see that depending on the shop category, specific clusters are more densely populated than others. For instance, for the shop category *Toys*, we observe that cluster 2 has an posterior size of around 20%, while cluster 23 has an posterior size below 1%.

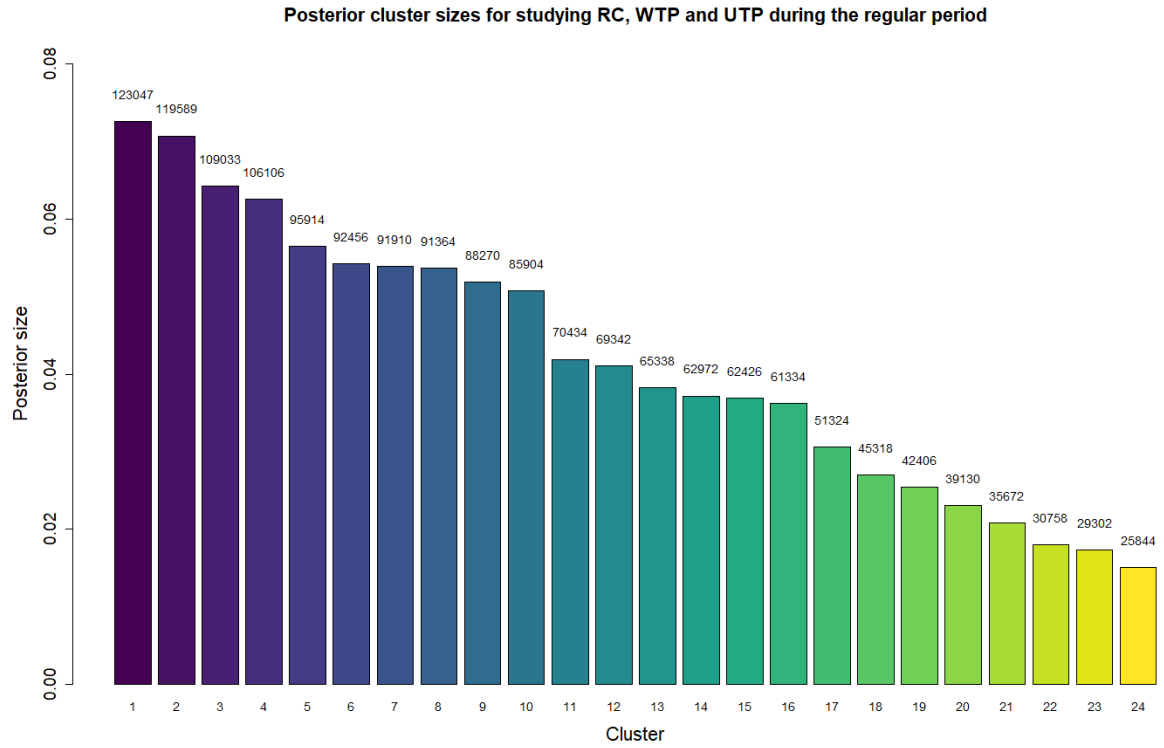

Figure D.45: Posterior cluster sizes for studying over all products. Number on the bars indicate number of observations per cluster

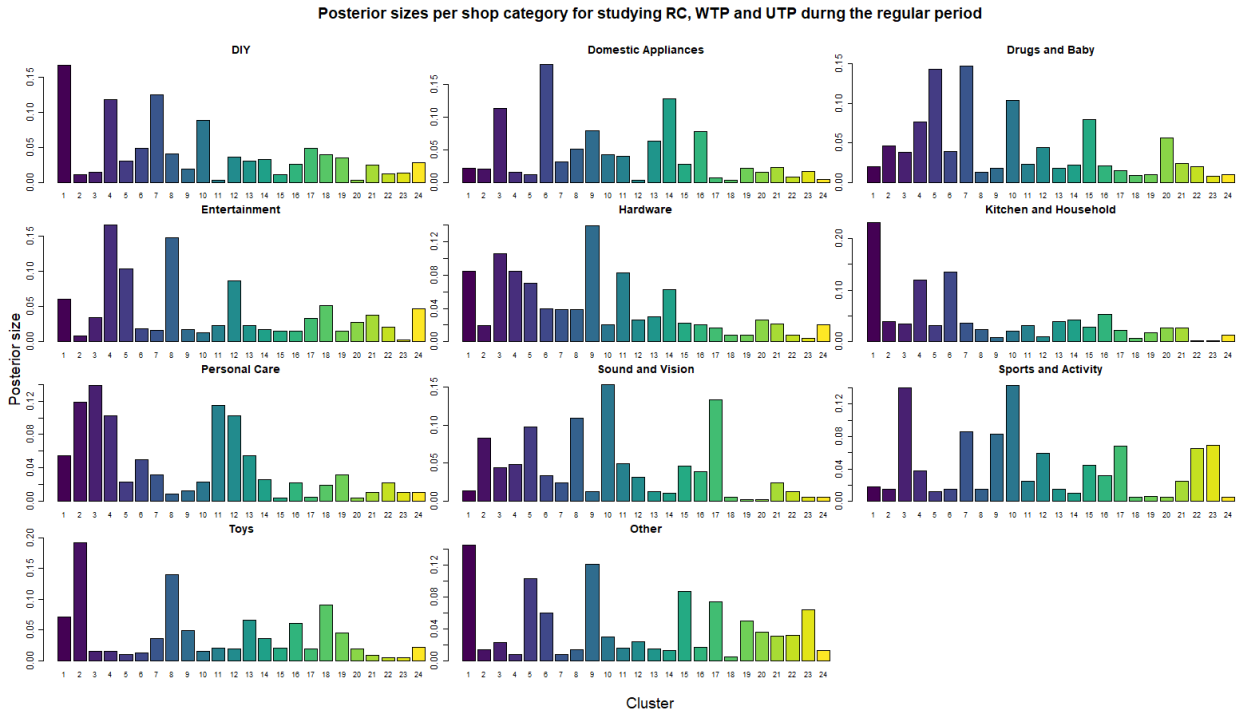

Figure D.46: Posterior cluster sizes per shop category

Cluster Similarity. In Table D.24 and Figure D.36 we depict the cluster similarity based on KL-divergence. The larger the KL-divergence the more dissimilar clusters are. Based on these results we occasionally see clusters which share similarity. For instance cluster 6 is relatively most similar to clusters 7 and 14.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	0	84	147	161	127	174	81	198	168	186	74	148	132	152	195	163	41	140	127	192	209	68	149	102
2	84	0	46	112	93	58	47	214	89	118	118	69	75	44	153	72	84	97	91	155	183	96	69	77
3	106	68	0	66	119	37	66	192	57	113	63	50	46	26	191	59	105	65	76	157	149	81	71	75
4	257	170	77	0	218	158	149	328	259	191	78	153	210	125	350	132	227	203	236	252	234	122	224	144
5	156	168	176	170	0	137	129	272	164	139	136	125	198	124	161	182	176	156	123	106	130	139	214	92
6	79	61	36	95	85	0	34	187	42	74	92	29	42	30	127	33	79	61	49	121	125	69	48	58
7	57	46	46	80	68	34	0	209	68	70	79	41	72	33	112	39	59	73	53	97	123	50	53	33
8	366	488	362	561	448	346	516	0	240	397	270	460	182	376	459	327	302	196	300	433	325	498	380	348
9	109	119	53	160	136	47	103	173	0	141	111	85	55	60	147	98	123	57	80	159	175	87	71	99
10	265	176	174	265	138	123	124	242	192	0	212	92	169	206	168	94	136	166	131	172	213	188	151	164
11	134	223	93	118	187	163	148	230	187	183	0	159	130	132	282	138	133	147	116	227	183	132	243	137
12	98	60	50	100	83	32	40	222	88	56	100	0	64	66	158	57	76	80	68	144	137	62	59	70
13	103	137	48	162	191	56	150	108	50	166	79	85	0	77	256	95	108	44	84	235	163	144	94	130
14	77	52	27	83	83	24	37	197	47	104	79	48	51	0	129	44	94	61	51	123	138	83	60	49
15	318	379	378	481	198	225	214	200	205	171	354	375	301	250	0	119	185	301	192	99	237	343	238	209
16	137	102	91	154	112	39	52	174	91	56	119	95	85	61	92	0	93	110	55	93	138	138	75	75
17	69	123	189	225	147	174	98	177	180	137	126	186	155	183	155	134	0	154	123	175	190	112	140	120
18	130	131	85	189	174	102	153	123	70	168	102	125	64	92	247	153	130	0	97	229	180	163	131	89
19	148	239	102	204	176	90	98	279	105	112	80	129	118	73	153	68	131	133	0	161	188	195	210	146
20	302	315	285	313	102	200	170	286	232	126	247	283	294	220	126	115	239	277	161	0	107	278	291	106
21	329	406	263	230	120	252	226	495	358	209	184	227	351	266	354	236	271	312	189	106	0	247	409	110
22	89	121	87	111	119	109	78	283	106	160	92	101	141	119	166	141	105	133	133	164	178	0	122	94
23	88	58	53	124	100	29	34	189	52	75	107	47	57	48	116	45	72	76	67	138	148	72	0	75
24	98	97	78	108	66	72	45	211	105	94	82	81	107	57	144	67	97	74	67	78	74	94	117	0

Table D.25: Values of KL-divergence of different clusters for modeling RC, WTP, and UTP during the regular period. Note that we have divided the numbers by 100,000 for readability

Appendix D.4.2. Parameter Estimates

In Table 10 we have provided the parameter estimates for the variables RC, WTP and UTP over the different shop categories during the regular period. Note here that the shop category *DIY* is

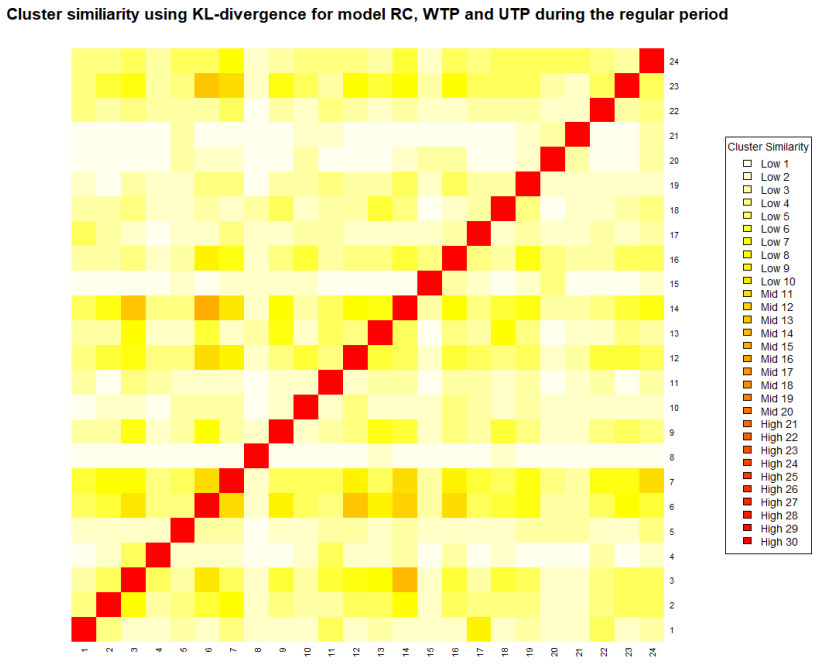

Figure D.47: Heatmap of cluster similarity based on KL-divergence values of Table D.25. The darker the color, the more clusters share similarity.

taken as a baseline. For an overview of the full model output, we refer to Table D.19 in Appendix D.1. Figure D.48 provides visual guidance in terms of visualising statistical power and parameter significance at a 1% α-level, while Figure D.49 pictures the significant marginal effects at an α-level of 1% of the different study variables over the different clusters and shop categories by means of boxplots. Recall that in Figure D.48 bars corresponding to a value of -1 indicate that the parameter estimate is insignificant at a 1% α-level, and that the marginal effects of Figure D.49 are shown in bi-symmetric log-scale.

In Figure D.48 we can see that the variable RC is significant in most clusters for all shop categories. The lowest amount of significant parameters is 17, accounting for 71% of all clusters. In addition, for all clusters in which the parameter estimates of RC are significant, the statistical power is strong as many average shop category powers are close to 1. For the variable WTP, we find that less parameters are significant at an α-level of 1%. Conditioned on a shop category, we can see that the maximum number of significant parameters for WTP is 17, which was the minimum for the variable RC. What is more, we occasionally observe only 11 significant effects, accounting for merely 46% of all clusters. However, the statistical power of the significant parameter estimates which are significant can be considered as strong, given that the average shop category power is close to 1. Moving to the results of the variable UTP, we observe that in terms of statistical significance, the results of UTP fall in between those of RC and WTP. In terms of statistical power of significant parameter estimates, the parameter estimates for the variable UTP also exhibit average shop category power levels close to 1.

By inspecting Figure D.49, we can make a couple of observations. First of all, we see observe that the boxplots are stretched out for many clusters of all shop categories. This indicates that the range

different marginal effects is large for a given group of products belonging to a cluster. Secondly, the marginal effects for RC are non-negative in a majority of the time, although we occasionally observe negative marginal effects as well. This indicates that for a majority of the products (see the posterior sizes of Figures D.45 and D.46), at least on average a rational purchase decision was made. Moving to the results for the variable WTP, we observe that for most shop categories the marginal effects are in a majority of the time negative, although for the shop categories *DIY*, *Kitchen and Household* and *Other* this claim is more nuanced. Negative marginal effects might indicate towards an unwillingness to pay more for receiving a faster delivery promise. By moving to the variable UTP, we can find more proof for this argument, as we find that many marginal effects for UTP are positive conditioned on the clusters for which the marginal effect of WTP is negative. For example, for the shop category *Toys*, we see that for most clusters for which WTP has negative marginal effects, UTP has positive marginal effects. However, this theory fails to hold for some clusters in every shop category. In some circumstances, the marginal effects of WTP are positive, while those of UTP are negative (take cluster 17 of the shop category *Sound and Vision* for example). In others, given that the marginal effects for RC are non-negative, either both WTP and UTP are positive (see cluster 20 of the shop category *Domestic Appliances*) or negative (see cluster 17 of the shop category *Toys*). The former indicates that there might be evidence for willingness to pay more for a faster delivery promise, while in the latter other purchase considerations might play a role, consumers are unaware of offer propositions of other retailers, or consumers behave irrational for other reasons. In the main text, we put these observations to the test.

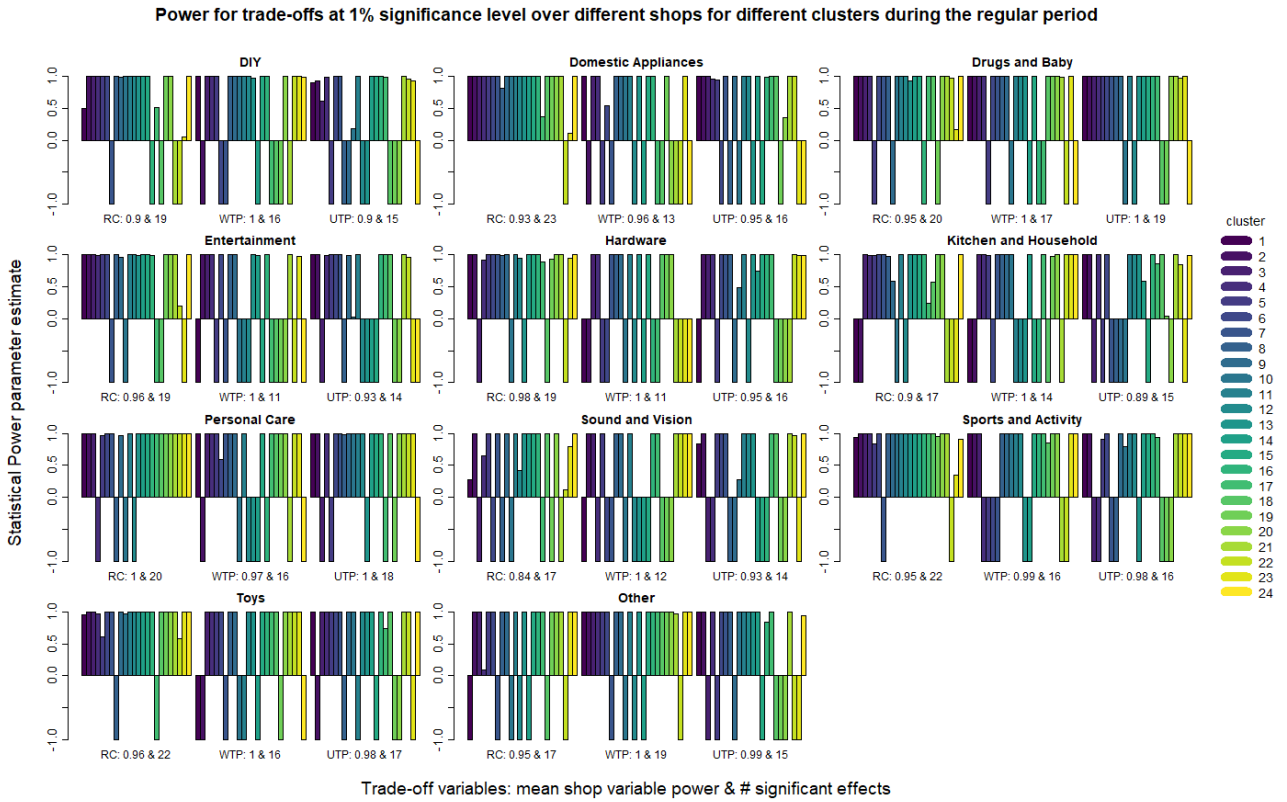

Figure D.48: Statistical power for the different parameter estimates of Table 9. A value of minus one indicates an insignificant effect at $\alpha = 0.01$. Values next to variables RC, WTP and UTP indicate average cluster power, and the number of significant effects.

Figure D.49: Significant marginal effects using Equation C.49 in bi-symmetric log-scale (with base 10). Significance is determined at $\alpha = 0.01$.

Appendix D.4.3. Additional Plots Hypothesis Tests

Categorisation of Different Effect Types. Using the results of Figure 8, we now want to determine to what extent the different effect types differ in terms of product popularity (sales), price proposition, and delivery promise proposition. Similar to the analysis of the effect types for studying $\sigma_{9.21}(\mathrm{RP}_p)$ and $\sigma_{9.21}(\mathrm{RP}_d)$, we provide the results in two steps. First, we conduct a Lepage test for different locations and/or scales for when we compare the sample distributions of two different effect types for a given variable (sales, price or delivery promise), see Lepage (1971), and adjust for FWER using holm-procedure. Given these results, we use boxplots to visualise possible difference in terms of one of these variables.

In Figure D.50 we can find the results of the Lepage tests for the median daily sales. Note here that we have in total 28 possible comparisons per shop category. Also note that we have added one additional effect type (*irrational*) compared to the shown effect types of Figure 8. This is the effect type which categorises all products for which the parameter estimates of RC are significantly negative. Recall that we color a cell in red in case a test cannot be performed. For the cells which are not colored in red, we find that for most shop categories, the null hypothesis is rejected for an α-level of at least 5%. However, for the shop categories *DIY* and *Sound and Vision* we fail to reject the null hypothesis for a majority of the comparisons.

Using the results of Figure D.50 and moving to Figure D.51, we can see how the different effect types differ in terms of product popularity. The interpretation of this figure depends on the shop category we are conditioning on. For instance, for the shop category *DIY* the spread of effect type *Weak WTP* is not that different to that of the other effect types (except *other effect (positive)*), while for the shop category *Personal Care* this effect type seems to correspond to products with higher median daily sales.

For prices and delivery promises we have done a similar analysis which we can see by considering Figures D.52, D.53, D.54, D.55. Compared to the results on sales, we find that for prices and delivery promises there are in general no significant changes for the different effect types.

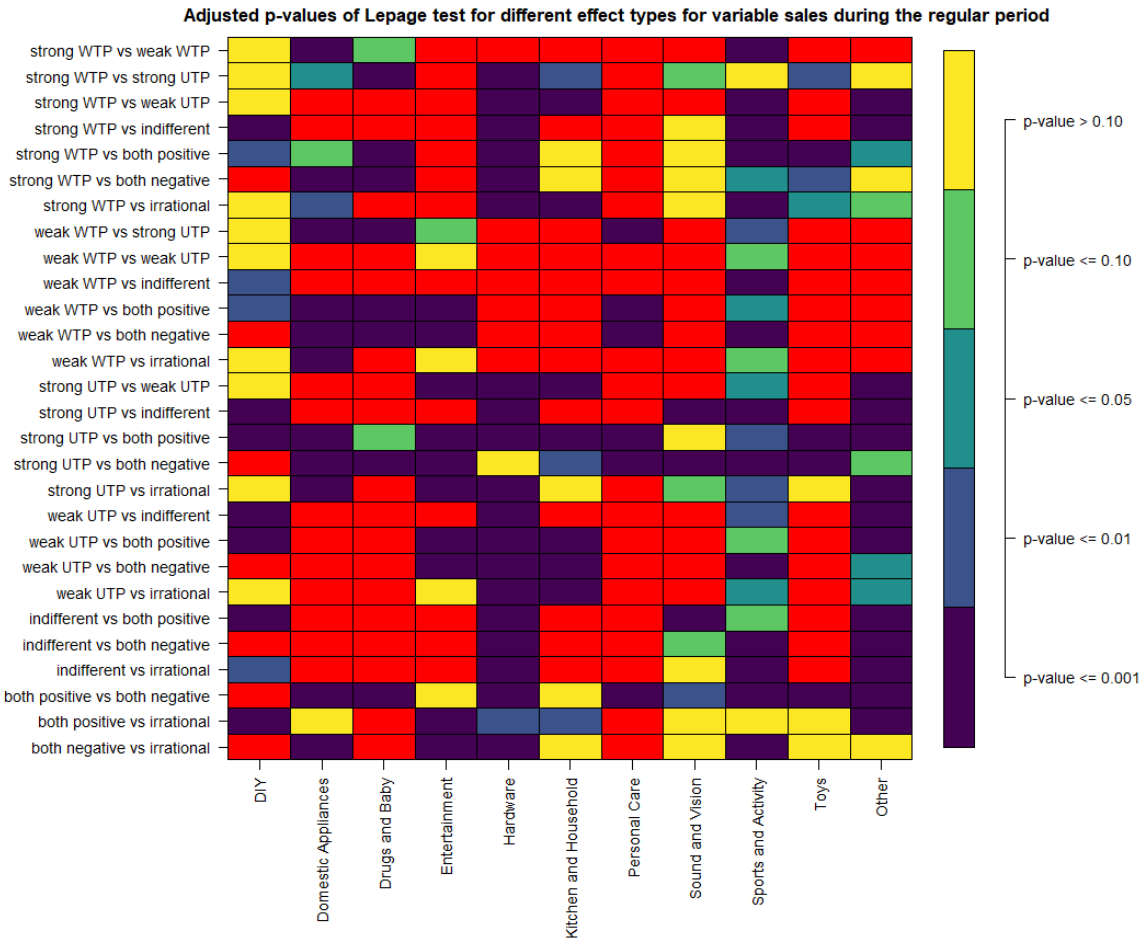

Figure D.50: Table of adjusted p-values based on Holm-procedure (Holm (1979)) for different effect type combinations. Cells in red indicate that the combination does not exist for a given shop category. The effect types are based on the results of Figure 8.

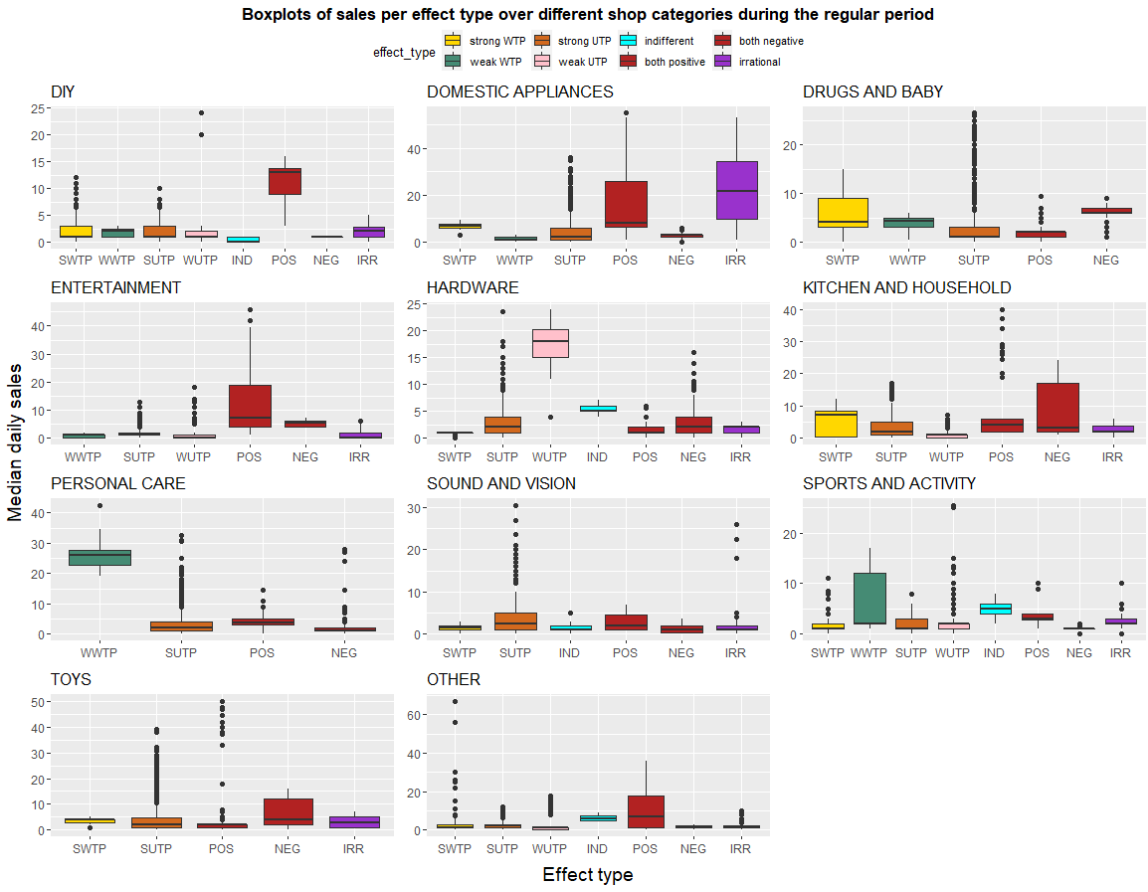

Figure D.51: Boxplots of median daily sales per product for different effect types during the regular period

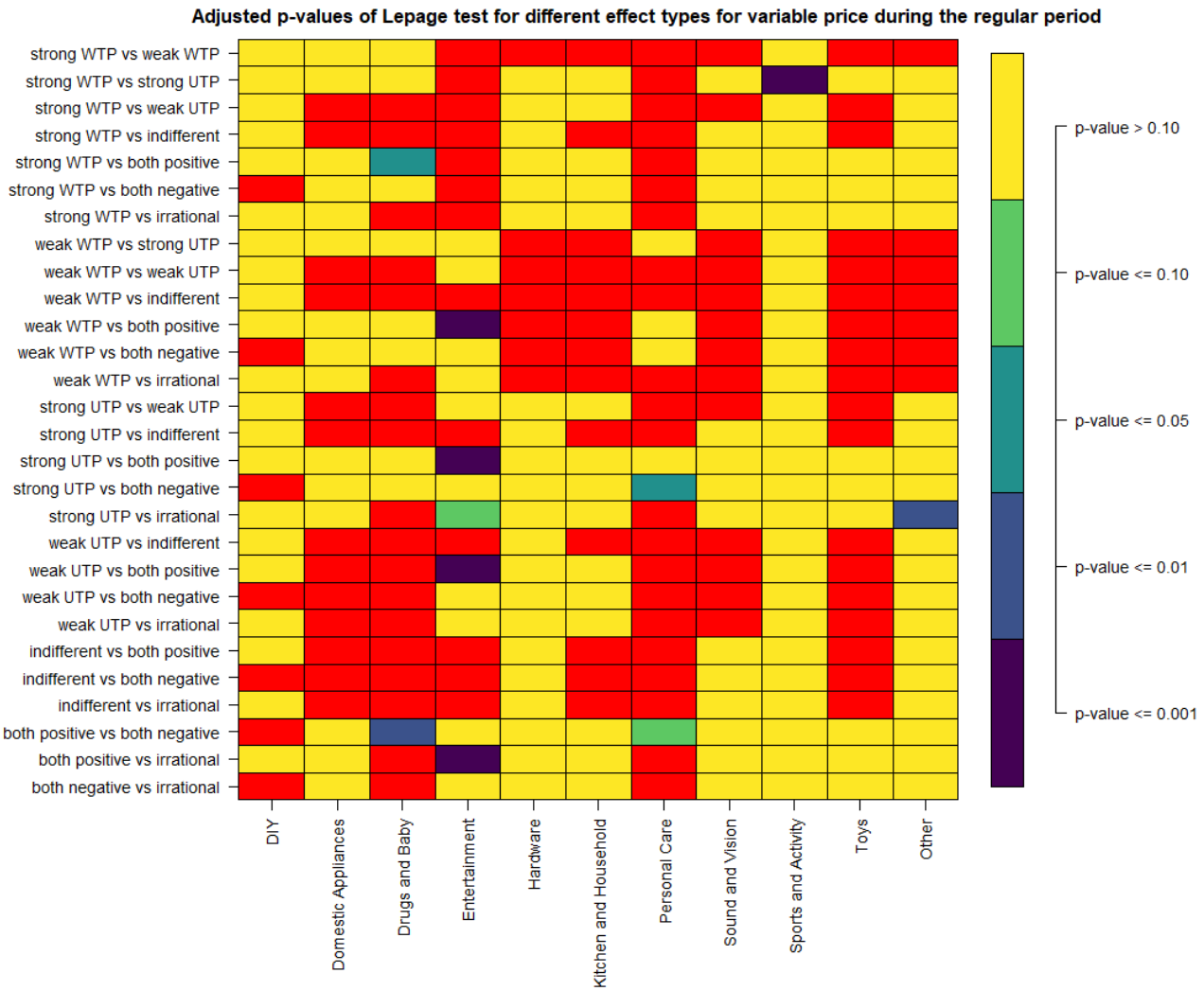

Figure D.52: Table of adjusted p-values based on Holm-procedure (Holm (1979)) for different effect type combinations. Cells in red indicate that the combination does not exist for a given shop category. The effect types are based on the results of Figure 8.

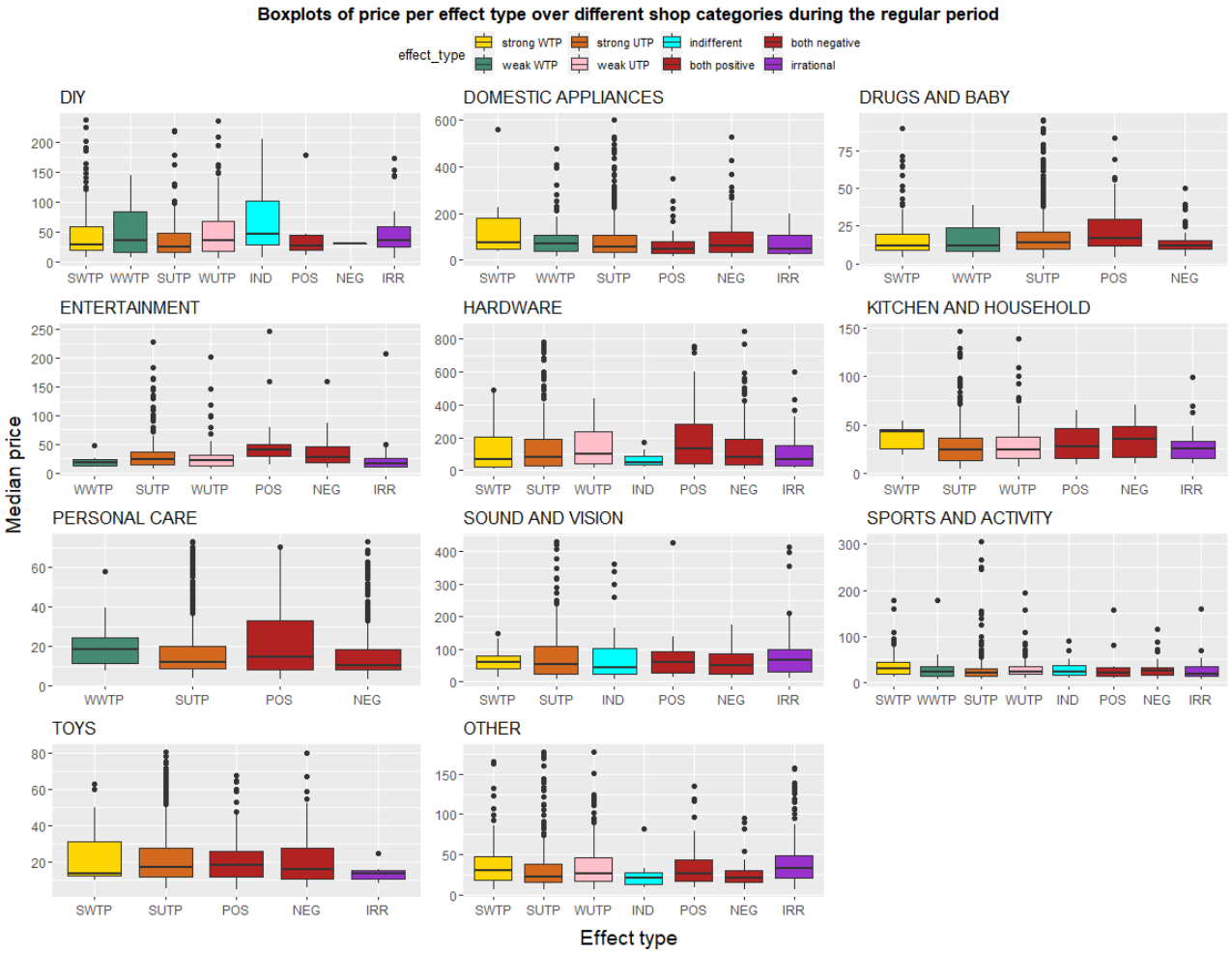
Boxplots of price per effect type over different shop categories during the regular period
effect_type
strong WTP
weak WTP
strong UTP
weak UTP
indifferent
both positive
both negative
irrational
DIY
DOMESTIC APPLIANCES
DRUGS AND BABY
ENTERTAINMENT
HARDWARE
KITCHEN AND HOUSEHOLD
PERSONAL CARE
SOUND AND VISION
SPORTS AND ACTIVITY
TOYS
OTHER
Median price
Effect type

Figure D.53

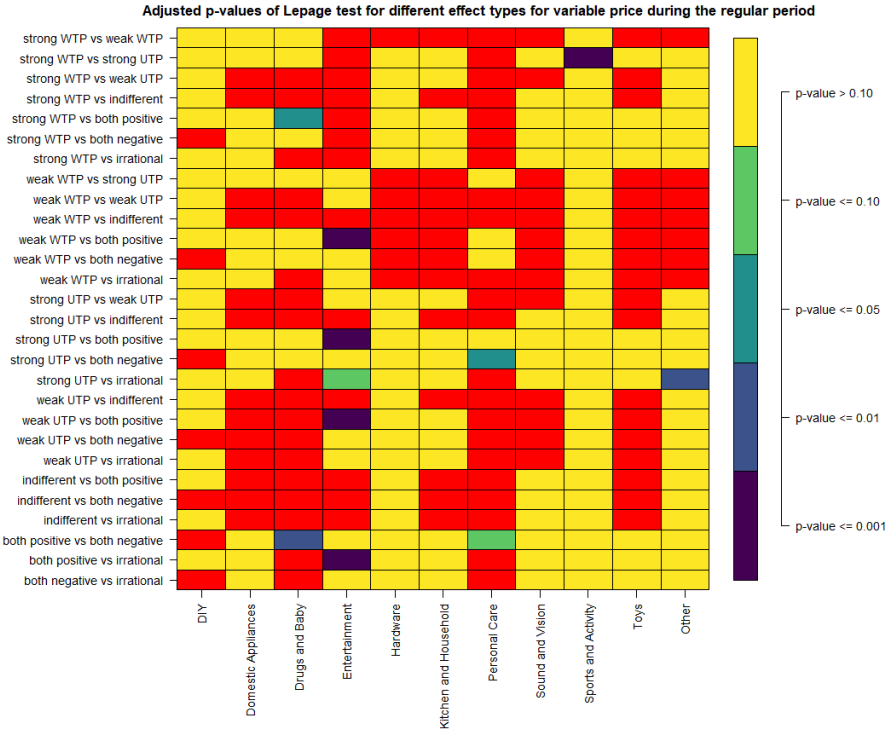

Figure D.54: Table of adjusted p-values based on Holm-procedure (Holm (1979)) for different effect type combinations. Cells in red indicate that the combination does not exist for a given shop category. The effect types are based on the results of Figure 8.

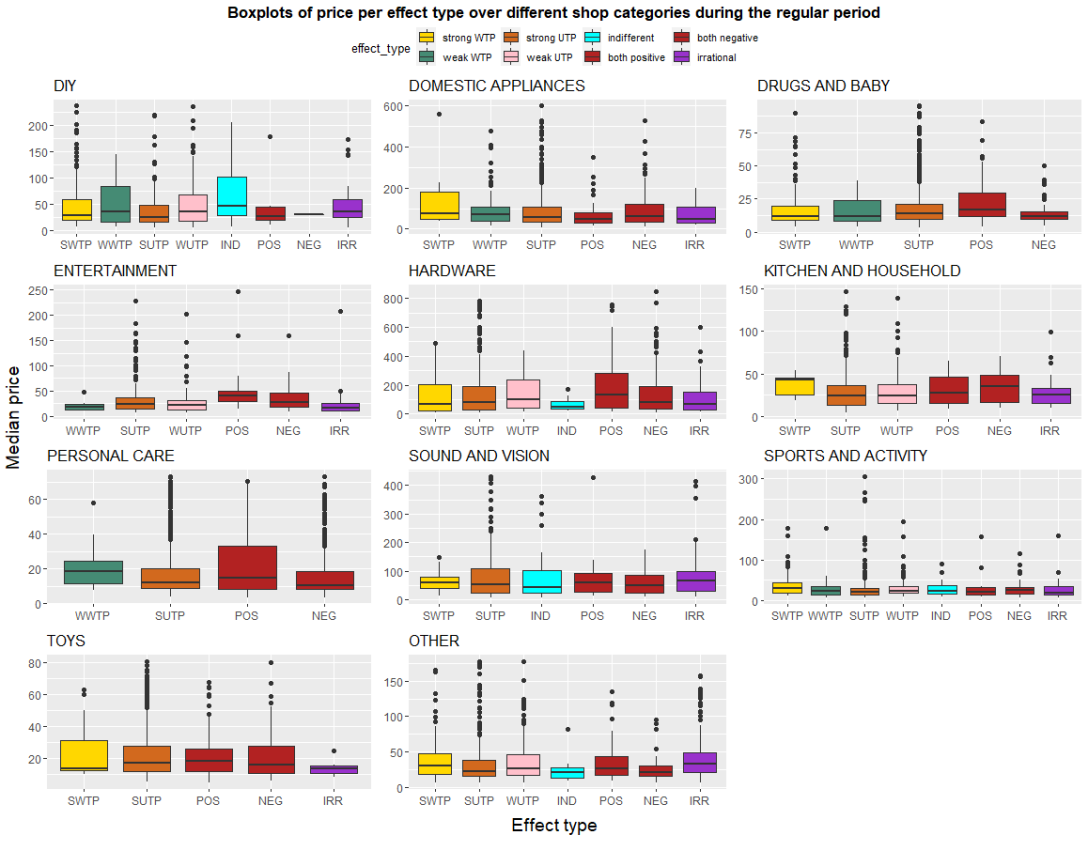

Figure D.55

Appendix D.5. RC, WTP, and UTP during Holiday Period

Appendix D.5.1. Results Model Training

In Table D.26 we have provided the results of the model training of studying RC, WTP and UTP during the Holiday Period. Recalling the explanation of the previous modeling tables, and relating that explanation to the results to this table, we find that up to and including 20 clusters we have no problems of fitting at least 1% of all products per cluster. For mixtures with 22 and 25 different components, we see that some clusters fail to capture at least 1% of all products. Given that the selection criteria are only increasing for mixtures with more clusters, we therefore decide to select the model configuration with 20 different components.

#S start	#S above threshold	log likelihood	AIC	CAIC	AWE	BIC	CLC	NEC	ICL-BIC
5	5	-3707749.41	7416056.81	14835066.45	14839414.26	7419288.63	7429892.25	**0.001**	7433682.07
10	10	-3469713.36	6940544.72	13887005.67	13895716.89	6947019.94	7018848.59	0.01	7026441.82
15	15	-3387747.51	6777173.02	13563225.66	13576300.29	6786891.64	6906051.61	0.01	6917448.23
16	16	-3372392.41	6746574.83	13502621.96	13516569.26	6756942.13	6885826.06	0.01	6897983.36
17	17	-3360012.92	6721927.84	13453920.67	13468740.65	6732943.83	6866062.97	0.01	6878980.95
18	18	-3354042.11	6710098.23	13430854.12	13446546.79	6721762.89	6875498.90	0.01	6889177.56
19	19	-3347276.08	6696678.16	13404606.66	13421172.01	6708991.50	6849249.16	0.01	6863688.50
20	**20**	-3336254.53	6674747.06	13361337.14	13378775.16	6687709.08	6844680.65	0.02	6859880.67
22	20	**-3333831.31**	**6669900.61**	**13351644.25**	**13369082.27**	**6682862.64**	**6841875**	0.02	**6857075.05**
25	20	-3340463.67	6683165.34	13378173.70	13395611.72	6696127.36	6850480.43	0.02	6865680.45

Table D.26: Results for modelling RC, WTP and UTP during the holiday period.
Gold: selected cluster size
Gray: best solution for selection criterion
Red: Contains segments below threshold of 1%

In Figures D.56 and D.57 we have depicted the posterior cluster sizes of the different cluster components (recall that we relabel the clusters based on posterior size). Based on Figure D.56, we see that three clusters stand out above all other clusters. Additionally, from the fourth cluster onwards, the posterior size decreases gradually as we move to the right of the plot. In Figure D.57 we can see how the posterior sizes deviate from the general shape of Figure D.56. These results are in line with those we have obtained for the previously explained models.

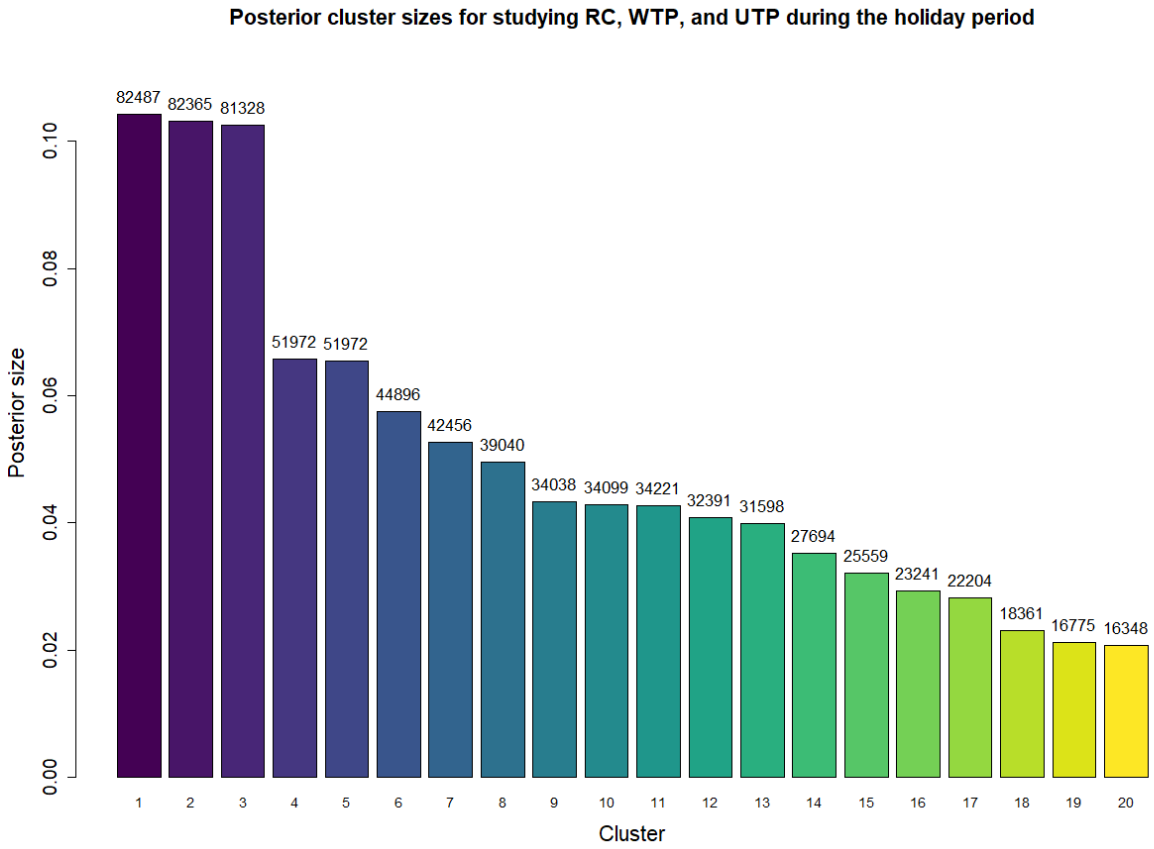

Figure D.56: Posterior cluster sizes for studying over all products. Number on the bars indicate number of observations per cluster

Figure D.57: Posterior cluster sizes per shop category

Cluster Similarity. In Table D.24 and Figure D.36 we depict the cluster similarity based on KL-divergence. The larger the KL-divergence the more dissimilar clusters are. Based on these results we can for example see that clusters 3 and 4 are relatively most similar, while cluster 20 is most dissimilar from all other clusters.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0	68	63	49	118	104	137	68	327	61	105	211	410	109	93	146	181	156	119	370
2	40	0	32	30	58	134	123	40	300	61	176	163	323	63	141	82	107	103	88	362
3	47	25	0	41	44	144	125	67	293	61	148	132	319	73	138	84	100	103	111	344
4	52	39	48	0	75	116	106	31	318	58	166	165	318	56	110	88	131	110	118	379
5	122	86	64	130	0	220	154	113	289	104	193	140	336	75	216	97	116	167	130	279
6	216	457	430	284	480	0	178	332	525	225	208	501	745	372	232	504	570	358	344	539
7	246	281	270	193	183	159	0	145	318	101	349	124	300	104	201	184	107	110	202	254
8	85	65	128	41	91	133	114	0	346	114	235	205	344	93	163	120	151	148	143	391
9	848	953	1187	1022	739	660	557	738	0	1027	760	538	599	584	695	449	918	908	317	478
10	90	106	98	57	113	127	85	80	307	0	186	147	318	64	83	119	120	83	133	336
11	173	532	404	337	595	295	477	443	746	302	0	562	972	512	240	667	707	534	425	551
12	443	367	267	266	222	417	202	298	432	238	366	0	269	184	318	271	187	133	281	249
13	1172	981	781	719	544	983	332	731	746	547	1008	218	0	401	407	517	598	222	765	276
14	177	125	131	74	71	214	84	98	263	68	258	102	238	0	140	57	106	104	124	326
15	167	307	258	175	322	199	210	234	473	108	194	326	478	205	0	346	378	226	240	416
16	192	146	148	126	63	248	136	129	214	116	258	144	289	56	178	0	143	168	148	387
17	257	302	317	247	186	192	85	159	403	136	411	153	457	151	320	218	0	134	248	306
18	287	224	188	154	134	272	78	151	368	86	341	79	168	85	131	148	117	0	212	235
19	226	196	340	252	247	225	205	193	290	263	307	213	384	136	279	208	260	250	0	247
20	976	981	969	1081	538	848	583	841	615	832	778	407	618	607	839	731	683	685	479	0

Table D.27: Values of KL-divergence of different clusters for modeling RC, WTP, and UTP during the holiday period. Note that we have divided the numbers by 100,000 for readability

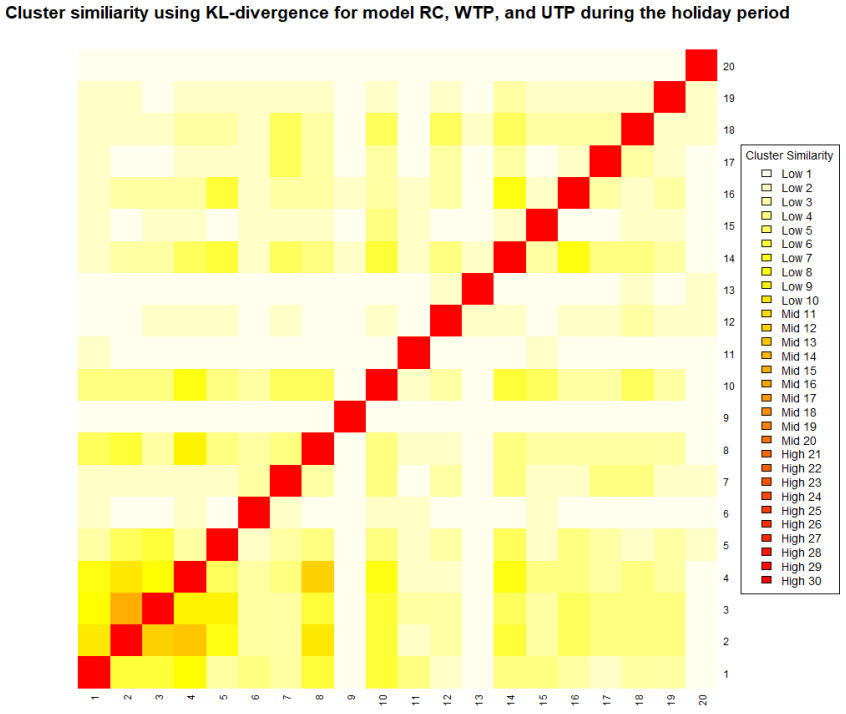

Figure D.58: Heatmap of cluster similarity based on KL-divergence values of Table D.27. The darker the color, the more clusters share similarity.

Appendix D.5.2. Parameter Estimates

In Table 11 we present the coefficient estimates of the study variables RC, WTP and RC for the different shop categories during the holiday period, which we complement with the visual aid of Figures D.60 and D.59. For an complete overview of all parameter estimates of this model specification we refer to Table D.20 in Appendix D.1. In these two figures the statistical power and significant marginal effects are respectively shown, both at an α-level of 1%. By inspecting Figure D.60 we see that a majority of all parameter estimates are statistically significant over all shop categories. For the variable RC we overall observe the most significant parameters, while for the variables WTP and UTP we observe slightly less significant parameter estimates in general. In terms of statistical power of the significant parameters, we find the average shop category cluster power is at least 0.81. With respect to the individual clusters, we find that most powers are above 0.8, with occasional powers below this value. For instance for the study variable RC in the shop category *DIY* we find three clusters which have powers below 0.8, varying from powers close to 0.5 (cluster 1) to clusters with power levels close to 0 (cluster 20). Comparing the results of D.60 to the statistical powers of the same variables during the regular period, we should note that the overall statistical power for the holiday period is a couple of percentage points lower contrasted to the regular period.

Given the statistical powers of Figure D.60, let us next consider the significant marginal effects of Figure D.59 for the study variables RC, WTP and UTP. Using the same view as we did for analysing the marginal effects of these variables during the regular period, we can observe both similarities and differences between the two periods. In terms of similarities, we see that a majority of the boxplots are wide, indicating a large range of marginal effects. Additionally, we see that most marginal effects for the variable RC are non-negative, although we also have at least one cluster with negative marginal effects for this variable in every shop category. Furthermore, by comparing the marginal effects of WTP and UTP per cluster and shop category, at a first glance we find that most marginal effects of WTP and UTP have opposite signs. This indicates that we observe behaviour which falls in the theoretical framework we want to study. Compared to the marginal effects of the regular period, we observe relatively more cases in which WTP has non-negative marginal effects, conditioned on clusters with non-positive effects of UTP in a majority of the shop categories. This might indicate that there is more willingness to pay more for receiving a faster delivery promise during the holiday period contrasted to the regular period. However, by more critically assessing the marginal effects, we also observe relatively more cases in which both variables share the same sign. This could indicate that consumers consider other purchase considerations, are less aware product offers of other retailers, or behave irrational for other reasons during the holiday period compared to the regular period. In the main text we more formally test these observations.

Figure D.59: Significant marginal effects using Equation C.49 in bi-symmetric log-scale (with base 10). Significance is determined at $\alpha = 0.01$.

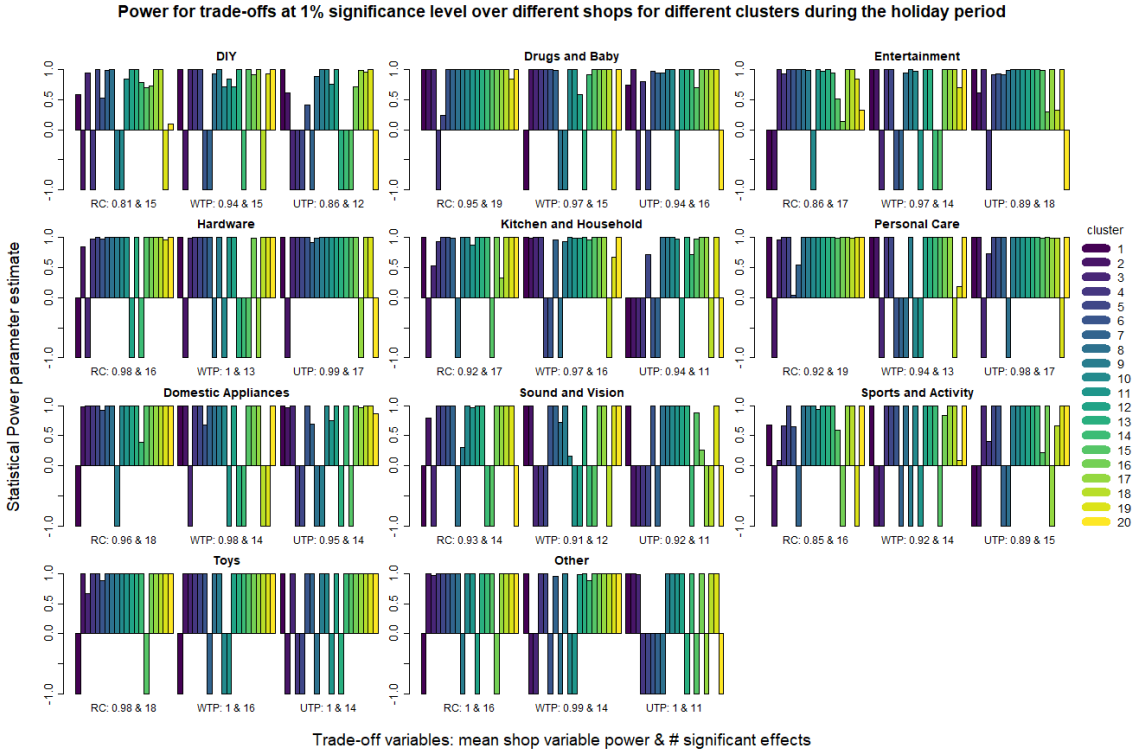

Figure D.60: Statistical power for the different parameter estimates of Table 11. A value of minus one indicates an insignificant effect at $\alpha = 0.01$. Values next to variables RC, WTP, and UTP indicate average cluster power and the number of significant effects.

Appendix D.5.3. Additional Plots Hypothesis Tests

Based on the effect types of Figure 9, we can determine to what extent the different effect types differ in terms of product popularity by consulting Figures D.61 and D.62. Given the results of Figure D.61 we see that for all combinations which we can test, we reject the null hypothesis for a large majority of possible combinations at a significance level of 0.1%. In Figure D.62 we find that the differences based on product popularity over the different effect types seem to differ from shop category to shop category. For instance, for the shop category *DIY* we find significant differences between the effect types *strong WTP* and *weak WTP*, while for the shop category *Domestic Appliances this is not the case*.

For prices and delivery promises we have done a similar analysis which we can see by considering Figures D.63, D.64, D.65, D.66. Compared to the results on sales, we find that for prices and delivery promises there are in general no significant changes for the different effect types.

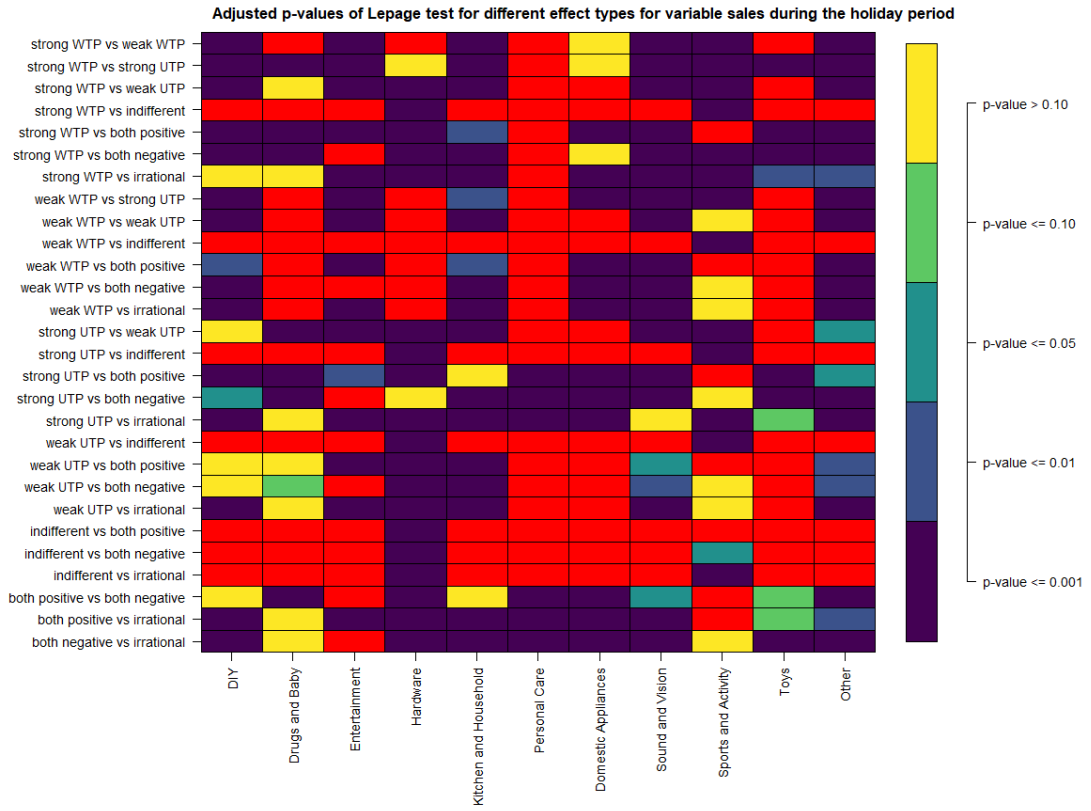

Figure D.61: Table of adjusted p-values based on Holm-procedure (Holm (1979)) for different effect type combinations. Cells in red indicate that the combination does not exist for a given shop category. The effect types are based on the results of Figure 9.

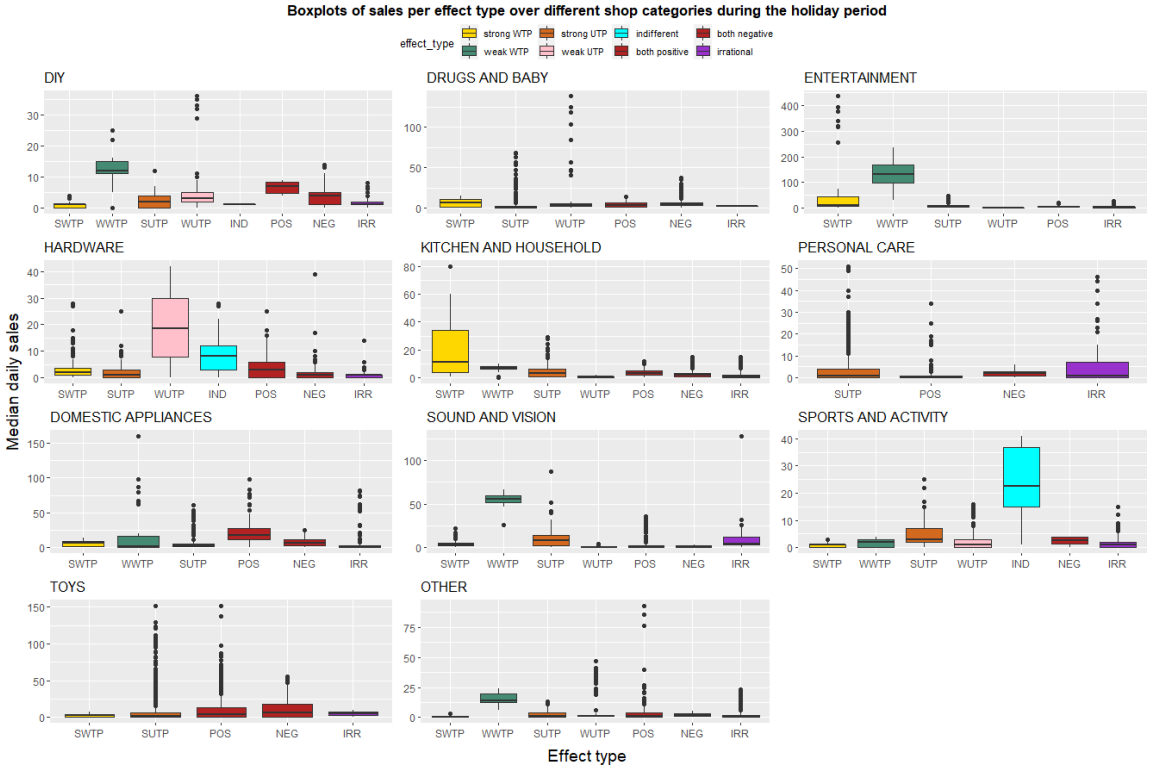

Figure D.62: Boxplots of median daily sales per product for different effect types during the holiday period

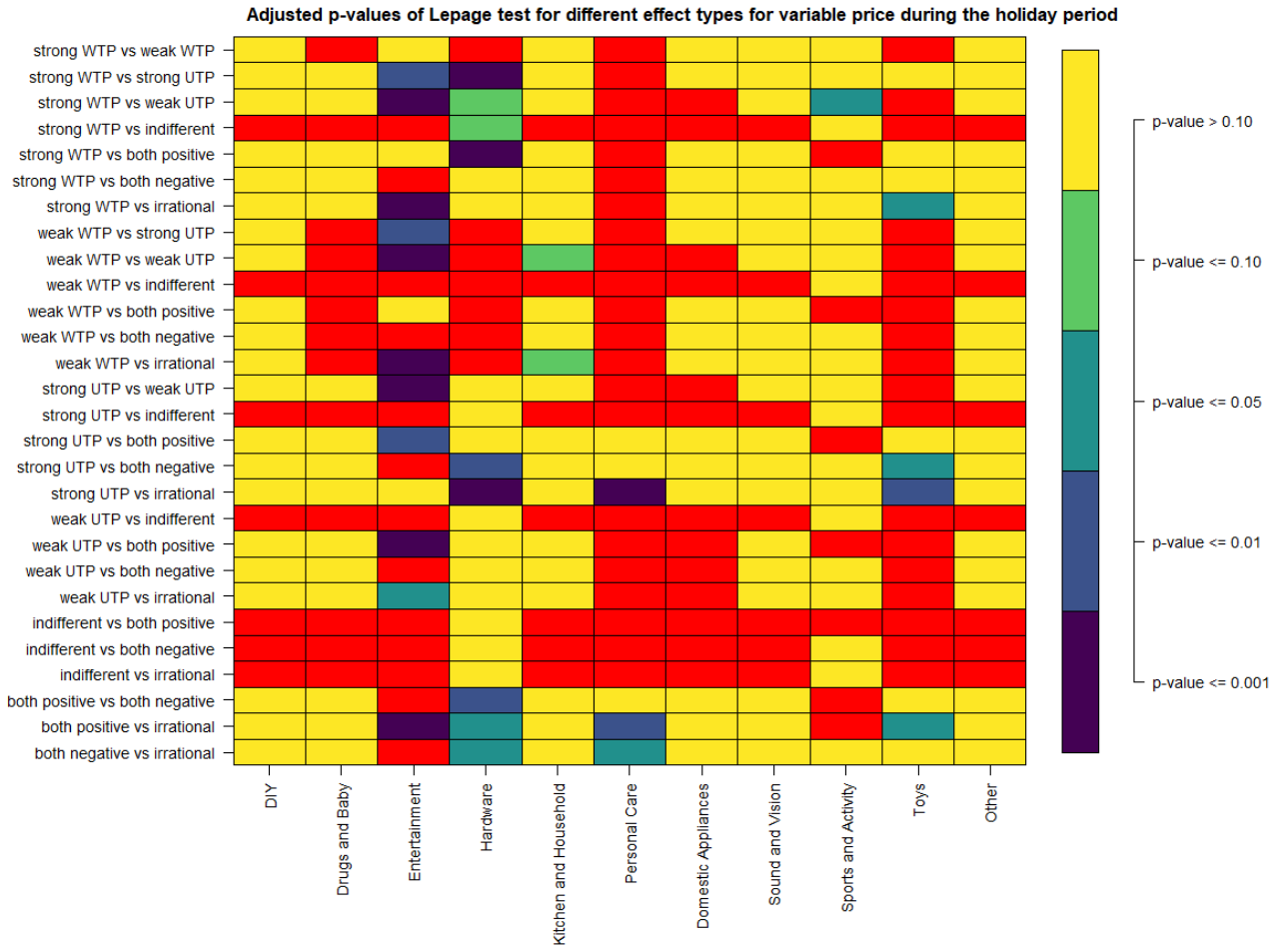

Figure D.63: Table of adjusted p-values based on Holm-procedure (Holm (1979)) for different effect type combinations. Cells in red indicate that the combination does not exist for a given shop category. The effect types are based on the results of Figure 9.

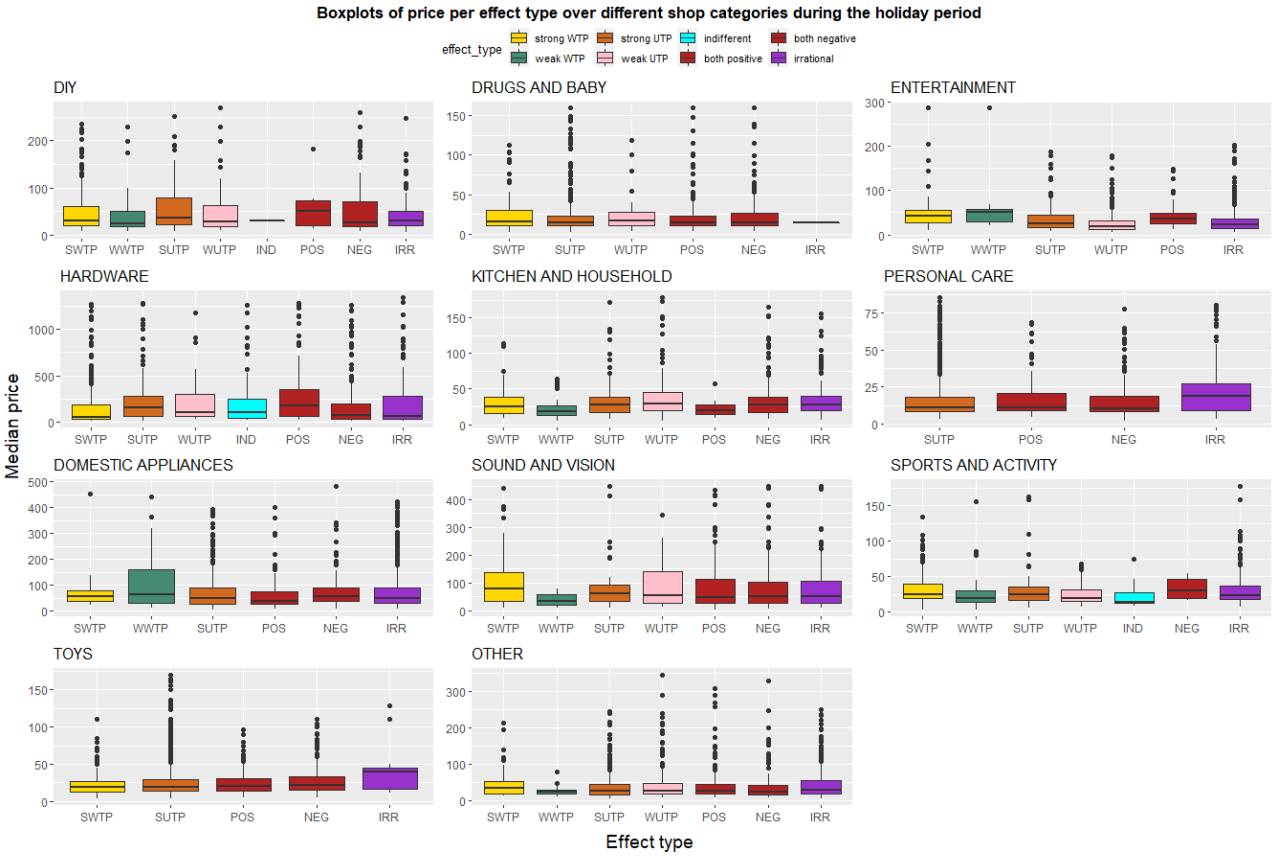
Boxplots of price per effect type over different shop categories during the holiday period
effect_type
strong WTP
weak WTP
strong UTP
weak UTP
indifferent
both positive
both negative
irrational
DIY
DRUGS AND BABY
ENTERTAINMENT
HARDWARE
KITCHEN AND HOUSEHOLD
PERSONAL CARE
DOMESTIC APPLIANCES
SOUND AND VISION
SPORTS AND ACTIVITY
TOYS
OTHER
Median price
Effect type
SWTP
WWTP
SUTP
WUTP
IND
POS
NEG
IRR

Figure D.64

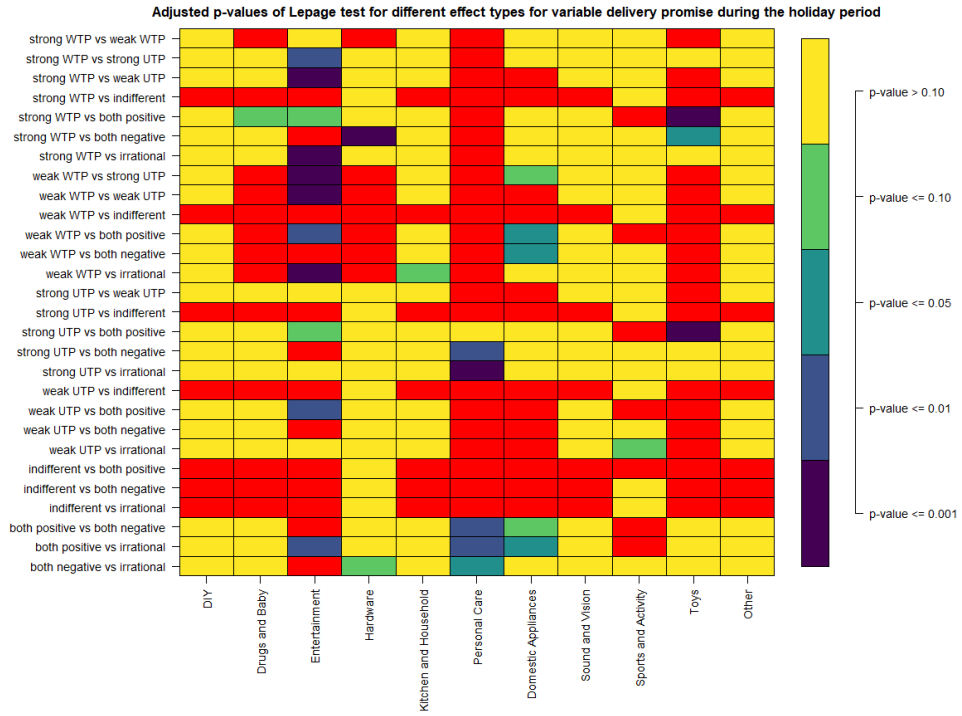

Figure D.65: Table of adjusted p-values based on Holm-procedure (Holm (1979)) for different effect type combinations. Cells in red indicate that the combination does not exist for a given shop category. The effect types are based on the results of Figure 9.

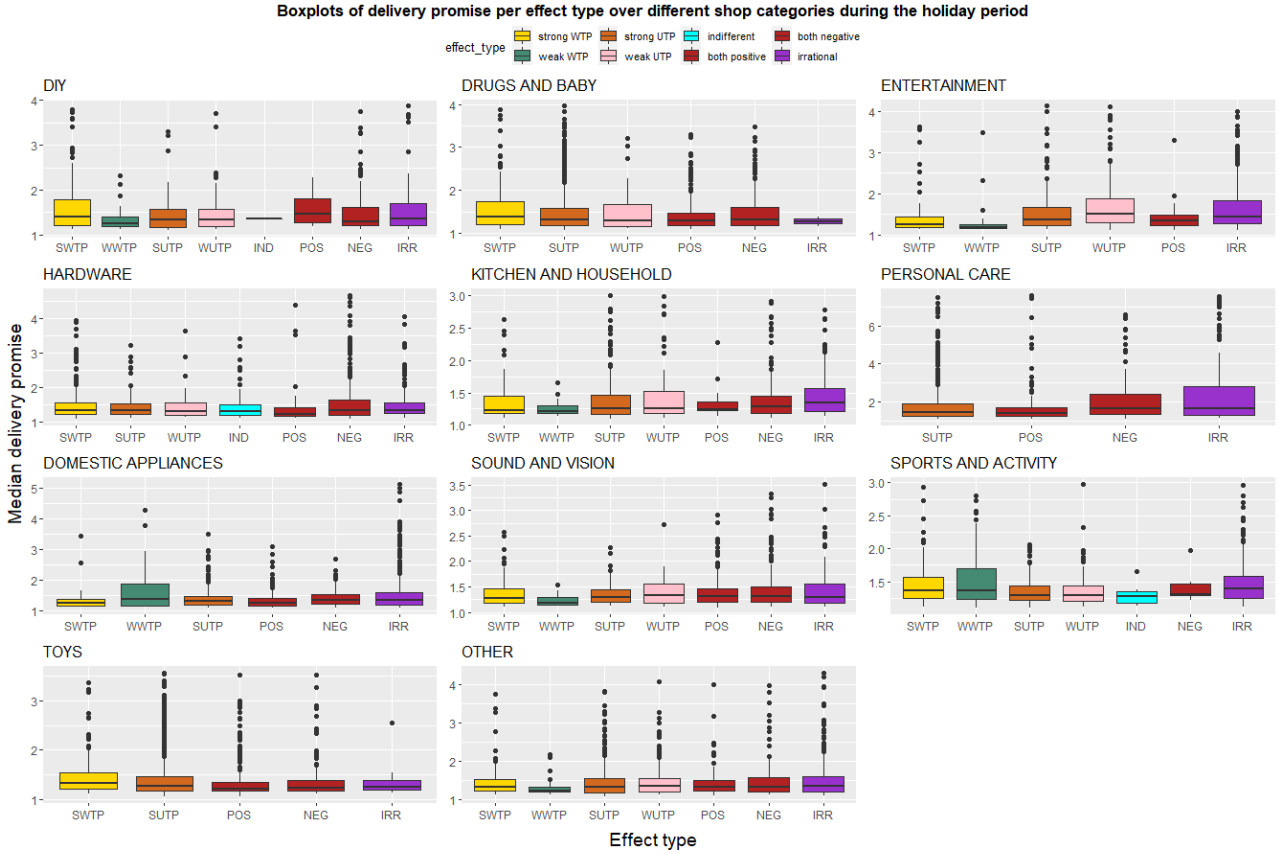

Figure D.66

Appendix D.6. Willingness to Pay around Sinterklaas and Christmas

Appendix D.6.1. Results Model Training

In Table D.28 we present the results of the model training for estimating Willingness to Pay around Sinterklaas and Christmas. Table D.28 is structured in the same way as the other four tables in which we have shown the results of the model training. Similar to the other model specifications, the model selection criteria are decreasing as we add more components to our mixture model. However, in contrast to the other model specifications, for model specifications of 14 different clusters and above we observe multiple clusters which are not able to capture at least 100 different products. The reason for this is due to the smaller set of products which we can use in this model specification. Therefore, we select the model configuration with 13 different mixture components.

#S start	#S above threshold	log likelihood	AIC	CAIC	AWE	BIC	CLC	NEC	ICL-BIC
5	5	-1105083.66	2210565.32	4422979.53	4425823.42	2212613.21	2216422.38	0.001	2218868.28
10	10	-1046160.83	2093119.65	4189946.38	4195648.46	2097225.73	2114043.67	0.006	2118947.75
11	11	-1043128.24	2087134.47	4178347.66	4184621.37	2091652.18	2114538.04	0.008	2119933.75
12	12	-1034234.35	2069426.70	4143303.74	4150149.09	2074356.05	2093748.09	0.007	2099635.44
13	13	-1027133.34	2055304.67	4115431.33	4122848.32	2060645.66	2082108.59	0.008	2088487.58
14	12	-1033889.41	2068736.82	4141923.98	4148769.33	2073666	2095207.63	0.008	2101094.98
15	11	-1036676.57	2074231.13	4152540.97	4158814.68	2078748.84	2097001.81	0.007	2102397.53
20	10	-1045789.01	2092376.02	4188459.11	4194161.18	2096482.09	2114832.64	0.007	2119736.71
25	13	-1031848.39	2064734.78	4134291.55	4141708.54	2070075.77	2092598.16	0.009	2098977.15

Table D.28: Results for modelling willingness to pay around Sinterklaas and Christmas.
Gold: selected cluster size
Gray: best solution for selection criterion
Red: Contains segments below threshold of 100 products

In Figures D.67 and D.68 we can see the posterior sizes over the different clusters. In terms of overall posterior size, Figure D.67 shows that cluster 1 contains most observations with a posterior size of approximately 13%. Clusters 2 follows with an posterior size of approximately 11%, followed by clusters 3 to 10 which form the middle class of clusters. Cluster 11 is a a couple of percentage points lower than the clusters in the middle class, while clusters 12 and 13 are the clusters with the smallest posterior size. In Figure D.67 we can see that depending on the particular shop category, the posterior cluster size can be hugely different. For instance cluster 3 of the shop category *Entertainment* has an posterior size of 40%, while cluster 4 reaches barely a size of 1%.

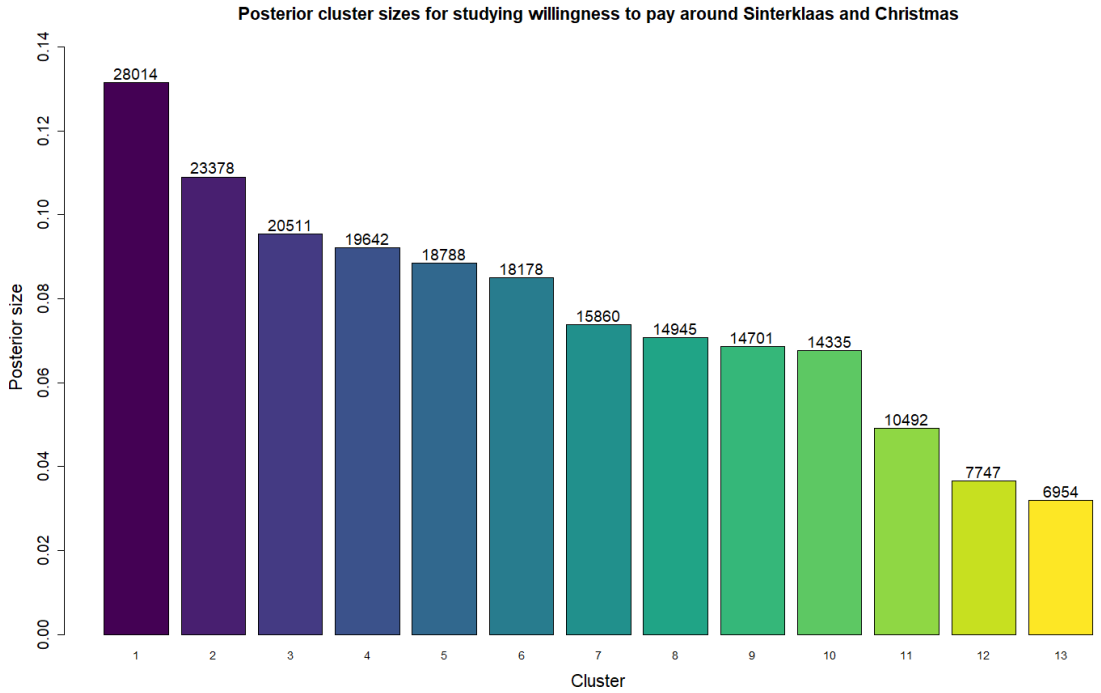

Figure D.67: Posterior cluster sizes for studying willingness to pay around Sinterklaas and Christmas. Number on the bars indicate number of observations per cluster

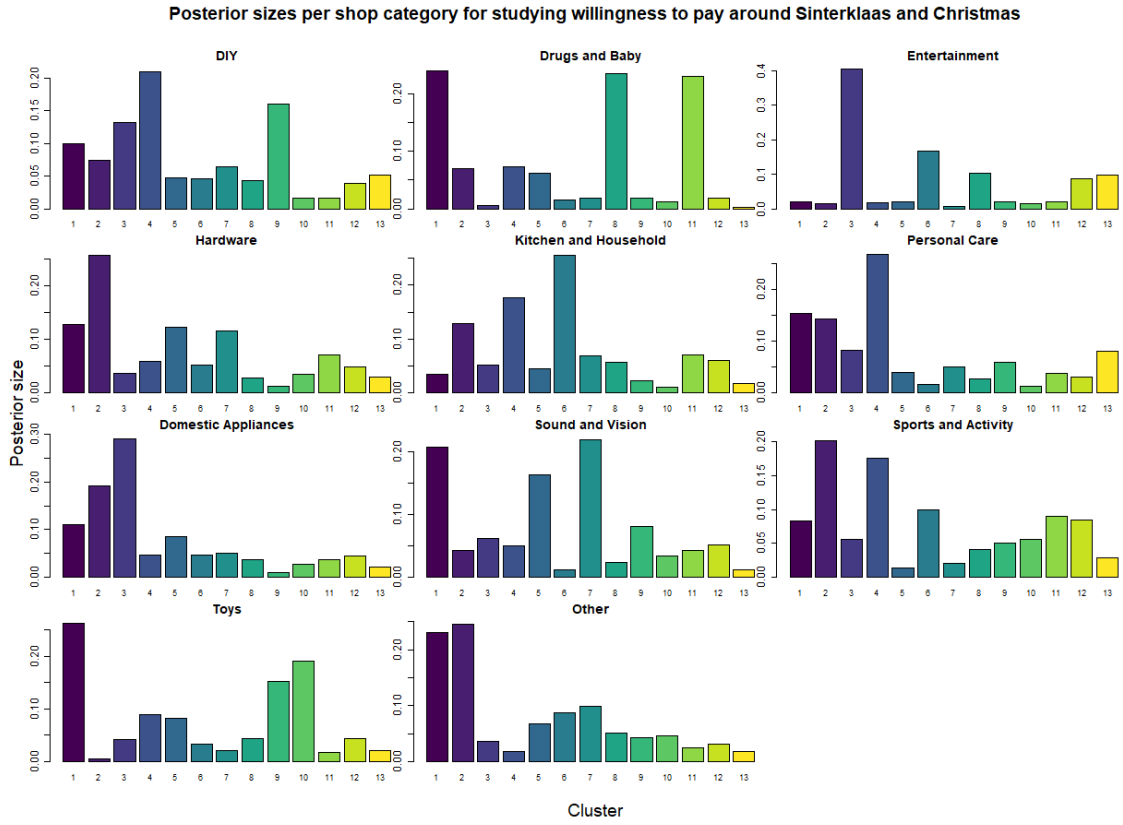

Figure D.68: Posteriors over the different shop categories

Cluster Similarity. In Table D.24 and Figure D.36 we depict the cluster similarity based on KL-divergence. The larger the KL-divergence the more dissimilar clusters are. Based on these results we can see for instance that cluster 13 shares similarity with clusters 2,6 and 8.

	1	2	3	4	5	6	7	8	9	10	11	12	13
1	0	37	40	54	107	39	50	73	32	68	59	117	31
2	32	0	24	23	77	18	59	47	41	55	66	77	21
3	41	42	0	24	98	37	29	38	57	35	46	56	33
4	43	40	23	0	87	15	46	69	51	40	49	86	45
5	155	133	225	161	0	100	296	203	46	285	184	290	74
6	31	27	38	20	62	0	65	68	25	54	61	95	26
7	81	120	65	71	122	113	0	56	97	90	120	139	101
8	133	137	46	94	137	136	45	0	88	90	108	140	119
9	47	46	80	66	41	27	125	83	0	115	77	151	24
10	125	111	106	88	184	70	90	126	115	0	105	107	130
11	136	191	85	106	247	115	127	223	167	128	0	156	166
12	269	192	103	178	357	202	187	247	340	165	118	0	200
13	25	17	37	32	48	15	77	58	19	72	68	99	0

Table D.29: Values of KL-divergence of different clusters for willingness to pay around Sinterklaas and Christmas. Note that we have divided the numbers by 100,000 for readability

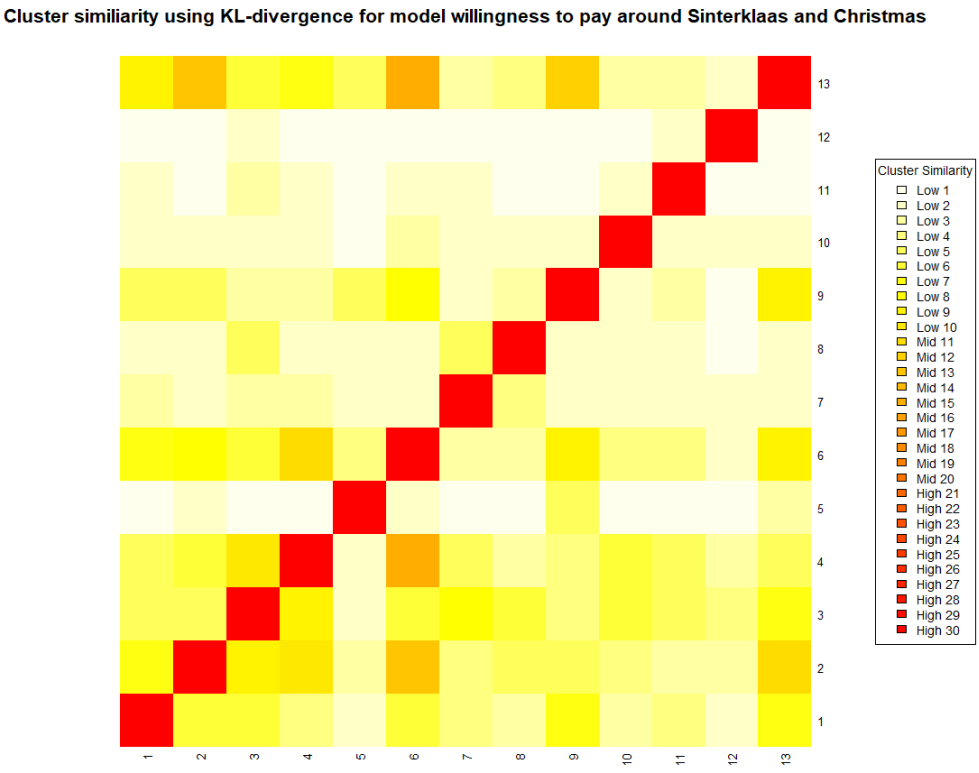

Figure D.69: Heatmap of cluster similarity based on KL-divergence values of Table D.29. The darker the color, the more clusters share similarity.

Appendix D.6.2. Parameter Estimates

In Table 12 we present the coefficient estimates of the study variables for studying willingness to pay around Sinterklaas and Christmas. For an overview of the estimation of all parameters (including control variables) we refer to Table D.16 in Appendix D.1. In Figures D.70 and D.71 we can respectively find the statistical power of the parameter estimates and the significant marginal effects at an α-level of 1%. Comparing the statistical power for the variables RC and WTP to those obtained in Figure D.60 we can see that in this model specification the statistical power is overall lower for these two variables, which can be explained due to the smaller sample size. Moving to the variable WTPSC, the first notable observation we can make is that for a majority of the shop categories this variable is insignificant in most clusters. One possible explanation why we observe this can simply be because it is very unlikely that there are significant effects for this variable in the real world. Another explanation can be that in reality more significant effects exist, but the data we use to estimate these effects have insufficient variability. Given that for most products in the dataset we observe exactly one observation for which WTPSC is non-zero, this second explanation can be plausible. On the upside, we observe high levels of statistical power for the parameter estimates which are significant at an α-level of 1%.

By considering the marginal effects of Figure D.71 we find that most of the marginal effects for RC are non-negative in all shop categories, with occasional negative marginal effects occurring. By comparing the marginal effects of WTP and WTPSC per cluster, we first of all see that many marginal effects of WTPSC are insignificant, which is not surprising given the plots of Figure D.70. For the marginal effects of WTPSC which are significant, we see that these share the same sign as those of WTP if we condition on cluster and shop category. In terms of size of the marginal effects of WTP and WTPSC, from the eye it seems per cluster shop category combination most two marginal effects are not that different from each other. We test this observation more formally in the main text.

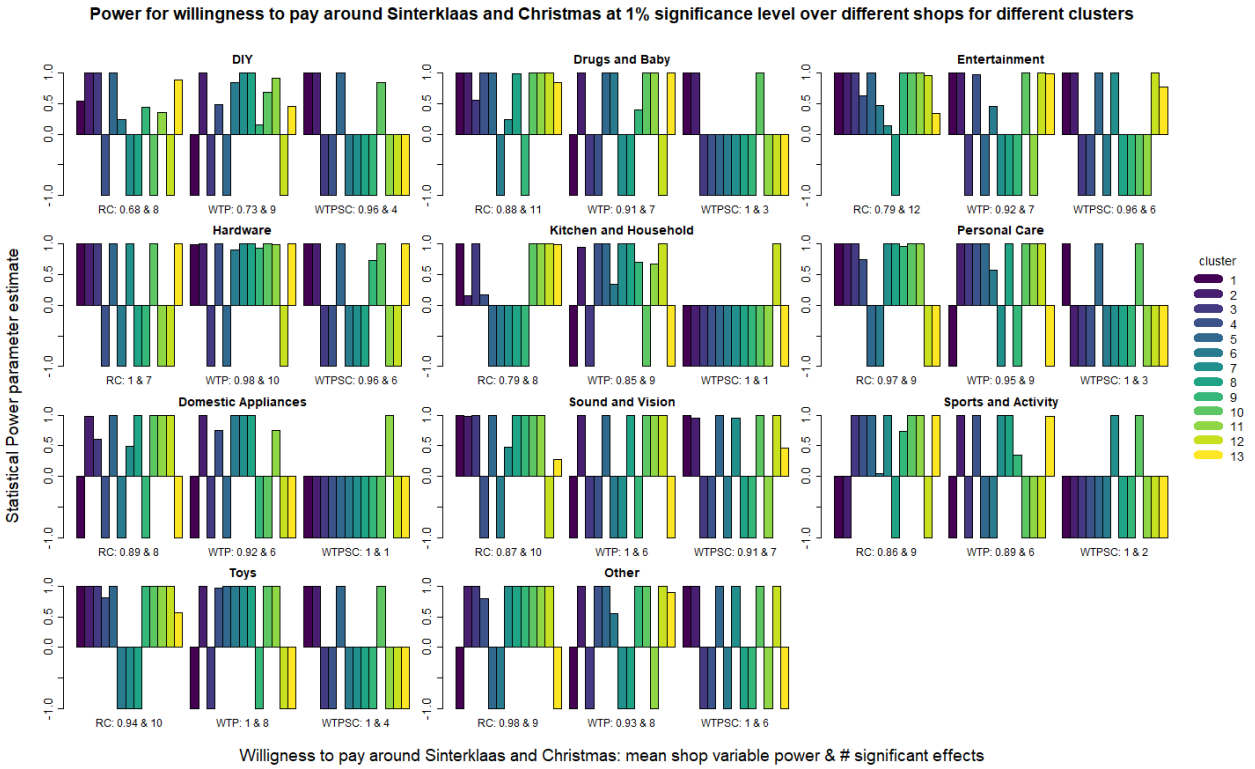

Figure D.70: Statistical power for the different parameter estimates of Table 12. A value of minus one indicates an insignificant effect at $\alpha = 0.01$. Values next to variables RC, WTP, and WTPSC indicate average cluster power and the number of significant effects.

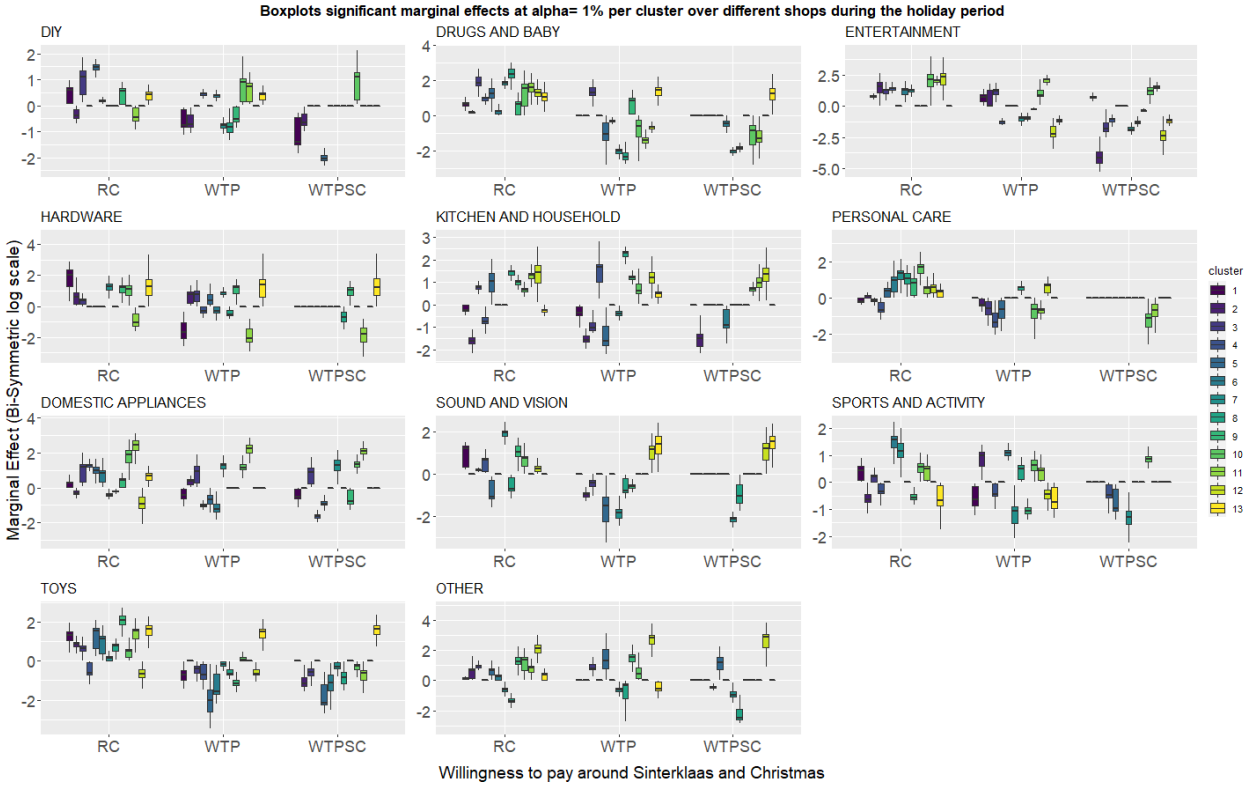

Figure D.71: Significant marginal effects using Equation C.49 in bi-symmetric log-scale (with base 10). Significance is determined at $\alpha = 0.01$.