university of groningen
faculty of economics and business

2021012-MARK

Asking Less, Getting More? The Influence of Fixed-Fee and Threshold-Based Free Shipping on Online Orders and Returns

June 2021

Christian F. Hirche
Maarten J. Gijsenberg
Tammo H.A. Bijmolt

SOM is the research institute of the Faculty of Economics & Business at the University of Groningen. SOM has six programmes:

- Economics, Econometrics and Finance
- Global Economics & Management
- Innovation & Organization
- Marketing
- Operations Management & Operations Research
- Organizational Behaviour

Research Institute SOM
Faculty of Economics & Business
University of Groningen

Visiting address:
Nettelbosje 2
9747 AE Groningen
The Netherlands

Postal address:
P.O. Box 800
9700 AV Groningen
The Netherlands

T +31 50 363 9090/7068/3815

www.rug.nl/feb/research

university of groningen

faculty of economics and business

Asking Less, Getting More? The Influence of Fixed-Fee and Threshold-Based Free Shipping on Online Orders and Returns

Christian F. Hirche
University of Groningen, Faculty of Economics and Business, Department of Marketing

Maarten J. Gijsenberg
University of Groningen, Faculty of Economics and Business, Department of Marketing
m.j.gijsenberg@rug.nl

Tammo H.A. Bijmolt
University of Groningen, Faculty of Economics and Business, Department of Marketing

Asking Less, Getting More?

The Influence of Fixed-Fee and Threshold-Based Free Shipping

on Online Orders and Returns

Christian F. Hirche[a]

Maarten J. Gijsenberg[b]

Tammo H.A. Bijmolt[c]

[a] Department of Marketing – University of Groningen, PO Box 800, 9700 AV Groningen, The Netherlands. C.F.Hirche@rug.nl

[b] Department of Marketing – University of Groningen, PO Box 800, 9700 AV Groningen, The Netherlands. M.J.Gijsenberg@rug.nl. ***Corresponding author***

[c] Department of Marketing – University of Groningen, PO Box 800, 9700 AV Groningen, The Netherlands. T.H.A.Bijmolt@rug.nl

Abstract

Online retailers can recoup part of the relatively high logistics cost by instating a shipping policy which includes shipping fees on some or all of the orders. This paper compares two wide-spread shipping policies: fixed-fee shipping and threshold-based free shipping. The authors contrast both policies' influence on sales – aggregate as well as decomposed into order value and order count – and returns. Regarding the latter, they investigate whether filler purchases – purchases that make the order surpass the required threshold value for threshold-based free shipping – explain contrasting return quotas. Insights are based on the analysis of a unique database from a major European online retailer containing 26.21 million orders of 83.79 million items from 3.81 million customers and covering a broad range of product categories. Results show that threshold-based free shipping leads to substantially higher overall sales and more orders, while fixed-fee shipping leads to less returns, even though the effect is not driven by filler purchases. Finally, a simulation shows that the positive effects (on orders) of threshold-based free shipping likely outweigh the negative effects (on product returns) under most conditions.

Keywords: online retailing; e-commerce; product returns; shipping policy; fixed-fee shipping; threshold-based free shipping

Abstract

Online retailers can recoup part of the relatively high logistics cost by instating a shipping policy which includes shipping fees on some or all of the orders. This paper compares two wide-spread shipping policies: fixed-fee shipping and threshold-based free shipping. The authors contrast both policies' influence on sales – aggregate as well as decomposed into order value and order count – and returns. Regarding the latter, they investigate whether filler purchases – purchases that make the order surpass the required threshold value for threshold-based free shipping – explain contrasting return quotas. Insights are based on the analysis of a unique database from a major European online retailer containing 26.21 million orders of 83.79 million items from 3.81 million customers and covering a broad range of product categories. Results show that threshold-based free shipping leads to substantially higher overall sales and more orders, while fixed-fee shipping leads to less returns, even though the effect is not driven by filler purchases. Finally, a simulation shows that the positive effects (on orders) of threshold-based free shipping likely outweigh the negative effects (on product returns) under most conditions.

Keywords: online retailing; e-commerce; product returns; shipping policy; fixed-fee shipping; threshold-based free shipping

1. Introduction

Online retailing has grown heavily over the last two decades. While online retailers do save on rent compared to traditional brick-and-mortar stores, they incur new logistical costs. Every shipped and returned order needs to be handled separately, threatening to make logistics costly (Bijmolt et al. 2019; Caro, Kök, and Martínez-de-Albéniz 2020). A popular way to recover (part of) this cost for retailers is to make customers pay a shipping fee. A shipping fee increases the price that customers have to pay for an order online, and usually is either a fixed fee or a fee that increases or decreases in steps. Such fixed or variable shipping fees may incentivize differing purchase and return behaviors (Lewis 2006; Shehu, Papies, and Neslin 2020). As retailers strive to maximize orders while keeping returns low (Minnema et al. 2018; Petersen and Kumar 2015) and customers are particularly reluctant to pay for shipping fees (Smith and Brynjolfsson 2001), the choice of shipping fee policy should be taken with care.

The differences between paid shipping policies are under-researched, in spite of recent managerial interest (Retail Detail 2019), and no paper so far investigates the consequential difference in returns, even though returns are crucial for profitability. In this paper, we contrast two exemplary and widely used shipping fee policies: fixed-fee shipping and threshold-based free shipping, i.e. shipping fees that are waived for bigger orders (e.g. Lewis 2006). Thus, we contribute to prior research, notably by Lewis (2006) and, more recently, by Lepthien and Clement (2019) and Sahoo, Dellarocas, and Srinivasan (2018), by comparing two different paid shipping policies with regards to both orders and returns.

In the remainder of the paper, we first reason why customers are motivated to order *and* return more with a threshold-based free shipping policy, and why it additionally may lead to strategic behavior, i.e., customers ordering additional goods to reach the free-shipping threshold. Those so-called filler purchases might either be to the benefit or detriment of the retailer, depending on their return rate (Minnema et al. 2018). Next, we conduct an empirical analysis using data from a natural experiment of a large European online retailer, which recently changed its shipping policy from fixed-fee to threshold-based free shipping. Our findings show that threshold-based free shipping does influence sales and the number of orders, and substantively changes return rates. While the return rate in general is higher, filler purchases are returned less rather than more compared to regular purchases. In a post-hoc analysis, we further investigate such filler purchases and reasons why they are returned less.

2. Theoretical background

2.1. Research framework

A shipping fee is a mark-up on the price of an order to get the products delivered at home. Depending on the shipping policy, this mark-up is a fixed fee (independent of the order) or it is determined by characteristics of the order (like its value). For example, an order of a book at €10 and a jacket at €100 might both have a shipping fee of €2.50 with a fixed-fee policy, or of €5 and €0, respectively, with a threshold-based free shipping policy, a policy whereby shipping cost is waived when the order value surpasses a certain threshold (e.g., €20 in this case). In addition, as the order size varies, the relative price increase per product varies, too. In the example above, a shipping fee of €2.50 for a €10 book means a price increase of 25% whereas a shipping fee of €2.5 for a €100 jacket only means a price increase of 2.5% (Hess, Chu, and Gerstner 1996). This sort of price is a so-called partitioned price, with a fixed partition (the original product price) and a variable partition (the price increase due to shipping cost). Customers are very sensitive to variable price partitions, especially in the case of shipping fees (Hamilton and Srivastava 2008; Smith and Brynjolfsson 2001).

In our research, we will focus on the difference between fixed fee shipping and a threshold-based free shipping. The defining difference is that with threshold-based free shipping, the shipping fee is waived for large orders. This difference, however, leads to different incentives with regards to overall order amount (i.e., sales), order frequency, the value of each order, and the return probability. As the research framework in Figure 1 shows, we expect a range of effects based on that difference, which we will explain in detail in the next sections.

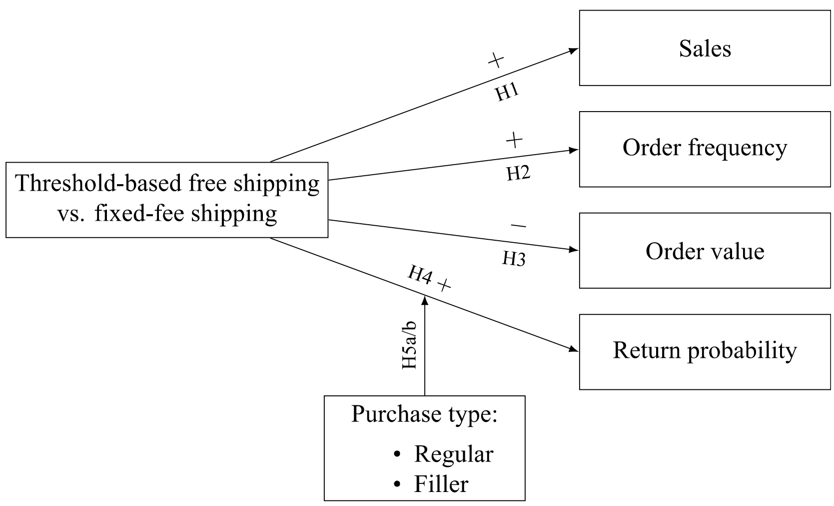

Fig.1. Research Framework: Expected effects of shipping policy

2.2. Embedding into prior research

Our paper positions itself in a stream of empirical work, which compares the effects of different elements of shipping policies. Most research focuses on the effect of shipping fees on orders (e.g. Lewis 2006; Lewis, Singh, and Fay 2006) but recently, three papers have integrated product returns into the analysis (Lepthien and Clement 2019; Sahoo, Dellarocas, and Srinivasan 2018; Shehu, Papies, and Neslin 2020). Table 1 provides an overview of the main findings of prior work. Previous research focused either on free shipping and its difference to other shipping policies or on parameters within one shipping policy. Little is known concerning the differences between two *paid* shipping policies. Therefore, this paper contributes to the stream of literature as it is the first to contrast the consequences of a threshold-based free-shipping policy with those of a fixed-fee shipping policy on multiple outcome variables. This wide array of dependent variables allows us to not only predict atomic effects concerning one outcome but also to realistically compare two shipping policies in their overall effect.

Table 1
Prior research regarding shipping fees

Paper	DV	IV	Relationship
	order-related dependent variables		
Lewis (2006)	Order frequency	Shipping fee	−
Lewis, Singh, and Fay (2006)	Order frequency	Free shipping (vs. threshold-based free shipping)	+
Lepthien and Clement (2019)	Order frequency	Free shipping threshold	−
Shehu, Papies, and Neslin (2020)	Order frequency	Free shipping (vs. fixed-fee shipping)	+
Lewis (2006)	Order value (before returns)	Penalizing larger orders	−
Lewis (2006)	Order value (before returns)	Penalizing smaller orders	+
Lewis, Singh, and Fay (2006)	Order value (before returns)	Free shipping (vs. threshold-based free shipping)	−
Lepthien and Clement (2019)	Order value (before returns)	Shipping fee	+
Lepthien and Clement (2019)	Order value (after returns)	Shipping fee	+
Shehu, Papies, and Neslin (2020)	Ordering of riskier products	Free shipping (vs. fixed-fee shipping)	+
	return-related dependent variables		
Shehu, Papies, and Neslin (2020)	Return probability	Free shipping (vs. fixed-fee shipping)	+
Sahoo, Dellarocas, and Srinivasan (2018)	Return probability	Order value <$5 above free shipping threshold	−
Lepthien and Clement (2019)	Return probability of “strategic returns”	Free shipping threshold	+

2.2.1. Effects on product orders

Prior research shows that customers adapt *how* they order as a response to different shipping fees incentives (Table 1). Higher shipping fees correlate with reduced ordering, while fees penalizing a certain order size lead to a different order size (Lewis 2006). Comparing concrete policies, free shipping leads to smaller and more frequent orders than threshold-based free shipping (Lewis, Singh, and Fay 2006) and, in line with that, also more frequent orders than fixed-fee shipping (Shehu, Papies, and Neslin 2020). For threshold-based free shipping, a higher threshold leads to less orders (Lepthien and Clement 2019). In addition to all aforementioned aggregate effects, shipping policies may also change *what* customers order: Shehu, Papies, and Neslin (2020) find that customers tend to purchase more products that are difficult to evaluate online with free shipping.

2.2.2. Effects on product returns

Prior research also shows that customers adapt *how* they return products as a response to different shipping fees incentives – although insights are more limited. Free shipping leads to more returns than fixed-fee shipping (Shehu, Papies, and Neslin 2020). Threshold-based free shipping has been argued to lead to more returns due to strategic order and return-behavior (Lepthien and Clement 2019). Conflicting with that proposition is that threshold-based free shipping has been shown to lead to less returns for orders just above the free shipping threshold (Sahoo, Dellarocas, and Srinivasan 2018).

2.3. Hypotheses

2.3.1. The influence of shipping fees on orders

There are two reasons, why we expect that fixed-fee shipping leads to lower sales than threshold-based free shipping. First, with a fixed-fee shipping, the customer has to pay the shipping fee for every order, regardless of order value, whereas with a threshold-based free shipping, the shipping fee is waived for large orders. In other words, shipping is potentially free and on average cheaper with threshold-based free shipping than with fixed-fee shipping. In general, higher cost leads to less demand, since price elasticity is usually negative (Bijmolt, Van Heerde, and Pieters 2005). In particular, shipping fees have been found to be even more influential than regular price (Lewis 2006; Smith and Brynjolfsson 2001). Thus, we expect that fixed-fee shipping leads to less sales overall than threshold-based free shipping due to higher average costs for the customers.

Second, with fixed-fee shipping, the more individual orders customers make, the more shipping fees they have to pay. This incentivizes customers to distribute the same product purchases among fewer orders, as this allows them to economize on shipping fees. A practical way to do so is, to accumulate planned purchases by postponing them (which customers are willing to do to save money, see e.g. Greenleaf and Lehmann 1995). We therefore expect customers to postpone purchases with fixed-fee shipping. Postponement of purchases, in turn, can lead to abandonment of purchases, e.g., because preferences change (Stigler and Becker 1977) or because the purchase was made somewhere else in the meantime. Abandoned purchases, in turn, have a detrimental effect on sales. The situation is different for threshold-based free shipping: here, more orders do not generally equal more shipping fees and customers have no incentive to postpone purchases beyond reaching the free shipping threshold. Thus, we expect less abandoned purchases resulting in a less detrimental effect on sales. Therefore, when comparing both policies, we expect fixed-fee shipping to lead to less sales than threshold-based free shipping. In sum, both arguments lead to the following hypothesis:

H1: Threshold-based free shipping leads to *higher sales* compared to fixed-fee shipping.

Fixed-fee shipping may incentivize customers to delay purchases in order to distribute them among (a) fewer and (b) larger orders and, thereby, reduce the total of due shipping fees. For threshold-based free shipping, on the other hand, this is true only to a limited extent. Once the order size is above the free shipping threshold, postponing and combining orders does not further reduce total shipping costs. Therefore, threshold-based free shipping only provides a constrained incentive for combining smaller into larger orders – until the free shipping threshold is reach – whereas fixed-fee shipping provides an unconstrained incentive for combining smaller into larger orders – because the higher the purchase value, the lower the relative weight of the shipping fee. This results in the following two hypotheses:

H2: Threshold-based free shipping leads to *more orders* compared to fixed-fee shipping.

H3: Threshold-based free shipping leads to *a lower average order value* compared to fixed-fee shipping.

2.3.2. The influence of shipping fees on returns

Fixed-fee shipping results in every order having to pay a shipping fee whereas threshold-based free shipping results in many orders not having to pay a shipping fee. Having to pay a non-refundable fee more often will lead to less returns for two reasons. The first reason is similar irrational behavior as in comparable situations with sunk cost. When customers decide to return their order, they have to write off the money spent on shipping fees. Instead, they have a tendency to continue on their path, once an investment has been made, even if it results in financially detrimental outcomes (Carter, Kaufmann, and Michel 2007; Domeier, Sachse, and Schäfer 2018). We expect customers to consider shipping fees as money wasted when returning and therefore expect them to return less with fixed-fee shipping, where shipping is always paid, than with threshold-based free shipping, where shipping is regularly free. The second reason for expecting less returns due to a non-refundable shipping fee is economic customer behavior due to costly re-ordering. Customers might decide to return a product, if a product does not fully align with their preferences, and re-order another one. However, the benefit of returning and re-ordering has to outweigh the cost (Anderson, Hansen, and Simester 2009; Petersen and Kumar 2015), which is increased by having to pay shipping fees. Therefore, if the ordered new product has only a slight advantage over the returned old product, having to pay additional shipping fees might render the exchange unattractive. Since fixed-fee shipping always results in shipping fees and threshold-based free shipping does not, fixed-fee shipping more often renders returning unattractive in such cases. In sum, based on both explanations, we expect that:

H4: Threshold-based free shipping leads to *more returns* compared to fixed-fee shipping.

Shipping fees might also influence *what* customers return. Threshold-based free shipping is free when ordering above the threshold. Hence, as long as the order size is below the threshold, customers have to compromise between paying the shipping fee or paying more for the order itself – by ordering more. When the customer chooses the latter option and orders an additional product in order to surpass the free-shipping fee threshold, we call this purchase a “filler” purchase. Thus, we define a filler purchase as a purchase that was added to the shopping basket at the end of the shopping trip, with the order value without it being below the free shipping threshold and with it being above the free shipping threshold. From a theoretical point of view, such filler purchases could be returned both less often than "regular", i.e., non-filler purchases – or more often, and we formulate opposing hypotheses about the effect.

On the one hand, customers have the possibility of economizing their purchase behavior by adding a product to their order, which they can anticipate to purchase anyway in the future, such as regularly purchased goods (e.g., beauty or sanitary products). Customers can perceive such additional purchase as a smart bargain, because they spend their money on a product instead of on shipping costs. Customers are prone to bargain hunting, which is the biggest source of enjoyment in brick-and-mortar retail shopping (Cox, Cox, and Anderson 2005), especially when they perceive their own action as responsible for the lowered price (Schindler 1989). If customers add regularly purchased goods to their order, returns of these purchases are likely lower, since familiar purchases are returned less than unfamiliar purchases (Petersen and Kumar 2009).

H5a: Threshold-based free shipping leads to *less returns of filler purchases* compared to regular purchases.

There are also reasons for which filler purchases might be returned more often. First, customers might intentionally plan to order and return a filler purchase and only order the filler purchase to save shipping cost with a higher order value. Previous research shows that customers are known to strategically abuse retailer policies for their personal gain (Wachter et al. 2012) and this case provides a tangible gain without any risk. Customers could extend their order by any random product, provided it lets the order surpass the free shipping threshold, and thereby save out the shipping fee. A second, unrelated, explanation for higher returns of filler purchases is that customer might decide spontaneously to order more when confronted with the threshold-based free shipping. In this case, however, the resulting filler purchases are unplanned purchases, which, being more likely to be regretted post-purchase

(Saleh 2012) and therefore, have a higher return probability. In sum, we therefore hypothesize that:

H5b: Threshold-based free shipping leads to *more returns of filler purchases* compared to regular purchases.

3. Data

For this study, we have access to a unique dataset from a major European online retailer. The dataset contains 26.21 million orders of 83.79 million items from 3.81 million customers in a three years period (from July, 2017 to June, 2019). The assortment of the retailer is broad and consists of, among others, fashion, furniture, electronics, and toys. Fashion has the largest share, reflecting its popularity in e-commerce overall (Eurostat 2018), but other product categories are far from insignificant in terms of economic value. Fig. 2 shows the distribution of orders among the retailer's product categories.

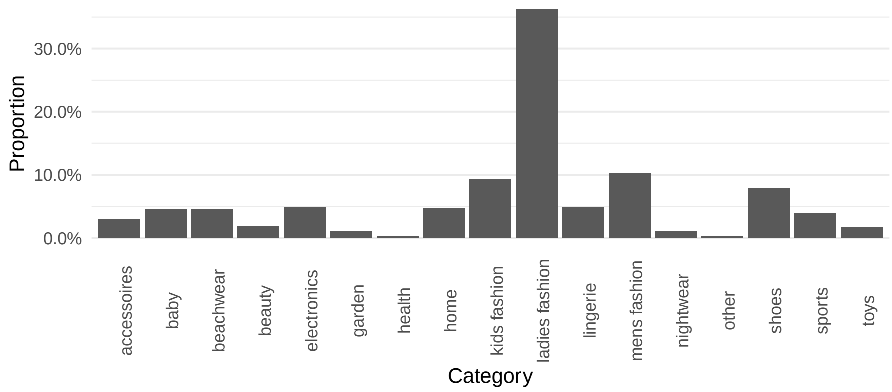

Fig. 2. Distribution of Purchased Products among Categories

In November, 2017, the retailer changed its shipping policy from fixed-fee shipping with fees depending on the product category (e.g., €0 for laptops and printers, €1.95 for

DVDs and software, and €5.95 for fashion and small domestic appliances, among others) to threshold-based free shipping with a unified €2.95 shipping fee and a free-shipping threshold of €20, This provides a valuable natural experiment for the effects of the shipping policy change. The retailer continued to charge no additional cost for shipping of product returns.

3.1. Datasets and variables

For our analyses, we use two datasets. Table 2 presents an overview of the datasets and variables used in our empirical study. The first dataset is at the daily level and contains variables related to the online retailer's sales. Here, we focus on three dependent variables: sales, order count, and order value, all on a daily level. The focal independent variable for these analyses at the daily level is an indicator variable for threshold-based free shipping that allows us to compare the effect of threshold-based free shipping with fixed-fee shipping. Besides, we include a range of control variables for weekday, month, and year. Since the firm unified shipping fees across categories when introducing threshold-based free shipping – resulting in an increased fee for some orders and a decreased fee for others – we group orders according to the direction of shipping fee change. As a result, we have two time-series, one for each group of orders.

Table 2
Dependent and independent variables used in the analysis

Variable	Definition	Summary	
Dataset: Day level (n = 2,188)			
$sales_{t,g}$[3]	Sales at day t (for orders in group g)	g = shipping fee up avg: 2,946,583 (sd: 1,000,423)	g = shipping fee down avg: 243,511 (sd: 103,020)
order $count_{t,g}$[3]	Count of orders at day t (for orders in group g)	avg: 21,603.28 (sd: 7,270.24)	avg: 2,323.93 (sd: 1,039.89)
order $value_{t,g}$	Average order value at day t (for orders in group g)	avg: 137.16 (sd: 13.75)	avg: 106.92 (sd: 20.810)
shipping $policy_t$	Whether threshold-based free shipping is valid at day t (1), or not (0)	0: 11.32%, 1: 88.68%	
$day_{day,t}$, $month_{month,t}$, and $year_{year,t}$	Whether (1) or not (0) day t is Monday, Tuesday, etc. / in February, March, etc. / in 2017, 2018, or 2019	see Fig. 3.	
Dataset: Product-purchase level (n = 83,704,086)			
$returned_p$	Whether product p is returned (1), or not (0)	0: 55.23%, 1: 44.77%	
shipping $policy_p$	Whether the product p was ordered on the threshold-based free shipping policy (1) or on a fixed-fee shipping policy (0)	0: 8.52%, 1: 91.48%	
$regular_p$ / $filler_p$	Whether product p is added to the order after all other products and lifts the shopping basket from below the free-shipping threshold to above it ($filler_p = 1$), or not ($regular_p = 1$)	$regular_p$: 97.51%, $filler_p$: 2.49%	
fee_up_p / fee_down_p	Whether product p's category shipping fee increased ($fee\_up_p = 1$) or decreased with the shipping policy change ($fee\_down_p = 1$)	fee_up_p: 7.05%, fee_down_p: 92.95%	
$price_p$[1]	Product price of product p	avg: 42.81€ (sd: 69.25€)	
$category_p$	The category of product p	see Fig. 2	
$discounted_p$	Whether product p has a discounted price when purchased (1), or not (0)	0: 53.61%, 1: 46.39%	
basket $size_p$[2]	Count of products ordered together with product p	avg: 7.06 (sd: 7.00)	
last in $basket_p$	Whether product p is added to the order after all other products (1), or not (0)	0: 68.71%, 1: 31.29%	
$day_{day,p}$, $month_{month,p}$, and $year_{year,p}$	Whether (1) or not (0) product p is purchased on Monday, Tuesday, etc. / in February, March, etc. / in 2017, 2018, or 2019	see Fig. 3	
age_p[1]	Age of the customer of product p	avg: 42.91 (sd: 11.28)	
$gender_{male,p}$[1]	Whether gender of the customer of product p is female (0) or male (1)	0: 83.18%, 1: 16.82%	
$crel\_years_p$[1]	Length of patronage of the customer of product p in years	avg: 10.22 (sd: 8.84)	

For estimation, variables are: [1]mean-centered, [2]subtracted by one, [3]on the (natural) logarithmic scale

The second dataset is at the product-purchase level and contains variables related to the product returns. The dependent variable "returned" indicates whether or not an individual purchase was returned. Analyzing returns at the product-purchase level allows us to provide insights both at the product level – the impact of purchase type (whether or not the product is a filler purchase) and shipping fee change – and at the order level – whether or not the order was placed with a fixed-fee or threshold-based free-shipping policy. We also control for other aspects at the product level – price and product category –, at the order level – discounts, order size, and whether or not the product was the last in the order, as well as day, month, and year of the order – and at the customer-level – age, gender, and the length of the customer relationship.

3.2. Model-free insights

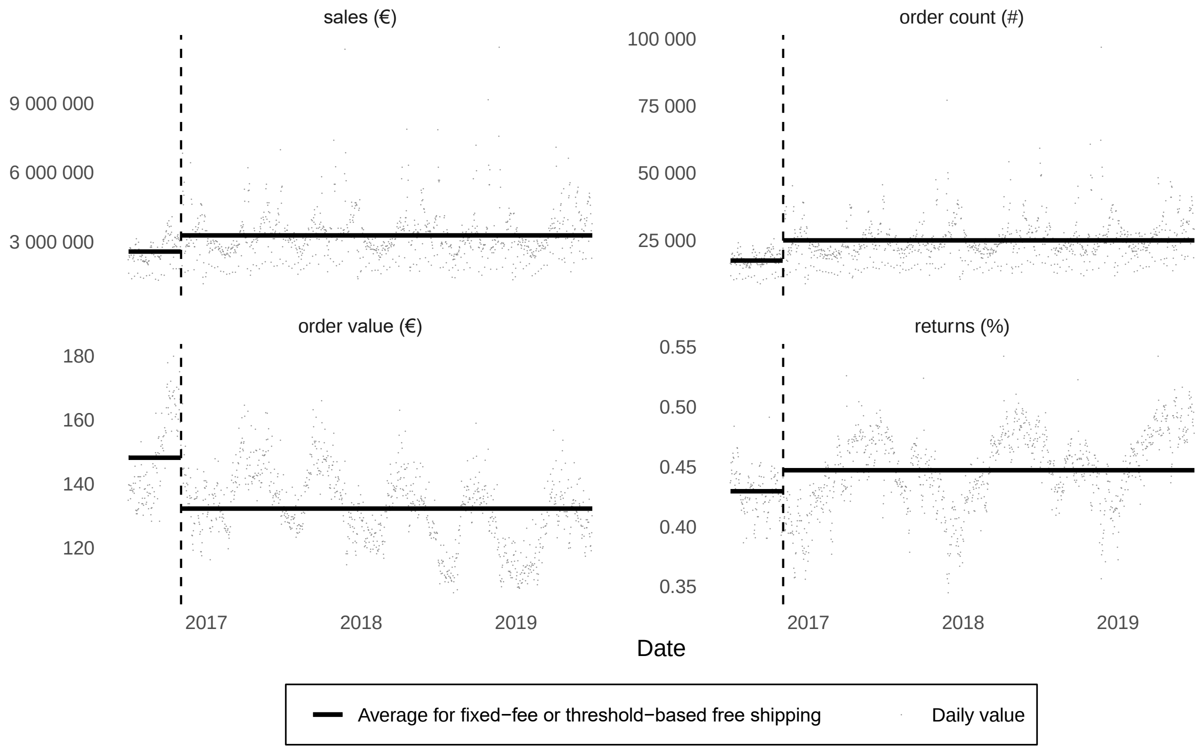

Fig. 3. Daily sales, order counts, order values, and return percentages

Over-time plots of daily order and return variables (Fig. 3) indicate seasonal variation plus an additional shift in value at the time when the shipping policy is changed. In line with our hypotheses, threshold-based free shipping seems to increase daily sales, the number of orders, and decrease order value in comparison with fixed-fee shipping. Specifically, the mean daily value of all sales is €2.57m for fixed-fee shipping and €3.27m for threshold-based free shipping (+€.70m); the daily number of all orders is 17,313 for fixed-fee shipping and 24,786 for threshold-based free shipping (+7,473); the average order size of all orders is €148.12 for fixed-fee shipping and €132.22 for threshold-based free shipping (-€15.9); and the daily percentage of returned products is 43% with fixed-fee shipping and 45% with threshold-based free shipping. Hence, in general, the model-free evidence tends to support our hypotheses, but it does not control for other explanatory factors, so we continue with more detailed analyses of the data.

4. Methodology

We employ two sets of models: the first to analyze daily-level sales outcomes, i.e., sales value, order count, and order value, and the second, to analyze product-purchase level product returns.

4.1. Analyzing sales, order count, and order value

For sales, order count, and order value, we use data at a daily level. This allows us to identify the effect of the introduction of threshold-based free shipping while controlling for seasonal effects. We analyze the daily data using cross-sectional time-series regression models (StataCorp 2020). We account for changing shipping fees by fixed-effects and estimating the effect of threshold-based free shipping separately for the group of orders with increasing and decreasing shipping fees. Besides, we control for day of week, month, and year. In addition, we allow for autocorrelation in the error term. We estimate the same model (denoted model I, see below) for all time-dependent outcome variables: daily sales, order count, and order value:

$$
\begin{gathered}
y_{g,t} = \alpha + \beta_{1,g} sp_{g,t} + \sum_{i=2}^{21} \beta_i x_{i,t} + \nu_g + \varepsilon_{g,t} \\
\text{with } \varepsilon_{g,t} = \rho \varepsilon_{g,t-1} + \eta_{g,t},\ \ g \in \{up, down\},\ \ t \in \{0,1,\ldots,1094\}, \\
\text{for } y_{g,t} \in \{\text{logged sales, logged order count, order value}\}
\end{gathered} \tag{1}
$$

where t is the day, g is the group of orders (with "up" consisting of orders with increasing and "down" consisting of orders with decreasing shipping fees), $sp_{g,t}$ is an indicator variable for shipping policy at day t of group g (with threshold-based free shipping = 1, fixed-fee shipping = 0), $x_{i,t}$ with $i = \{2, 3, \ldots, 21\}$ are the control variables for year, month, and weekday, ν_g is the group fixed effect, and $\varepsilon_{g,t}$ is the error term. We apply a log-transformation to the dependent variables to deal with the long right-hand tail and make the distribution more symmetric and Normal.

4.2. Analyzing returns

4.2.1. Base model

For product returns, we use data at the product-purchase level. This allows us to control for the effect of purchase type (i.e., filler and regular purchases) and other purchase-, product- and customer-level variables. To assess our hypothesized effects on the binary dependent variable product return, we use three binomial logit regression models. First, we start by estimating the influence of shipping policy on product returns in general, and compare returns with threshold-based free shipping to returns with fixed-fee shipping. We control for whether the product belongs to the group with increasing or decreasing shipping fees and include the interaction of this factor with threshold-based-free shipping indicator. Additionally, we control for a range of additional purchase-level variables. This is our base model for product returns.

$$logit(returned_p) = \alpha_{up} fee\_up_p + \alpha_{down} fee\_down_p + \beta_{1,up} sp_p \times fee\_up_p + \beta_{1,down} sp_p \times fee\_down_p + \sum_{i=2}^{44} \beta_i x_{i,p} + \varepsilon_p \quad (2)$$

where p is the product purchase, sp_p indicates shipping policy as before, fee_up_p and fee_down_p denote whether the shipping fee increased or decreased, $x_{i,p}$ are the control variables for year, month, weekday, and product category, and ε_p is the error term.

4.2.2. Return probability for filler versus regular purchases

Second, we extend our base model by indicators for the type of product purchase, i.e., whether it is a regular or a filler purchase. In the resulting model, we compare the baseline return probabilities (under fixed-fee shipping) with the return probabilities of filler and regular purchases under threshold-based free shipping. The extended model is:

$$\begin{aligned} logit(returned_p) = {} & \alpha_{up} fee\_up_p \\ & + \alpha_{down} fee\_down_p \\ & + \beta_{1,up} sp_p \times fee\_up_p \times filler_p \\ & + \beta_{2,up} sp_p \times fee\_up_p \times regular_p \\ & + \beta_{1,down} sp_p \times fee\_down_p \times filler_p \\ & + \beta_{2,down} sp_p \times fee\_down_p \times regular_p \\ & + \sum_{i=3}^{45} \beta_i x_{i,p} + \varepsilon_p \end{aligned} \quad (3)$$

where the variables are defined similarly to before and we include an additional indicator for whether product p is a filler purchase or regular purchase (denoted by $filler_p$ and $regular_p$).

Third, as a control for the findings of the second model, we estimate the effect of threshold-based free shipping as well as fixed-fee shipping on returns of both purchase types. In particular, we proceed by splitting coefficients α_{up} and α_{down} of model (3) into two coefficients each ($\alpha_{1,up}, \alpha_{2,up}$ and $\alpha_{1,down}, \alpha_{2,down}$) – for distinguishing filler from regular purchases with fixed-fee shipping. By doing so, we obtain

$$
\begin{aligned}
logit(returned_p) = {} & \alpha_{1,up}(1 - sp_p) \times fee\_up_p \times filler_p \\
& + \alpha_{2,up}(1 - sp_p) \times fee\_up_p \times regular_p \\
& + \alpha_{1,down}(1 - sp_p) \times fee\_down_p \times filler_p \\
& + \alpha_{2,down}(1 - sp_p) \times fee\_down_p \times regular_p \\
& + \beta_{1,up} sp_p \times fee\_up_p \times filler_p \# \\
& + \beta_{2,up} sp_p \times fee\_up_p \times regular_p \\
& + \beta_{1,down} sp_p \times fee\_down_p \times filler_p \\
& + \beta_{2,down} sp_p \times fee\_down_p \times regular_p \\
& + \textstyle\sum_{i=3}^{45} \beta_i x_{i,p} + \varepsilon_p
\end{aligned}
\tag{4}
$$

where $(1 - sp_p)$ is the reverse of indicator variable sp_p (i.e., having fixed-fee shipping = 1 and threshold-based free shipping = 0).

Model (4) has as a full factorial design for shipping policy (threshold-based free shipping versus fixed-fee shipping) and purchase type (filler purchase versus regular purchases). The further distinction between purchase types allows us to contrast “real” filler purchases (i.e., goods that comply with the filler purchase definition and are purchased with threshold-based free shipping) with purchases that are fully alike filler purchases without being actual filler purchases (i.e., goods that comply with the filler purchase definition but are purchased with fixed-fee shipping).

5. Results

5.1. Effect of shipping fee on sales, order frequency, and order value

First, we find that threshold-based free shipping significantly increases daily sales, considering the group of orders where the shipping fees decreased (model 1a in Table 3). The increase is large with an effect size of .373 in logged sales ($p < .001$) or, by exponentiating the coefficient, 45.21% in non-logged sales. The effect of threshold-based free shipping is not significant for the group of orders where the shipping fee increased. The difference in effect between both groups suggests that an increase in shipping fee alone would have a negative effect on sales which is countered by threshold-based free shipping. In sum, we have partial evidence in support of H1, which stated that threshold-based free shipping would lead to more sales compared to fixed-fee shipping.

Second, we find that threshold-based free shipping significantly increases the daily number of orders (model 1b in Table 3) for the group of orders where shipping fees decreased. The increase amounts to .361 in the logged order count ($p < .001$) or, by exponentiating, 43.58% in the non-logged order count. We do not find a significant effect within the group of orders where shipping fees increased. As before, this is an indication for a negative effect of increased shipping fees on the number of orders, which is parried by threshold-based free shipping. In sum, there is partial evidence in support of H2, which stated that threshold-based free shipping would lead to more orders compared to fixed-fee shipping.

Third, we find no evidence for a significant effect of threshold-based free shipping on the daily average order value (model 1c in Table 3), though both groups of orders have a consistent negative effect direction. Consequently, we cannot confirm H3, which stated that threshold-based free shipping would lead to smaller orders compared to fixed-fee shipping.

Table 3

Influence of threshold-based free shipping on sales, order count, and order value

	Dependent variable:		
	log of sales	log of order count	order value
	(1a)	(1b)	(1c)
Constant	13.613*** (.019)	8.643*** (.019)	142.397*** (.950)
threshold-based free shipping$_{\text{shipping fee up}}$	-.057 (.089)	-.020 (.089)	-3.298 (4.530)
threshold-based free shipping$_{\text{shipping fee down}}$	.373*** (.089)	.361*** (.089)	-2.665 (4.530)
year_2017	-.040 (.067)	.051 (.067)	-9.865** (3.409)
year_2018	-.201** (.069)	.008 (.068)	-22.789*** (3.489)
year_2019	-.166* (.080)	.118 (.079)	-31.030*** (4.060)
month_feb	-.039 (.053)	-.037 (.054)	.244 (2.725)
month_mar	-.031 (.058)	-.084 (.058)	7.350* (2.950)
month_apr	.026 (.059)	.007 (.059)	3.926 (3.011)
month_may	.039 (.059)	.057 (.059)	-.130 (3.007)
month_jun	-.027 (.060)	.025 (.060)	-3.865 (3.051)
month_jul	.043 (.063)	.112. (.063)	-7.414* (3.210)
month_aug	-.014 (.063)	.054 (.063)	-7.001* (3.202)
month_sep	.104 (.063)	.151* (.063)	-2.622 (3.221)
month_oct	.066 (.063)	.114. (.062)	-3.039 (3.181)
month_nov	.127* (.063)	.219*** (.063)	-8.701** (3.202)
month_dec	.134* (.059)	.243*** (.059)	-11.275*** (3.003)
day_tue	-.027* (.011)	-.030* (.012)	.007 (.579)
day_wed	.022 (.014)	.020 (.015)	-.041 (.738)
day_thu	.011 (.016)	-.004 (.016)	1.588* (.801)
day_fri	-.039* (.016)	-.070*** (.016)	3.365*** (.802)
day_sat	-.512*** (.014)	-.504*** (.015)	-.554 (.737)
day_sun	-.111*** (.011)	-.127*** (.012)	3.029*** (.579)
ρ (autocorrelation)	.729	.717	.726
σu (between-group std.-dev.)	1.512	1.357	20.99
σe (within-group std.-dev.)	.190	.194	9.715
R^2 (within-group explained variance)	.561	.517	.121
R^2 (overall explained variance)	.584	.549	.227
Observations	2,188	2,188	2,188
F Statistic (df = 22;2164)	125.5***	105.5***	13.53***

*** p<.001, ** p<.01, * p<.05, standard errors in parentheses

Regarding control variables in the three models 1a-1c, we find significant effects of various year, month and day control variables. First, sales decrease in 2018 and 2019. This effect seems to be driven by a substantial and steady decrease in order value over time instead of order count over time, as year has no significant effect on the logged order count. Second, we find evidence for monthly variation in all models: Sales and the number of orders show an increase especially in the last two months of the year, while the value of an order is lowest during this period. Third, regarding days of the week, sales and the number of orders are lowest in the weekend and highest in the middle of the week, and the order value is highest on Fridays. All models show high temporal autocorrelation (above .7). Finally, the explained variance for each model is highly significant, though the model fit is considerably higher for sales and order count than for order value.

5.2. Influence of shipping fee on product returns

5.2.1. Return probability across all products

Regarding the product-purchase level dataset, we find that threshold-based free shipping significantly increases the return probability (model 2 in Table 4). This holds both for products where shipping fees increased and for products where shipping fees decreased, although the strength of the effect varies (.014, $p = .034$, for increasing shipping fees, and .091, $p < .001$, for decreasing shipping fees). Transforming the log odds into probabilities[1], we get that expected product returns increase from 30.07% to 30.36% with threshold-based free shipping and increased product shipping fees, and from 52.30% to 54.56% with threshold-based free shipping and decreased product shipping fees. This is empirical support in favor of H4, which stated that threshold-based free shipping would lead to more returns compared to fixed-fee shipping.

---

[1] By taking the inverse logit function of the log odd of the baseline $\frac{\exp(-.844)}{1+\exp(-.844)} = .3007$ and of the baseline plus the respective effect of threshold-based free shipping $\frac{\exp(-.844+.014)}{1+\exp(-.844+.014)} = .3036$. The remaining probabilities are obtained similarly.

Table 4
Influence of threshold-based free shipping and type of purchase (filler versus regular) on return probability

	Dependent variable:	
	Returned	Returned
	(2)	(3)
Constant$_{\text{shipping fee up}}$	-.844*** (.006)	-.857*** (.006)
Constant$_{\text{shipping fee down}}$	.092*** (.002)	.087*** (.002)
threshold-based free shipping$_{\text{shipping fee up}}$	.014* (.006)	
filler purchase × threshold-based free shipping$_{\text{shipping fee up}}$		-.131*** (.011)
regular purchase × threshold-based free shipping$_{\text{shipping fee up}}$		.018** (.006)
threshold-based free shipping$_{\text{shipping fee down}}$	.091*** (.002)	
filler purchase × threshold-based free shipping$_{\text{shipping fee down}}$		-.363*** (.003)
regular purchase × threshold-based free shipping$_{\text{shipping fee down}}$		.098*** (.002)
Price	.003*** (.000)	.003*** (.000)
Discounted	-.040*** (.001)	-.039*** (.001)
basket size	.052*** (.000)	.051*** (.000)
last in basket	-.322*** (.001)	-.294*** (.001)
Age	-.004*** (.000)	-.004*** (.000)
gender_male	-.253*** (.001)	-.253*** (.001)
years of customer patronage	.011*** (.000)	.011*** (.000)
year_2017	.028*** (.001)	.029*** (.001)
year_2018	.054*** (.001)	.055*** (.001)
year_2019	.096*** (.001)	.098*** (.001)
month_Feb	.029*** (.001)	.029*** (.001)
…		
month_Dec	.028*** (.001)	.027*** (.001)
day_Tue	.002* (.001)	.002* (.001)
…		
day_Sun	-.005*** (.001)	-.005*** (.001)
cat_Accessoires	-1.145*** (.001)	-1.141*** (.001)
…		
cat_Toys	-2.811*** (.004)	-2.799*** (.004)
Observations	83704086	83704086
Log-likelihood	-49282562.71	-49254263.10
BIC	98565982.84	98509420.10

*** p<.001, ** p<.01, * p<.05, standard errors in parentheses

5.2.2. Return probability of filler and regular purchases under the threshold-based policy

Next, we estimate the effect on threshold-based free shipping on the returns of filler purchases and regular purchases (model 3 in Table 4). Here, we find a significant effect of threshold-based free-shipping policy for filler and regular purchases, but in opposite directions. Filler purchases are returned significantly *less* with threshold-based free shipping whereas regular purchases are returned *more*. Again, the strength of the effect depends on whether the product belongs to the group with increasing or decreasing shipping fees. For filler purchases, returns decrease by -.131 (from 29.80% to 27.13%, $p < .001$) in the former case and by -.363 (from 52.17% to 43.14%, $p < .001$) in the latter case. For regular purchases, returns increase by .018 (from 29.80% to 30.17%, $p = .005$) and by .098 (from 52.17% to 54.61%, $p < .001$), respectively. These findings are supportive empirical evidence for H5a (against H5b), which stated that, with threshold-based free shipping, filler purchases would be returned less (more) than regular purchases.

5.2.2. A priori return probability of filler and regular purchases

Finally, we extend the previous model 3 by also distinguishing between products that fall under the definition of regular and filler purchases within a fixed-fee shipping policy (model 4). By doing so, we can uncover differences in return probability that might be an outcome of the definition of the purchase type alone. As such, it helps us to understand to what extent regular and filler purchases have a different return probability, regardless of the shipping policy, and to what extent this difference is attenuated/mitigated by the introduction of the new policy.

The results confirm and extend the findings of the previous model: purchases classified as regular purchases have a higher inherent return probability than purchases classified as filler purchases – with both shipping policies. The introduction of threshold-based free shipping then further widens the gap between both types of purchases, i.e., it further *increases* the return probability of regular purchases and *decreases* the return probability of filler purchases. Concretely, for regular purchases, we observe an *increase* in returns from 29.82% to 30.17% (-.856 to -.839 in log odds) and from 52.25% to 54.59%

(.090 to .184 in log odds) for the product group with increased and decreased shipping fees, and for filler purchases, we find a *decrease* in returns from 28.19% to 27.11% (-.935 to -.989 in log odds) and from 45.02% to 43.09% (-.200 to -.278 in log odds) for both product groups (Table 5).

Table 5
Influence of shipping policy (threshold-based free shipping versus fixed-fee shipping) and type of purchase (filler versus regular) on return probability in a full factorial design

	Dependent variable:
	Returned
	(4)
filler purchase × fixed-fee shipping$_{\text{shipping fee up}}$	-.935*** (.047)
filler purchase × threshold-based free shipping$_{\text{shipping fee up}}$	-.989*** (.009)
regular purchase × fixed-fee shipping$_{\text{shipping fee up}}$	-.856*** (.006)
regular purchase × threshold-based free shipping$_{\text{shipping fee up}}$	-.839*** (.003)
filler purchase × fixed-fee shipping$_{\text{shipping fee down}}$	-.200*** (.008)
filler purchase × threshold-based free shipping$_{\text{shipping fee down}}$	-.278*** (.003)
regular purchase × fixed-fee shipping$_{\text{shipping fee down}}$	.090*** (.002)
regular purchase × threshold-based free shipping$_{\text{shipping fee down}}$	.184*** (.002)
Price	.003*** (.000)
Discounted	-.039*** (.001)
basket size	.051*** (.000)
last in basket	-.293*** (.001)
Age	-.004*** (.000)
gender_male	-.253*** (.001)
years of customer patronage	.011*** (.000)
year_2017	.029*** (.001)
year_2018	.055*** (.001)
year_2019	.098*** (.001)
month_Feb	.029*** (.001)
…	
month_Dec	.027*** (.001)
day_Tue	.002* (.001)
…	
day_Sun	-.005*** (.001)
cat_Accessoires	-1.141*** (.001)
…	
cat_Toys	-2.799*** (.004)
Observations	83704086
Log-likelihood	-49253549.63
BIC	98508029.64

*** p<.001, ** p<.01, * p<.05, standard errors in parentheses

In order to test the significance of the difference in return probability due to purchase type (i.e., filler and regular purchase) and shipping policy, we conduct post-hoc Wald tests (Table 6).

Table 6
Wald test results for inequality of parameter estimates

Parameter	**Significance of difference (p-value Wald test)**						
	vs.	(a)	(b)	(c)	(d)	(a)-(c)	(b)-(d)
filler purchase × fixed-fee shipping$_{\text{shipping fee up}}$	(a)		.257	.090			
filler purchase × threshold-based free shipping$_{\text{shipping fee up}}$	(b)	.257			< .001		
regular purchase × fixed-fee shipping$_{\text{shipping fee up}}$	(c)	.090			.009		
regular purchase × threshold-based free shipping$_{\text{shipping fee up}}$	(d)		< .001	.009			
	(a)-(c)						.139
	(b)-(d)					.139	
	vs.	(e)	(f)	(g)	(h)	(e)-(g)	(f)-(h)
filler purchase × fixed-fee shipping$_{\text{shipping fee down}}$	(e)		< .001	< .001			
filler purchase × threshold-based free shipping$_{\text{shipping fee down}}$	(f)	< .001			< .001		
regular purchase × fixed-fee shipping$_{\text{shipping fee down}}$	(g)	< .001			< .001		
regular purchase × threshold-based free shipping$_{\text{shipping fee down}}$	(h)		< .001	< .001			
	(e)-(g)						< .001
	(f)-(h)					< .001	

We find that influence of purchase type is significant in all cases, i.e., that regular purchases are always returned less than filler purchases regardless of changes in shipping policy and shipping fee ($p<.001$ to $p=.090$, conditions (a) vs. (c) and (b) vs. (d) as well as (e) vs. (g) and (f) vs. (h) in Table 6). The influence of shipping policy is significant, i.e., increasing returns for regular purchases and decreasing returns for filler purchases ($p < 0.001$, conditions (c) vs. (d) as well as (e) vs. (f) and (g) vs. (h) in Table 6) – except for such filler purchases, where shipping fees increased ($p=.257$, condition (a) vs. (b) in Table 6). Finally, by combining these effects, we find that threshold-based free shipping leads to a significantly wider gap in return probability when shipping fees decrease and to a non-significantly wider gap when shipping fees increase ($p < .001$ and $p=.139$, conditions (a) - (c) vs. (b) - (d) in Table 6). Thus, filler purchases have a significantly lower return rate than regular purchases, and this difference increases under the threshold-based free shipping policy.

5.2.3. Product return model diagnostics

We find each new version of the return model performing slightly better than the previous one, as indicated by a decreasing BIC. With regards to control variables, we find very similar effects across all three models for product returns. Price, a larger shopping basket size, and years of customer patronage have a significant, positive influence on return probability, whereas a discount, being the last product in the shopping basket, an additional year of age of the customer, and male gender have a significant, negative influence on return probability. Product returns significantly increase each year and vary per month and product category. Table A1 and Table A2 in Appendix A show the estimates of model 3 and 4 including all control variables (i.e., encompassing all product category and month dummy variables).

5.3. Post-estimation profiling of filler purchases

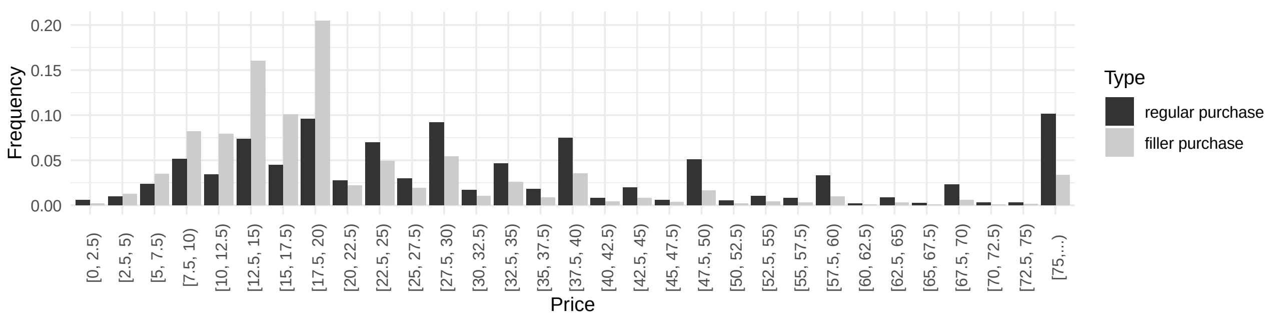

Fig. 4. Price distribution of filler and regular purchases.

In the previous section, we showed empirically that filler purchases have a distinct return pattern – with a lower return rate than that of regular purchases – and that this pattern is reinforced under the threshold-based free shipping policy. To further the understanding of filler purchases and why they are returned less than regular purchases, we proceed with a post-hoc analysis and contrast both types of purchases in terms of price and product categories. First, regarding the price distribution, we observe that filler purchases have a median price of €17.95 (mean: €25.63), which is substantially lower than the median price of regular purchases of 29.95€ (mean: €43.25) and just below the free shipping threshold. The histogram (Fig. 4) shows that filler and regular purchases have a roughly similar price distribution with the important difference that filler purchases are much more likely to lie in the €0-20 price range. Second, regarding product categories, we find that filler purchases belong more often to product categories such as toys, health, and beauty, and less often to ladies' fashion, men's fashion, and shoes, compared to regular purchases (Fig. 5).

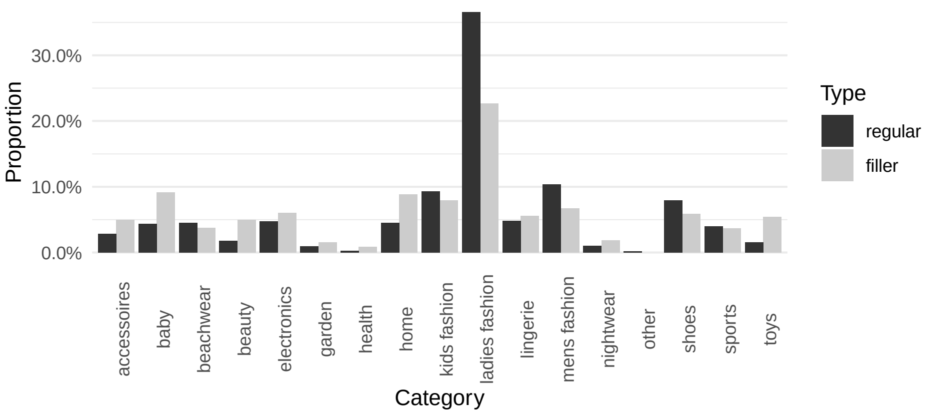

Fig 5. Category distribution of filler and regular purchases.

In conclusion, both the price and product category distributions show that filler purchases are distinct from regular purchases. Moreover, their different characteristics fit well with our reasoning for why their return rate would be lower: categories in which filler purchases are overrepresented often contain products that are recurring purchases (e.g., the categories health, beauty, and baby), or are purchased as gifts (toys).

5.4. Simulation of the impact of shipping policy on profitability

In our results, we find that the overall effect of the shipping policy change is composed of both beneficial (i.e., higher sales) as well as detrimental (i.e., higher returns) effects from the retailer's perspective. In order to have an overall assessment of profit implications, taking into account both beneficial and detrimental effects, we proceed to simulate the effect of the shipping policy change on the one-year sales-based cumulative profit. We vary both the profit margin and return processing cost, thus providing insights on the circumstances under which a threshold-based shipping fee policy is relatively more/less profitable compared to a fixed-fee shipping policy.

We calculate the overall change in one-year cumulative profits between the two shipping policies as the sum of three components: (1) change in daily net sales (i.e., sales excluding returns) times the gross margin, (2) change in daily received shipping fees, and (3) change in daily cost of return handling[2]:

$$(5) \qquad \Delta\,{}^{\text{profit}}/_{\text{year}} = \left(\Delta\,{}^{\text{netsales}}/_{\text{day}} \cdot \text{margin} + \Delta\,{}^{\text{shippingfees}}/_{\text{day}} - \Delta\,{}^{\text{returncost}}/_{\text{day}}\right) \cdot 365$$

with the components calculated as follows:

1. We input the assumed margin directly (e.g., $margin = 45\%$) and then calculate the difference of net sales with threshold-based free shipping and net sales with fixed-fee

[2] As our models are estimated at the daily level, we first determine the change in profit at the daily level, and subsequently multiply with 365 (days) to obtain the total change in cumulative profit for the whole year.

shipping. To obtain net sales, we predict sales from model (1a), calculate the probability of not returning – using predicted product returns from model (2), as we use overall return probability – and then multiply both values.

2. For the change in daily received shipping fees, we calculate the daily received shipping fees for both fixed-fee shipping and threshold-based free shipping and calculate their difference. We obtain daily received shipping fees by multiplying the shipping fee per order under the respective shipping policy with the predicted number of orders from model (1c).
3. For the change in daily cost of return handling, we calculate daily return cost with fixed-fee shipping and subtract it from the daily return cost with threshold-based free shipping. The daily return cost is the return processing cost (i.e., the cost of an individual return) times the number of daily returns. We input the return processing cost directly (e.g., $return\ processing\ cost = €6$) and calculate the number of daily returns by multiplying the predicted number of daily orders from model (1c) with the average number of products per order and with the predicted return probability from model (2).

We present detailed calculations for each step in Appendix B. Fig 6. shows the resulting difference in one-year cumulative profits based on a range of plausible return processing costs and gross margins. We assume that the return processing cost is at least as high as the current shipping fee (about €3) of our retailer and vary the profit margin around the reported gross margin for online retailing (of 42.5%, Damodaran 2021).

We find that, across all return processing cost scenarios, retailers with average and above-average gross margins always profit from introducing threshold-based free shipping, even when return processing costs are high. In other words, in all included scenarios, these retailers win when switching to this policy, and additional profits of doing so are substantial.

When the profit margin is considerably below average, return processing cost should become a consideration. However, even for retailers with below-average gross margins, threshold-based free shipping is almost always more profitable. Only in case of very high return processing costs (12 euro) and low margins (37.5%), fixed-fee shipping is the more profitable option.

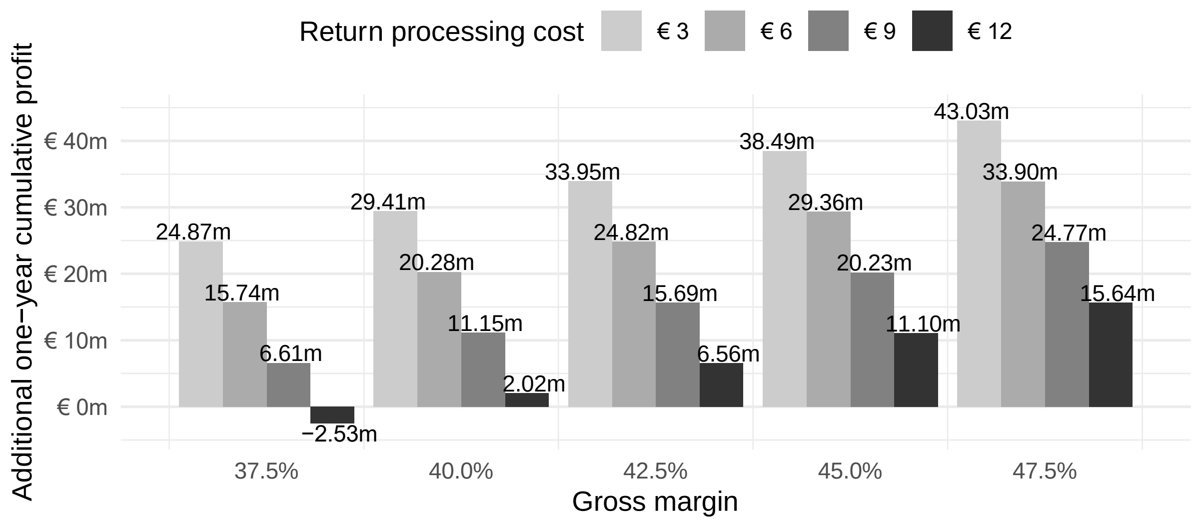

Fig. 6. Profitability of shipping policy change

6. Discussion

6.1. Conclusions

In this paper, we compared the consequences of two wide-spread shipping policies of online retailers –threshold-based free shipping and fixed-fee shipping – on both purchases and returns. Regarding purchases, we decompose overall sales into order value and order count. Regarding returns, we investigate whether so-called filler purchases – purchases that make the order value surpass the required threshold for threshold-based free shipping – explain contrasting return quotas for fixed-fee and threshold-based free shipping. Insights provided in this paper are based on the analysis of a unique dataset from a major European online retailer that contains information on 26.21 million orders of 83.79 million items from 3.81 million customers in a three years period (from July, 2017 to June, 2019), and covers a broad range of product categories. Since the retailer introduced threshold-based free shipping together with order-dependent shipping fee changes, we separately consider two groups of purchases: those where shipping fees have increased, and those where shipping fees have decreased.

Table 7
Summary of the findings

Hypothesis		Findings
H1:	Threshold-based free shipping leads to *higher sales* compared to fixed-fee shipping	Partially supported
H2:	Threshold-based free shipping leads to *more orders* compared to fixed-fee shipping	Partially supported
H3:	Threshold-based free shipping leads to *a lower average order value* compared to fixed-fee shipping	Not supported
H4:	Threshold-based free shipping leads to *more returns* compared to fixed-fee shipping	Supported
H5a:	Threshold-based free shipping leads to *less returns of filler purchases* compared to regular purchases	Supported
H5b:	Threshold-based free shipping leads to *more returns of filler purchases* compared to regular purchases	Not supported

The results are partly in line with what we predicted (Table 7). In partial support of our theoretical argument, threshold-based free shipping is likely to increase sales and the number of orders. We reasoned that fixed-fee shipping always results in shipping fees whereas threshold-based free shipping policy is, as the name implies, potentially free. Consequently, customers have to pay less shipping fees on average with threshold-based free shipping. Since customers are very sensitive to price, in general, and shipping cost, in particular, theory predicts that customers will order less with the more expensive policy, i.e., fixed-fee shipping (Bijmolt, Van Heerde, and Pieters 2005; Smith and Brynjolfsson 2001). The empirical results show that there are more orders and, consequently, higher sales with threshold-based free shipping than with fixed-fee shipping for one group of orders. In particular, for the group of orders with decreasing shipping fees, we find 45.21% higher sales and 43.58% more orders. For the remaining orders – with increasing shipping fees, we find no significant effect of threshold-based free shipping versus free shipping. The combination of a large positive effect in the first group and the absence of a negative effect in the second group (with increasing shipping fees) is likely evidence of an overall positive effect of threshold-based free shipping on the number of orders and sales.

We find no evidence for our theoretical argument that threshold-based free shipping would lead to orders with lower value. We theorized that fixed-fee shipping would be an incentive for customers to delay purchases in order to distribute them among fewer and larger orders and, thereby, reduce the total of due shipping fees. Threshold-based free shipping, on the other hand, would only incentivize customers to delay purchases up to the free shipping threshold, as a further delay does not reduce total shipping costs. Therefore, threshold-based free shipping is a more constrained incentive for combining smaller into larger orders than fixed-fee shipping and thus retains smaller orders. However, our results indicate that order size (in terms of monetary value) is not influenced by shipping policy.

In addition, we find that the shipping policy influences return behavior. We expected that threshold-based free shipping would increase returns for two reasons. The first reason is irrational customer behavior with regards to sunk cost (Domeier, Sachse, and Schäfer 2018). Shipping fees are non-refundable and therefore a sunk cost when returning. However, customers tend to not admit that cost is sunk, because it appears wasteful (Arkes and Blumer 1985), and so they choose a course of action that avoids writing it off – the so-called "Concorde fallacy" (Carter, Kaufmann, and Michel 2007). When keeping products instead of returning them, customers do not have to write off shipping fees. Since fixed-fee shipping more often necessitates writing off shipping fees than threshold-based free shipping, the former incentivizes keeping instead of returning more than the latter. The second reason for expecting threshold-based free shipping to lead to more returns than fixed-fee shipping is economic customer behavior with regards to the cost of re-ordering. When customers think about returning a purchase and ordering a slightly different product, the benefit of returning and re-ordering has to outweigh its cost (Anderson, Hansen, and Simester 2009; Petersen and Kumar 2015). This cost is often lower with threshold-based free shipping, where shipping is potentially free, than with fixed-fee shipping, where shipping is always paid, and therefore the cost-benefit-ratio with the former more often permits returning than with the latter. Our empirical results show that shipping policy influences returns. Threshold-based free shipping slightly increases returns by 0.29% and 2.26%, depending on how shipping fees changed. Therefore, in line with our theoretical argument, we find that shipping policy influences returns, although effect sizes are small to moderate.

Besides, we find that the small, positive effect of threshold-based free shipping on returning is both reversed and amplified for returning of filler purchases. Here, threshold-based free shipping leads to less product returns. In particular, for filler purchases, returns decrease between 1.08% and 1.93% due to the introduction of threshold-based free shipping. A post-estimation analysis of filler purchases shows that categories in which such purchases are overrepresented comprise many recurring purchases (e.g., health, beauty and baby product categories) and gifts (toys product category). We hence find support for our hypothesis that threshold-based free shipping would incentivize customers to order additional products, which they would have ordered anyway but at a later point in time. Those products have been shown to be likely regularly purchased products with a consequently lower return rate (Petersen and Kumar 2009). We find no support for our opposite hypothesis that threshold-based free shipping would lead to more returns of filler purchases due to customers intentionally planning to order and return in order to abuse the shipping policy and obtain free shipping. While customers thus show intentional and planned behavior by ordering distinct, less returned products as filler purchases, customers show no signs of malevolent behavior by ordering and returning to circumvent shipping fees.

6.2. Managerial implications

Our paper compares the impact of two straightforward and widely used shipping fee policies, fixed-fee shipping and threshold-based free shipping, on both purchases and returns, and our findings have important managerial implications.

First, we find that threshold-based free shipping has the advantage of substantially higher sales and more orders, while fixed-fee shipping leads to a lower return rate. Thus, our findings indicate that threshold-based free shipping is in most circumstances advantageous for the retailer. In a simulation, we find that a retailer with an average gross margin for online retailing (of 42.5%, Damodaran 2021) makes higher profits with threshold-based free shipping than with fixed-fee shipping with return processing costs per product of up to €12. For retailers with lower gross margins, return processing costs are of greater concern and very low margins coupled with very high return processing costs can make fixed-fee shipping more profitable: in our simulation, only a retailer with a gross margin of 37.5% or less and return processing costs of €12 or more, would be better off with fixed-fee shipping than with threshold-based free shipping.

Second, we do not find evidence for strategic abuse of threshold-based free shipping policies. Instead, threshold-based free shipping leads customers to order products, which they anticipate to need anyway, as filler purchases and return those purchases less than their other purchases. Since filler purchases are thus returned less than regular purchases, it would be beneficial for retailers to actively promote such purchases, e.g., by having a wish list function or suggesting recurrently ordered products at the order checkout page.

6.3. Limitations and future research

Our study is based on the purchase and return data of several million customers over the course of three years at a generalist online retailer. Even though the retailer is large and carries an assortment that covers most products that a generally ordered online, it is still a single retailer in one country. Therefore, repeating the analysis for different retailers in different markets could give further support to our findings. In addition, having only data from one retailer prevents us from observing customer switching behavior. Therefore, we cannot say whether the increase in sales from our retailer is paralleled by decreased sales from its competitors. Finally, we do not find evidence for customers circumventing threshold-based free shipping using filler purchases, on average. A laboratory experiment might help to shed light on possible boundary conditions for such strategic behavior.

References

Anderson, Eric T., Karsten Hansen, and Duncan Simester (2009), "The Option Value of Returns: Theory and Empirical Evidence," *Marketing Science*, 28 (3), 405–23.

Arkes, Hal R and Catherine Blumer (1985), "The psychology of sunk cost," *Organizational Behavior and Human Decision Processes*, 35 (1), 124–40.

Bijmolt, Tammo H.A., Manda Broekhuis, Sander de Leeuw, Christian Hirche, Robert P. Rooderkerk, Rui Sousa, and Stuart X. Zhu (2019), "Challenges at the marketing–operations interface in omni-channel retail environments," *Journal of Business Research*, S014829631930699X.

Bijmolt, Tammo H.A., Harald J. Van Heerde, and Rik G.M. Pieters (2005), "New Empirical Generalizations on the Determinants of Price Elasticity," *Journal of Marketing Research*, 42 (2), 141–56.

Caro, Felipe, A. Gürhan Kök, and Victor Martínez-de-Albéniz (2020), "The Future of Retail Operations," *Manufacturing & Service Operations Management*, 22 (1), 47–58.

Carter, Craig R., Lutz Kaufmann, and Alex Michel (2007), "Behavioral supply management: a taxonomy of judgment and decision-making biases," *International Journal of Physical Distribution & Logistics Management*, 37 (8), 631–69.

Cox, Anthony D., Dena Cox, and Ronald D. Anderson (2005), "Reassessing the pleasures of store shopping," *Journal of Business Research*, 58 (3), 250–59.

Damodaran, Aswath (2021), "Margins by Sector (US)," NYU Stern School of Business.

Domeier, Markus, Pierre Sachse, and Bernd Schäfer (2018), "Motivational Reasons for Biased Decisions: The Sunk-Cost Effect's Instrumental Rationality," *Frontiers in Psychology*, 9, 815.

Eurostat (2018), "E-commerce statistics for individuals - Statistics Explained," 1–12.

Greenleaf, Eric A. and Donald R. Lehmann (1995), "Reasons for Substantial Delay in Consumer Decision Making," *Journal of Consumer Research*, 22 (2), 186.

Hamilton, Rebecca W. and Joydeep Srivastava (2008), "When 2 + 2 is Not the Same as 1 + 3: Variations in Price Sensitivity across Components of Partitioned Prices," *Journal of Marketing Research*, 45 (4), 450–61.

Hess, James D., Wujin Chu, and Eitan Gerstner (1996), "Controlling product returns in direct marketing," *Marketing Letters*, 7 (4), 307–17.

Lepthien, Anke and Michel Clement (2019), "Shipping fee schedules and return behavior," *Marketing Letters*, 30 (2), 151–65.

Lewis, M (2006), "The effect of shipping fees on customer acquisition, customer retention, and purchase quantities," *Journal of Retailing*, 82 (1), 13–23.

Lewis, Michael, Vishal Singh, and Scott Fay (2006), "An Empirical Study of the Impact of Nonlinear Shipping and Handling Fees on Purchase Incidence and Expenditure Decisions," *Marketing Science*, 25 (1), 51–64.

Minnema, Alec, Tammo H. A. Bijmolt, J. Andrew Petersen, and Jeffrey D. Shulman (2018), "Managing Product Returns Within the Customer Value Framework," in *Customer*

Engagement Marketing, R. W. Palmatier, V. Kumar, and C. M. Harmeling, eds., Cham: Springer International Publishing, 95–118.

Petersen, J. Andrew and V. Kumar (2009), "Are Product Returns a Necessary Evil? Antecedents and Consequences," *Journal of Marketing*, 73 (3), 35–51.

Petersen, J. Andrew and V. Kumar (2015), "Perceived Risk, Product Returns, and Optimal Resource Allocation: Evidence from a Field Experiment," *Journal of Marketing Research*, 52 (2), 268–85.

Retail Detail (2019), "Zalando cuts back on free shipping policy."

Sahoo, Nachiketa, Chrysanthos Dellarocas, and Shuba Srinivasan (2018), "The Impact of Online Product Reviews on Product Returns," *Information Systems Research*, 29 (3), 723–38.

Saleh, Mahmoud Abdel Hamid (2012), "An Investigation of the Relationship between Unplanned Buying and Post-purchase Regret," *International Journal of Marketing Studies*, 4 (4).

Schindler, Robert M (1989), "The Excitement of Getting a Bargain: Some Hypotheses Concerning the Origins and Effects of Smart-Shopper Feelings," *Advances in Consumer Research*, 16, 8.

Shehu, Edlira, Dominik Papies, and Scott A. Neslin (2020), "Free Shipping Promotions and Product Returns," *Journal of Marketing Research*, 57 (4), 640–58.

Smith, Michael D and Erik Brynjolfsson (2001), "Consumer Decision-making at an Internet Shopbot: Brand Still Matters," *Journal of Industrial Economics*, XLIX (4), 18.

StataCorp (2020), “xtregar — Fixed- and random-effects linear models with an AR(1) disturbance.”

Stigler, George J and Gary S Becker (1977), “De Gustibus Non Est Disputandum,” *The American Economic Review*, 67 (2), 76–90.

Wachter, Kathy, Scott J Vitell, Ruth K Shelton, and Kyungae Park (2012), “Exploring consumer orientation toward returns: unethical dimensions,” *Business Ethics*, 21 (1), 14.

Appendix A

Extended tables

Table A1

Influence of threshold-based free shipping and type of purchase (filler versus regular) on return probability (full table)

	Dependent variable:	
	returned (2)	returned (3)
$\text{Constant}_{\text{shipping fee up}}$	-.844*** (.006)	-.857*** (.006)
$\text{Constant}_{\text{shipping fee down}}$	.092*** (.002)	.087*** (.002)
threshold-based free shipping$_{\text{shipping fee up}}$	.014* (.006)	
filler purchase × threshold-based free shipping$_{\text{shipping fee up}}$		-.131*** (.011)
regular purchase × threshold-based free shipping$_{\text{shipping fee up}}$		.018** (.006)
threshold-based free shipping$_{\text{shipping fee down}}$	.091*** (.002)	
filler purchase × threshold-based free shipping$_{\text{shipping fee down}}$		-.363*** (.003)
regular purchase × threshold-based free shipping$_{\text{shipping fee down}}$		.098*** (.002)
Price	.003*** (.000)	.003*** (.000)
Discounted	-.040*** (.001)	-.039*** (.001)
basket size	.052*** (.000)	.051*** (.000)
last in basket	-.322*** (.001)	-.294*** (.001)
Age	-.004*** (.000)	-.004*** (.000)
gender_male	-.253*** (.001)	-.253*** (.001)
years of customer patronage	.011*** (.000)	.011*** (.000)
year_2017	.028*** (.001)	.029*** (.001)
year_2018	.054*** (.001)	.055*** (.001)
year_2019	.096*** (.001)	.098*** (.001)
month_Feb	.029*** (.001)	.029*** (.001)
month_Mar	.029*** (.001)	.028*** (.001)
month_Apr	-.015*** (.001)	-.016*** (.001)
month_May	-.029*** (.001)	-.030*** (.001)
month_Jun	-.024*** (.001)	-.025*** (.001)
month_Jul	-.069*** (.001)	-.068*** (.001)
month_Aug	-.040*** (.001)	-.040*** (.001)
month_Sep	.067*** (.001)	.066*** (.001)
month_Oct	.079*** (.001)	.078*** (.001)
month_Nov	.055*** (.001)	.053*** (.001)
month_Dec	.028*** (.001)	.027*** (.001)
day_Tue	.002* (.001)	.002* (.001)
day_Wed	.004*** (.001)	.004*** (.001)
day_Thu	.001 (.001)	.001 (.001)
day_Fri	-.008*** (.001)	-.008*** (.001)
day_Sat	.000 (.001)	-.000 (.001)
day_Sun	-.005*** (.001)	-.005*** (.001)
cat_Accessoires	-1.145*** (.001)	-1.141*** (.001)
cat_Baby	-1.384*** (.002)	-1.379*** (.002)
cat_Beachwear	.345*** (.001)	.348*** (.001)
cat_Beauty	-2.105*** (.004)	-2.099*** (.004)
cat_Electronics	-2.204*** (.002)	-2.201*** (.002)
cat_Garden	-2.236*** (.004)	-2.234*** (.004)
cat_Health	-2.427*** (.010)	-2.419*** (.010)
cat_Home	-2.026*** (.001)	-2.021*** (.001)
cat_Kids_fashion	-.961*** (.001)	-.959*** (.001)
cat_Lingerie	-.787*** (.001)	-.784*** (.001)
cat_Mens_fashion	-.617*** (.001)	-.617*** (.001)
cat_Nightwear	-.926*** (.002)	-.920*** (.002)
cat_Other	-9.126*** (.447)	-9.145*** (.447)
cat_Shoes	-.216*** (.001)	-.219*** (.001)
cat_Sports	-.500*** (.001)	-.500*** (.001)
cat_Toys	-2.811*** (.004)	-2.799*** (.004)
Observations	83704086	83704086
Log-likelihood	-49282562.71	-49254263.10
BIC	98565982.84	98509420.10

*** p<.001, ** p<.01, * p<.05, standard errors in parentheses

Table A2

Influence of shipping policy (threshold-based free shipping versus fixed-fee shipping) and type of purchase (filler versus regular) on return probability in a full factorial design (full table)

	Dependent variable:
	returned
	(4)
filler purchase × fixed-fee shipping$_{\text{shipping fee up}}$	-.935*** (.047)
filler purchase × threshold-based free shipping$_{\text{shipping fee up}}$	-.989*** (.009)
regular purchase × fixed-fee shipping$_{\text{shipping fee up}}$	-.856*** (.006)
regular purchase × threshold-based free shipping$_{\text{shipping fee up}}$	-.839*** (.003)
filler purchase × fixed-fee shipping$_{\text{shipping fee down}}$	-.200*** (.008)
filler purchase × threshold-based free shipping$_{\text{shipping fee down}}$	-.278*** (.003)
regular purchase × fixed-fee shipping$_{\text{shipping fee down}}$	.090*** (.002)
regular purchase × threshold-based free shipping$_{\text{shipping fee down}}$	.184*** (.002)
Price	.003*** (.000)
Discounted	-.039*** (.001)
basket size	.051*** (.000)
last in basket	-.293*** (.001)
Age	-.004*** (.000)
gender_male	-.253*** (.001)
years of customer patronage	.011*** (.000)
year_2017	.029*** (.001)
year_2018	.055*** (.001)
year_2019	.098*** (.001)
month_Feb	.029*** (.001)
month_Mar	.028*** (.001)
month_Apr	-.016*** (.001)
month_May	-.030*** (.001)
month_Jun	-.025*** (.001)
month_Jul	-.068*** (.001)
month_Aug	-.040*** (.001)
month_Sep	.066*** (.001)
month_Oct	.077*** (.001)
month_Nov	.053*** (.001)
month_Dec	.027*** (.001)
day_Tue	.002* (.001)
day_Wed	.004*** (.001)
day_Thu	.001 (.001)
day_Fri	-.008*** (.001)
day_Sat	-.000 (.001)
day_Sun	-.005*** (.001)
cat_Accessoires	-1.141*** (.001)
cat_Baby	-1.379*** (.002)
cat_Beachwear	.348*** (.001)
cat_Beauty	-2.099*** (.004)
cat_Electronics	-2.201*** (.002)
cat_Garden	-2.235*** (.004)
cat_Health	-2.419*** (.010)
cat_Home	-2.021*** (.001)
cat_Kids_fashion	-.959*** (.001)
cat_Lingerie	-.784*** (.001)
cat_Mens_fashion	-.617*** (.001)
cat_Nightwear	-.920*** (.002)
cat_Other	-9.146*** (.447)
cat_Shoes	-.219*** (.001)
cat_Sports	-.500*** (.001)
cat_Toys	-2.799*** (.004)
Observations	83704086
Log-likelihood	-49253549.63
BIC	98508029.64

*** p<.001, ** p<.01, * p<.05, standard errors in parentheses

Appendix B

Profitability simulation

We calculate the overall change in one-year cumulative profits between the two shipping policies as the sum of three components: (1) change in daily sales (excluding returns) × the gross margin, (2) change in daily received shipping fees, and (3) change in daily cost of return handling:

(B1)
$$\Delta^{profit}/_{year} = \left(\Delta^{netsales}/_{day} \times margin + \Delta^{shippingfees}/_{day} - \Delta^{returncost}/_{day}\right) \times 365$$

where we calculate the individual parts as follows:

1. The first part of the overall calculation consists of multiplying the difference in daily net sales (i.e., post-returns) with an assumed margin. We input the assumed margin directly (e.g., *margin* = 45%) and then calculate the difference of net sales with threshold-based free shipping (abbreviated as tbfs) and net sales with fixed-fee shipping (abbreviated as ffs). Since we estimated baseline sales and the effect of tbfs separately for categories with rising and falling shipping fees, we need to calculate 2x2 net sales values:

(B2)
$$\Delta^{netsales}/_{day} = \left({netsales_{tbfs,shippingfeedown}}/_{day} + {netsales_{tbfs,shippingfeeup}}/_{day} \right) - \left({netsales_{ffs,shippingfeedown}}/_{day} + {netsales_{ffs,shippingfeeup}}/_{day} \right)$$

Since sales estimations from model (1a) includes returned items, we need to calculate net sales first. We do so by multiplying predicted sales from model (1a) with the probability of not returning – using predicted returns from model (2). This needs to be done for all four *netsales* values from the last equation:

(B3) $$netsales_{ffs,shippingfeedown}/_{day} = sales_{tbfs,shippingfeedown}/_{day} \times (1 - prob\_returns_{ffs,shippingfeedown})$$

(B4) $$netsales_{tbfs,shippingfeedown}/_{day} = sales_{tbfs,shippingfeeup}/_{day} \times (1 - prob\_returns_{tbfs,shippingfeeup})$$

(B5) $$netsales_{ffs,shippingfeeup}/_{day} = sales_{ffs,shippingfeedown}/_{day} \times (1 - prob\_returns_{ffs,shippingfeedown})$$

(B6) $$netsales_{tbfs,shippingfeeup}/_{day} = sales_{ffs,shippingfeeup}/_{day} \times (1 - prob\_returns_{tbfs,shippingfeeup})$$

Now, we proceed to predict sales and returns. First, we predict sales using the estimates of model (Ia) using (a) the baseline sales + (b) effect of tbfs, if applicable + (c) effect of control variables. In particular, we only include (b) when calculating sales with threshold-based free shipping and we include (c) as: $^1/_4$ of each year covariate, $^1/_{12}$ of each month covariate, $^1/_7$ of each day covariate, and $\frac{orders\_in\_category_i}{total\_orders}$ times each category i covariate:

(B7) $$sales_{ffs,shippingfeedown}/_{day} = exp(\alpha_{shippingfee-} + covariates)$$

(B8) $$sales_{tbfs,shippingfeedown}/_{day} = exp(\alpha_{shippingfeedown} + \beta_{tbfs,shippingfeedown} + covariates)$$

(B9) $$sales_{ffs,shippingfeeup}/_{day} = exp(\alpha_{shippingfeeup} + covariates)$$

(B10) $$sales_{tbfs,shippingfeeup}/_{day} = exp(\alpha_{shippingfeeup} + \beta_{tbfs,shippingfeeup} + covariates)$$

$$\text{with: } covariates = \frac{1}{4}\sum_{i=1}^{3}\beta_{year\_i} + \frac{1}{12}\sum_{i=1}^{11}\beta_{month\_i} + \frac{1}{7}\sum_{i=1}^{6}\beta_{day\_i} + \sum_{i=1}^{16}\frac{orders\_in\_category_i}{total\_orders}\beta_{category\_i}$$

Second, we predict returns. We calculate the four $prob\_returns$ using the estimates of the logit model (2) and, besides, proceed similarly as for the prediction of sales:

(B11) $prob\_returns_{ffs,shippingfeedown} = logit^{-1}(\alpha_{shippingfeedown} + covariates)$

(B12) $prob\_returns_{tbfs,shippingfeedown} = logit^{-1}(\alpha_{shippingfeedown} + \beta_{tbfs,shippingfeedown} + covariates)$

(B13) $prob\_returns_{ffs,shippingfeeup} = logit^{-1}(\alpha_{shippingfeeup} + covariates)$

(B14) $prob\_returns_{tbfs,shippingfeeup} = logit^{-1}(\alpha_{shippingfeeup} + \beta_{tbfs,shippingfeeup} + covariates)$

with: covariates as defined above but using the estimates of the return model

2. The second part of the overall calculation consists of the change in daily received shipping fees. Here, we calculate the daily received shipping fees for both the ffs and tbfs policies and take the difference of both. Again, we need to do this two times – for categories where shipping fees decreased and for categories where shipping fees increased – and add the results:

(B15)
$$\Delta^{shippingfees}/_{day} = \left({}^{shippingfees_{tbfs,shippingfeedown}}/_{day} + {}^{shippingfees_{tbfs,shippingfeeup}}/_{day} \right) - \left({}^{shippingfees_{ffs,shippingfeedown}}/_{day} + {}^{shippingfees_{ffs,shippingfeeup}}/_{day} \right)$$

Each part of the equation is calculated by: (a) the applicable shipping fee × (b) predicted number of orders:

(B16) $^{shippingfees_{ffs,shippingfeedown}}/_{day} = fee_{ffs,shippingfeedown} \times count\_orders_{ffs,shippingfeedown}$

(B17) $^{shippingfees_{tbfs,shippingfeedown}}/_{day} = fee_{tbfs,shippingfeedown} \times count\_orders_{tbfs,shippingfeedown}$

(B18) $^{shippingfees_{ffs,shippingfeeup}}/_{day} = fee_{ffs,shippingfeeup} \times count\_orders_{ffs,shippingfeeup}$

(B19) $^{shippingfees_{tbfs,shippingfeeup}}/_{day} = fee_{tbfs,shippingfeeup} \times count\_orders_{tbfs,shippingfeeup}$

For (a), we calculate the average observed shipping fee for the respective orders, i.e., the average shipping fee for (1) orders with threshold-based free shipping in categories where shipping fees decreased, (2) orders with threshold-based free shipping in categories where shipping fees increased, etc.:

$$fee_{ffs,shippingfeedown} = 6.297€$$

$$fee_{tbfs,shippingfeedown} = .098€$$

$$fee_{ffs,shippingfeeup} = .766€$$

$$fee_{tbfs,shippingfeeup} = .247€$$

For (b), we get the number of daily orders using the estimates of model (Ic), similar to how we did the first two predictions:

(B20) $$count\_orders_{ffs,shippingfeedown}/_{day} = exp(\alpha_{shippingfeedown} + covariates)$$

(B21) $$count\_orders_{tbfs,shippingfeedown}/_{day} = exp(\alpha_{shippingfeedown} + \beta_{tbfs,shippingfeedown} + covariates)$$

(B22) $$count\_orders_{ffs,shippingfeeup}/_{day} = exp(\alpha_{shippingfeeup} + covariates)$$

(B23) $$count\_orders_{tbfs,shippingfeeup}/_{day} = exp(\alpha_{shippingfeeup} + \beta_{tbfs,shippingfeeup} + covariates)$$

with: covariates as defined above but using the estimates of the count order model

3. The third part of the overall calculation is the change in daily cost of return handling. We calculate this part by subtracting the daily return cost with fixed-fee shipping from the daily return cost with threshold-based free shipping:

(B24) $$\Delta^{returncost_{sum}}/_{day} = {}^{returncost_{sum,tbfs}}/_{day} - {}^{returncost_{sum,ffs}}/_{day}$$

where each part is (a) cost-per-return × (b) number-of-daily-returns with ffs or tbfs. We input (a) as fixed numbers (e.g., $returncost_{per\_return} = €6$) but do not have (b). We can calculate (b) by: the estimate of the number of daily orders × number of products per orders × the return probability of a product. Again, we need to do this separately for ffs and tbfs policies and for rising and falling shipping fees. We thus get:

$$returncost_{sum,ffs}/_{day} = returncost_{per\_return} \times \left(prob\_returns_{ffs,shippingfeedown} \times ordersize_{ffs,shippingfeedown} \times {count\_orders_{ffs,shippingfeedown}}/_{day} + prob\_returns_{ffs,shippingfeeup} \times ordersize_{ffs,shippingfeeup} \times {count\_orders_{ffs,shippingfeeup}}/_{day} \right) \quad \text{(B25)}$$

$$returncost_{sum,tbfs}/_{day} = returncost_{per\_return} \times \left(prob\_returns_{tbfs,shippingfeedown} \times ordersize_{tbfs,shippingfeedown} \times {count\_orders_{tbfs,shippingfeedown}}/_{day} + prob\_returns_{tbfs,shippingfeeup} \times ordersize_{tbfs,shippingfeeup} \times {count\_orders_{tbfs,shippingfeeup}}/_{day} \right) \quad \text{(B26)}$$

For the number of products per order, we calculate the average value for the respective orders with the following result:

$$ordersize_{ffs,shippingfeedown} = 3.619$$

$$ordersize_{tbfs,shippingfeedown} = 3.351$$

$$ordersize_{ffs,shippingfeeup} = 1.388$$

$$ordersize_{tbfs,shippingfeeup} = 1.593$$

For the return probability, we use the values predicted in the first step.

List of research reports

16001-GEM: Hoorn, A. van, How Are Migrant Employees Manages? An Integrated Analysis

16002-EEF: Soetevent, A.R., Te Bao, A.L. Schippers, A Commercial Gift for Charity

16003-GEM: Bouwmeerster, M.C., and J. Oosterhaven, Economic Impacts of Natural Gas Flow Disruptions

16004-MARK: Holtrop, N., J.E. Wieringa, M.J. Gijsenberg, and P. Stern, Competitive Reactions to Personal Selling: The Difference between Strategic and Tactical Actions

16005-EEF: Plantinga, A. and B. Scholtens, The Financial Impact of Divestment from Fossil Fuels

16006-GEM: Hoorn, A. van, Trust and Signals in Workplace Organization: Evidence from Job Autonomy Differentials between Immigrant Groups

16007-EEF: Willems, B. and G. Zwart, Regulatory Holidays and Optimal Network Expansion

16008-GEF: Hoorn, A. van, Reliability and Validity of the Happiness Approach to Measuring Preferences

16009-EEF: Hinloopen, J., and A.R. Soetevent, (Non-)Insurance Markets, Loss Size Manipulation and Competition: Experimental Evidence

16010-EEF: Bekker, P.A., A Generalized Dynamic Arbitrage Free Yield Model

16011-EEF: Mierau, J.A., and M. Mink, A Descriptive Model of Banking and Aggregate Demand

16012-EEF: Mulder, M. and B. Willems, Competition in Retail Electricity Markets: An Assessment of Ten Year Dutch Experience

16013-GEM: Rozite, K., D.J. Bezemer, and J.P.A.M. Jacobs, Towards a Financial Cycle for the US, 1873-2014

16014-EEF: Neuteleers, S., M. Mulder, and F. Hindriks, Assessing Fairness of Dynamic Grid Tariffs

16015-EEF: Soetevent, A.R., and T. Bružikas, Risk and Loss Aversion, Price Uncertainty and the Implications for Consumer Search

16016-HRM&OB: Meer, P.H. van der, and R. Wielers, Happiness, Unemployment and Self-esteem

16017-EEF: Mulder, M., and M. Pangan, Influence of Environmental Policy and Market Forces on Coal-fired Power Plants: Evidence on the Dutch Market over 2006-2014

16018-EEF: Zeng,Y., and M. Mulder, Exploring Interaction Effects of Climate Policies: A Model Analysis of the Power Market

16019-EEF: Ma, Yiqun, Demand Response Potential of Electricity End-users Facing Real Time Pricing

16020-GEM: Bezemer, D., and A. Samarina, Debt Shift, Financial Development and Income Inequality in Europe

16021-EEF: Elkhuizen, L, N. Hermes, and J. Jacobs, Financial Development, Financial Liberalization and Social Capital

16022-GEM: Gerritse, M., Does Trade Cause Institutional Change? Evidence from Countries South of the Suez Canal

16023-EEF: Rook, M., and M. Mulder, Implicit Premiums in Renewable-Energy Support Schemes

17001-EEF: Trinks, A., B. Scholtens, M. Mulder, and L. Dam, Divesting Fossil Fuels: The Implications for Investment Portfolios

17002-EEF: Angelini, V., and J.O. Mierau, Late-life Health Effects of Teenage Motherhood

17003-EEF: Jong-A-Pin, R., M. Laméris, and H. Garretsen, Political Preferences of (Un)happy Voters: Evidence Based on New Ideological Measures

17004-EEF: Jiang, X., N. Hermes, and A. Meesters, Financial Liberalization, the Institutional Environment and Bank Efficiency

17005-EEF: Kwaak, C. van der, Financial Fragility and Unconventional Central Bank Lending Operations

17006-EEF: Postelnicu, L. and N. Hermes, The Economic Value of Social Capital

17007-EEF: Ommeren, B.J.F. van, M.A. Allers, and M.H. Vellekoop, Choosing the Optimal Moment to Arrange a Loan

17008-EEF: Bekker, P.A., and K.E. Bouwman, A Unified Approach to Dynamic Mean-Variance Analysis in Discrete and Continuous Time

17009-EEF: Bekker, P.A., Interpretable Parsimonious Arbitrage-free Modeling of the Yield Curve

17010-GEM: Schasfoort, J., A. Godin, D. Bezemer, A. Caiani, and S. Kinsella, Monetary Policy Transmission in a Macroeconomic Agent-Based Model

17011-I&O: Bogt, H. ter, Accountability, Transparency and Control of Outsourced Public Sector Activities

17012-GEM: Bezemer, D., A. Samarina, and L. Zhang, The Shift in Bank Credit Allocation: New Data and New Findings

17013-EEF: Boer, W.I.J. de, R.H. Koning, and J.O. Mierau, Ex-ante and Ex-post Willingness-to-pay for Hosting a Major Cycling Event

17014-OPERA: Laan, N. van der, W. Romeijnders, and M.H. van der Vlerk, Higher-order Total Variation Bounds for Expectations of Periodic Functions and Simple Integer Recourse Approximations

17015-GEM: Oosterhaven, J., Key Sector Analysis: A Note on the Other Side of the Coin

17016-EEF: Romensen, G.J., A.R. Soetevent: Tailored Feedback and Worker Green Behavior: Field Evidence from Bus Drivers

17017-EEF: Trinks, A., G. Ibikunle, M. Mulder, and B. Scholtens, Greenhouse Gas Emissions Intensity and the Cost of Capital

17018-GEM: Qian, X. and A. Steiner, The Reinforcement Effect of International Reserves for Financial Stability

17019-GEM/EEF: Klasing, M.J. and P. Milionis, The International Epidemiological Transition and the Education Gender Gap

2018001-EEF: Keller, J.T., G.H. Kuper, and M. Mulder, Mergers of Gas Markets Areas and Competition amongst Transmission System Operators: Evidence on Booking Behaviour in the German Markets

2018002-EEF: Soetevent, A.R. and S. Adikyan, The Impact of Short-Term Goals on Long-Term Objectives: Evidence from Running Data

2018003-MARK: Gijsenberg, M.J. and P.C. Verhoef, Moving Forward: The Role of Marketing in Fostering Public Transport Usage

2018004-MARK: Gijsenberg, M.J. and V.R. Nijs, Advertising Timing: In-Phase or Out-of-Phase with Competitors?

2018005-EEF: Hulshof, D., C. Jepma, and M. Mulder, Performance of Markets for European Renewable Energy Certificates

2018006-EEF: Fosgaard, T.R., and A.R. Soetevent, Promises Undone: How Committed Pledges Impact Donations to Charity

2018007-EEF: Durán, N. and J.P. Elhorst, A Spatio-temporal-similarity and Common Factor Approach of Individual Housing Prices: The Impact of Many Small Earthquakes in the North of Netherlands

2018008-EEF: Hermes, N., and M. Hudon, Determinants of the Performance of Microfinance Institutions: A Systematic Review

2018009-EEF: Katz, M., and C. van der Kwaak, The Macroeconomic Effectiveness of Bank Bail-ins

2018010-OPERA: Prak, D., R.H. Teunter, M.Z. Babai, A.A. Syntetos, and J.E. Boylan, Forecasting and Inventory Control with Compound Poisson Demand Using Periodic Demand Data

2018011-EEF: Brock, B. de, Converting a Non-trivial Use Case into an SSD: An Exercise

2018012-EEF: Harvey, L.A., J.O. Mierau, and J. Rockey, Inequality in an Equal Society

2018013-OPERA: Romeijnders, W., and N. van der Laan, Inexact cutting planes for two-stage mixed-integer stochastic programs

2018014-EEF: Green, C.P., and S. Homroy, Bringing Connections Onboard: The Value of Political Influence

2018015-OPERA: Laan, N. van der, and W. Romeijnders, Generalized aplha-approximations for two-stage mixed-integer recourse models

2018016-GEM: Rozite, K., Financial and Real Integration between Mexico and the United States

2019001-EEF: Lugalla, I.M., J. Jacobs, and W. Westerman, Drivers of Women Entrepreneurs in Tourism in Tanzania: Capital, Goal Setting and Business Growth

2019002-EEF: Brock, E.O. de, On Incremental and Agile Development of (Information) Systems

2019003-OPERA: Laan, N. van der, R.H. Teunter, W. Romeijnders, and O.A. Kilic, The Data-driven Newsvendor Problem: Achieving On-target Service Levels.

2019004-EEF: Dijk, H., and J. Mierau, Mental Health over the Life Course: Evidence for a U-Shape?

2019005-EEF: Freriks, R.D., and J.O. Mierau, Heterogeneous Effects of School Resources on Child Mental Health Development: Evidence from the Netherlands.

2019006-OPERA: Broek, M.A.J. uit het, R.H. Teunter, B. de Jonge, J. Veldman, Joint Condition-based Maintenance and Condition-based Production Optimization.

2019007-OPERA: Broek, M.A.J. uit het, R.H. Teunter, B. de Jonge, J. Veldman, Joint Condition-based Maintenance and Load-sharing Optimization for Multi-unit Systems with Economic Dependency

2019008-EEF: Keller, J.T. G.H. Kuper, and M. Mulder, Competition under Regulation: Do Regulated Gas Transmission System Operators in Merged Markets Compete on Network Tariffs?

2019009-EEF: Hulshof, D. and M. Mulder, Renewable Energy Use as Environmental CSR Behavior and the Impact on Firm Profit

2019010-EEF: Boot, T., Confidence Regions for Averaging Estimators
2020001-OPERA: Foreest, N.D. van, and J. Wijngaard. On Proportionally Fair Solutions for the Divorced-Parents Problem

2020002-EEF: Niccodemi, G., R. Alessie, V. Angelini, J. Mierau, and T. Wansbeek. Refining Clustered Standard Errors with Few Clusters

2020003-I&O: Bogt, H. ter, Performance and other Accounting Information in the Public Sector: A Prominent Role in the Politicians' Control Tasks?

2020004-I&O: Fisch, C., M. Wyrwich, T.L. Nguyen, and J.H. Block, Historical Institutional Differences and Entrepreneurship: The Case of Socialist Legacy in Vietnam

2020005-I&O: Fritsch, M. and M. Wyrwich. Is Innovation (Increasingly) Concentrated in Large Cities? An Internatinal Comparison

2020006-GEM: Oosterhaven, J., Decomposing Economic Growth Decompositions.

2020007-I&O: Fritsch, M., M. Obschonka, F. Wahl, and M. Wyrwich. The Deep Imprint of Roman Sandals: Evidence of Long-lasting Effects of Roman Rule on Personality, Economic Performance, and Well-Being in Germany

2020008-EEF: Heijnen, P., On the Computation of Equilibrium in Discontinuous Economic Games

2020009-EEF: Romensen, G.J. and A.R. Soetevent, Improving Worker Productivity Through Tailored Performance Feedback: Field Experimental Evidence from Bus Drivers

2020010-EEF: Rao, Z., M. Groneck, and R. Alessie, Should I Stay or Should I Go? Intergenerational Transfers and Residential Choice. Evidence from China

2020011-EEF: Kwaak, C. van der, Unintended Consequences of Central Bank Lending in Financial Crises

2020012-EEF: Soetevent, A.R., Determinants choice set variation in demand estimation – with an application to the electric vehicle public charging market

2020013-EEF: Kwaak, C. van der, Old-Keynesianism in the New Keynesian model

2020014-EEF: Plaat, m. van der, Loan Sales and the Tyranny of Distance in U.S. Residential Mortgage Lending

2020015-I&O: Fritsch, M., and M. Wyrwich, Initial Conditions and Regional Performance in the Aftermath of Disruptive Shocks: The Case of East Germany after Socialism

2020016-OPERA: Laan, N. van der, and W. Romeijnders, A Converging Benders' Decomposition Algorithm for Two-stage Mixed-integer Recourse Models

2021001-OPERA: Baardman, L., K.J. Roodbergen, H.J. Carlo, and A.H. Schrotenboer, A Special Case of the Multiple Traveling Salesmen Problem in End-of-aisle Picking Systems

2021002-EEF: Wiese, R., and S. Eriksen, Willingness to Pay for Improved Public Education and Public Health Systems: The Role of Income Mobility Prospects.

2021003-EEF: Keller, J.T., G.H. Kuper, and M. Mulder, Challenging Natural Monopolies: Assessing Market Power of Gas Transmission System Operators for Cross-Border Capacity

2021004-EEF: Li, X., and M. Mulder, Value of Power-to-Gas as a Flexibililty Option in Integrated Electricity and Hydrogen Markets

2021005-GEM: Rozite, K., J.P.A.M. Jacobs, and D.J. Bezemer, Investor Sentiment and Business Investment

2021006-EEF: Spierdijk, L., and T. Wansbeek, Differencing as a Consistency Test for the Within Estimator

2021007-EEF: Katz, M., and C. van der Kwaak, To Bail-in or to Bailout: that's the (Macro) Question

2021008-EEF: Haan, M.A., N.E. Stoffers, and G.T.J. Zwart, Choosing Your Battles: Endogenous Multihoming and Platform Competition

2021009-I&O: Greve, M., M. Fritsch, and M. Wyrwich, Long-Term Decline of Regions and the Rise of Populism: The Case of Germany

2021010-MARK: Hirche, C.F., T.H.A. Bijmolt, and M.J. Gijsenberg, When Offline Stores Reduce Online Returns

2021011-MARK: Hirche, C.F., M.J. Gijsenberg, and T.H.A. Bijmolt, Promoting Product Returns: Effects of Price Reductions on Customer Return Behavior

2021012-MARK: Hirche, C.F., M.J. Gijsenberg, and T.H.A. Bijmolt, Asking Less, Getting More? The Influence of Fixed-Fee and Threshold-Based Free Shipping on Online Orders and Returns www.rug.nl/feb