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Free Shipping Promotions and Product Returns

Abstract

Free shipping promotions have become popular among online retailers. However, little is known about their influence on consumers' purchases, return behavior, and ultimately, firm profit. The authors propose that free shipping promotions encourage customers to make riskier purchases, leading to more product returns. They estimate the impact of these promotions on purchase incidence, high-risk and low-risk spend, and return share. The results show that free shipping promotions increase expenditure for high-risk products, increasing their share of the consumer's market basket, and hence increasing the overall return rate. This is validated in a field experiment. A field test and an online lab experiment analyze the mechanism linking free shipping and returns. They suggest that the free shipping effect occurs via consumers' perceptions that free shipping serves as a risk premium compensating them for potential returns, and through positive affect generated by the promotion. A simulation shows that for the focal firm, free shipping promotions increase net sales volume, but higher product returns and lost shipping revenue render these promotions unprofitable.

Free Shipping Promotions and Product Returns

Free shipping promotions have become a "go-to" incentive for many online companies (*CBS News 2016*). Consumers are highly cognizant of shipping costs (Smith and Brynjolfsson 2001), and free shipping increases retailers' sales, both in the short run (Lewis, Singh and Fay 2006) and long run (Bower and Maxham 2012).

At the same time, online retailers are very concerned about product returns (Venkatesan and Kumar 2004; Petersen and Kumar 2009). In 2013, consumers reportedly returned one-third of all U.S. Internet sales (*Wall Street Journal* 2013). Indeed, consumers in our data returned almost 37% of all purchases, and Zalando, a large European fashion retailer, is reported to have a return rate of around 50% (Forbes 2014). Returns decrease profits, directly by reducing revenues, and indirectly through the operational costs of managing returns (Stock, Speh and Shear 2006).

The core tenet of this research is that free shipping promotions are effective at stimulating sales, but they have a downside that has so far been neglected – an increase in product returns. Our objective is to integrate these two phenomena. We propose that free shipping promotions induce online customers to purchase riskier products, i.e., products whose attributes are difficult to evaluate without physical inspection. This skews the consumer's shopping basket toward riskier products. Since consumers return riskier products at a higher rate (Hong and Pavlou 2014), the overall return rate for the basket increases. We base the rationale behind this *free shipping effect* on dual-processing theories of decision-making, in particular, Loewenstein et al.'s (2001) theory, which argues that consumers assess risky choices drawing on both cognitions and feelings. We propose that by compensating consumers for making a risky choice, free shipping promotions serve as a risk premium, corresponding to cognitions. At the same time, free shipping promotions invoke positive affect, corresponding to feelings. Both mechanisms, cognition and feelings, lead consumers to purchase riskier products.

Consequently, free shipping promotions increase the percentage of the basket the customer returns, a downside we must consider to evaluate their full impact on profitability. However, researchers have not investigated this downside, leaving a gap in our understanding of the impact of free shipping promotions. We contribute to the literature by (1) addressing this gap, both theoretically and empirically, (2) investigating whether, to what extent, and why free shipping promotions influence product returns, and (3) documenting a connection between two marketing phenomena – free shipping promotions and product returns – that had previously not been established. We do this by measuring the impact of the free shipping promotions on returns, sales and profits, and by exploring the underlying mechanisms that cause it.

We conduct four studies. In Study 1 we develop a statistical model that considers the impact of free shipping promotions on purchase incidence, high-risk spend, low-risk spend, and returns. We estimate the model using a unique data set from an online retailer that ran several free shipping promotions over a three-year period. We find that free shipping promotions increase purchase incidence, but – as expected – also increase the purchase of high-risk products, which customers are more likely to return. Study 2, a randomized field experiment with over 700,000 customers, replicates the free shipping effect. In these studies, we also investigate the role of branding and find that the free shipping effect is more of a category phenomenon than a brand phenomenon. In Studies 3 and 4, we analyze the risk premium and positive affect mechanisms for the free shipping effect, using a field test and an online lab experiment. The studies suggest that both mechanisms are at work. The net result is that free shipping promotions increase high-risk purchases more than low-risk purchases.

A profit simulation suggests that, for our application, free shipping promotions are unprofitable. They increase high-risk purchases and, consequently, order volume goes up by 11%, but returns are also higher due to high-risk purchases. Because of higher returns and lost shipping revenue, profits decrease by .7%. The results show that free shipping promotions can increase return rates to a larger extent than other promotions (e.g., coupons). In the case of coupon promotions, the increase in order volume is driven by a higher spend for both high- and low-risk products, in contrast to free shipping, which only increases the spend for high-risk products. Consequently, coupon promotions do not increase the overall return rate and are profitable, while free shipping promotions are not. This shows the relevance of the free shipping effect on product returns.

We proceed to review the literature. Then we elaborate the theoretical rationale behind the free shipping effect and present the framework we use to guide our empirical analysis. We then present Studies 1 to 4. We conclude with implications for researchers and managers.

LITERATURE REVIEW

Free Shipping

Previous research has found that online consumers are sensitive to shipping costs and respond strongly to free shipping initiatives. Smith and Brynjolfsson (2001) examined consumers' choices of books when a shopbot provides information on price and shipping fees. The authors found that shipping fees have a pronounced negative effect on choice, and consumers are twice as sensitive to shipping fees as an equivalent discount in book prices. Lewis, Singh, and Fay (2006) examined an online retailer of non-perishable grocery and drugstore products. They found that free shipping increases purchase incidence compared to shipping fees that vary with order size, although it decreases order size. Similarly, Lewis (2006) found that purchase incidence is higher and order size lower under free shipping compared to shipping fees that vary by order size. Total order volume (incidence × order size) is highest for free shipping in both studies. In lab experiments, Chatterjee (2010) found that free shipping generates higher purchase intent than economically equivalent promotions. Chandran and Morwitz (2006) discovered higher sensitivity to shipping fees than prices in an experimental study of price promotions. Chatterjee and McGinnis (2010) found similar results in a study of online purchases of digital cameras.

Retailers have used free shipping not only as a promotion but also as a permanent part of their returns policy. Bower and Maxham (2012) found that free shipping return policies generate higher future sales. One reason is that return shipping fees produce negative consumer emotions, which explains why customers who do not pay return fees purchase more in the long run.

Returns

The operations literature has treated product returns as a cost to manage through "reverse logistics" (e.g., Guide et al. 2006). To mitigate this cost, Hess, Chu and Gerstner (1996) analyzed different return fees that minimize returns. Petersen and Kumar (2009) conducted the most extensive empirical analysis of returns in the marketing literature. They studied a multichannel company and found that purchases in unfamiliar categories are more likely to be returned, and that a moderate level of returns is associated with increased future purchases, consistent with Venkatesan and Kumar (2004) and Bower and Maxham (2012). Petersen and Kumar (2015) demonstrated how, by considering product returns, customer targeting can improve the firm's resource allocation. They compared their proposed strategy, which accounts for the possibility that customers will have to return products, with four benchmark models. The results show that short- and long-term profits are higher when companies account for the expected level of future returns when targeting customers.

In sum, we find that previous research has devoted considerable attention to free shipping and product returns separately. However, we are not aware of any study that connects the two and analyzes returns as a potential downside of free shipping promotions. We contribute to the literature by investigating this relationship theoretically and empirically.

CONCEPTUAL FRAMEWORK

Framework

We define risky products as those that are difficult for consumers to evaluate without physical inspection (Hong and Pavlou 2014). Hence, when consumers purchase a risky product, the product is less likely to meet their expectations, and they are more likely to return it. The "costs" to the consumer of buying and then having to return risky products are potentially the shipping fee for delivery, the inconvenience of possibly making a return, and the mailing cost if the retailer does not offer free shipping on returns. Purchasing in risky categories makes it more likely that consumers will incur these costs.

We propose that free shipping increases purchase of high-risk products, increasing their share of the shopping basket compared to low-risk products. The chance of an incorrect purchase is larger for high-risk products, which are therefore more likely to be returned. In consequence, the return rate for the shopping basket, taken as a whole, increases. We call this the "free shipping effect" on product returns. Thus, there are two conditions for the free shipping effect:

(1) high-risk goods have higher return rates than low-risk goods; and (2) free shipping increases purchase of high-risk goods *more* than purchase of low-risk goods.

With respect to the first condition, previous research shows that, in an online environment, risky products (i.e., those that must be physically seen to be fully evaluated) are more likely to be returned, since a full evaluation is only possible once the consumer has the product in hand. Hong and Pavlou (2014), for example, found in a survey study that experience goods (products associated with a higher perceived risk) are associated with higher return rates.

The more subtle question is why free shipping should especially increase purchase of high-risk products. We propose two mechanisms, "risk premium" and "positive affect," which we define and explain below.

Why Free Shipping Increases Purchase of Risky Products

Dual-process theories. Researchers have proposed "dual-process" theories of decision-making, comprising "rational" and "emotional" components (Sloman 1996; Evans 1984; Lizardo et al. 2016). One example is Loewenstein et al. (2001), who developed a dual-process theory that identifies two components of decision-making under uncertainty: "cognitive-based" and "feelings." Loewenstein et al. (2001) discuss expected utility as an example of the cognitive component, while emotions and affect are examples of the feelings component. We draw on expected utility, specifically the risk premium, to represent the cognitive component, and on affect to represent the feelings component.

Risk premium. Risk premium is fundamental to expected utility theory. Let us consider the decision between a risky option and a riskless option offering the same expected utility. A risk-averse decision-maker will choose the riskless option over the risky option. The compensation that leaves the consumer indifferent between the riskless and risky options is the risk premium (e.g., Blattberg and Neslin 1990, p. 50). In the context of our study, the risky option is an online purchase of a product category that requires physical inspection before the product can be fully evaluated. We propose that the free shipping promotion is the risk premium that compensates customers for taking the risk of purchasing from risky categories, that is, for taking the risk that they will need to return the product. This reasoning is in line with Blattberg and Neslin (1990, pp. 49–50), who argue that price promotions serve as risk premiums to compensate consumers for purchasing new products whose quality is difficult to evaluate.

Positive affect. We define “affect” as feelings of happiness (Arkes, Herren, and Isen 1988), and propose that positive affect, stimulated by the provision of free shipping, serves as the feelings component of Loewenstein et al.’s (2001) theory. We first note that shipping costs are an acute “pain point” for online shoppers. For example, eMarketer (2012) found that shipping costs were the most common reason for cart abandonment, and free/discounted shipping was the online feature that shoppers most desired to improve. Mulpuru et al. (2010) reported that customers are often “stunned by shipping costs”, and Chatterjee and McGinnis (2010) found that free shipping is associated positively with promotion fairness. Finally, e-tailers often do not specify shipping costs until the checkout page, calling attention to them as an additional charge. Mental accounting theory (Thaler 1985) suggests such segregation of price and shipping costs increases the disutility (“pain”) caused by the shipping costs.

We propose that free shipping promotions alleviate the pain point and thus generate positive affect among online shoppers. The psychological literature shows that positive affect can translate into risk-taking, unless the consequence of a negative outcome is so severe that it would obliterate the positive affect state (Arkes, Herren, and Isen 1988; also see Isen and Patrick

1983). Assuming the risk is meaningful, but not overly severe, we therefore propose that the positive affect created by free shipping encourages consumers to risk buying products whose quality they cannot fully evaluate without physical inspection.

Whether eliminating shipping costs creates enough affect or serves as a strong enough risk premium to stimulate purchase of risky products are empirical questions. In any case, risk premium and positive affect serve respectively as the cognitive and feelings components of Loewenstein et al.'s (2001) theory, and provide reasons why free shipping should encourage consumers to purchase risky products.

Summary

Our thesis is that free shipping promotions lead consumers to return a higher share of a shopping basket because they encourage consumers to purchase riskier products. We propose two potential mechanisms for this to happen, corresponding to Loewenstein et al.'s (2001) cognitive and feelings components of decision-making under uncertainty. The cognitive component is that free shipping promotions serve as a risk premium that compensates consumers for making a purchase in a risky category. The feelings component is that free shipping promotions create positive affect among consumers, which encourages them to make riskier choices. Both mechanisms lead to shopping baskets containing riskier purchases, which in turn leads to a higher return share. We use these ideas as the theoretical foundation for our empirical studies, which we present next.

OVERVIEW OF EMPIRICAL STUDIES

We investigate the free shipping effect in four studies. Study 1 uses a statistical model to analyze three years of observational data for a large sample of customers. We conduct several robustness checks for Study 1 (Table 3 and Web Appendix C). Study 2 is a randomized field experiment to validate Study 1. Studies 3 and 4 explore the risk premium and positive affect mechanisms for the free shipping effect. Study 3 is a field test, while Study 4 is an online lab experiment.

STUDY 1

Data

We obtained data from a leading retailer that engages in free shipping promotions. The retailer – originally a traditional mail-order company – has evolved into one of the largest European online retailers. While it retains its offline call center as a purchase channel, most of its business (more than 70%) is now online. It carries a wide product assortment ranging from apparel to electronics. The retailer's shipping policy provides free shipping for returns,[1] but not for "outbound" orders. The shipping fee for orders is fixed, independent of order size.[2] During free shipping promotions, the retailer offers free outbound shipping for all customer orders.

Our data are weekly over the three-year period from May 2010 to May 2013. During this time, the company ran six free shipping promotional campaigns. Each campaign ran in a different month, and the timing did not follow a regular pattern. Interviews with company

[1] Free shipping for returns is the *de facto* standard in the retailer's served market.
[2] We are not allowed to disclose the exact shipping fee, which is between €2.50 and €10. The flat fee policy is widely used in the retailer's served market.

managers revealed that the retailer did not intentionally place free shipping promotions in weak/strong sales periods. This suggests consumers could not anticipate the timing of these promotions, and we do not have to rely on just one promotion that could be confounded with seasonality or idiosyncratic events. The first campaign lasted three weeks; the others four weeks. The budgets for all campaigns were roughly the same. There were no differences in advertising channels or copy. All campaigns used multiple media (online, mailings, and print catalogs) and were offered to all customers – the retailer did not target a subset of customers, which could make free shipping endogenous. The retailer launched the first campaign in April 2011. We use the first 26 weeks to initialize control variables. The remaining 128 weeks are for estimation.

Sample and Variables

Sample. We use a random sample of 10,000 customers from the company's pool of active customers. We excluded those who spent more than €50,000 over the three-year observation period because the retailer considers these customers to be "commissioners" buying for other people. This leaves a final sample size of 9,460 customers. For each week, we have data on customer purchase history at the product (i.e., SKU) level, which we aggregate to the subcategory level. We follow the retailer's classification of products into 413 subcategories. Examples for subcategories are men's polo shirts, women's jeans, board games, or sunglasses.[3] We also observe print catalog mailings, other promotions (e.g., coupons), and online advertising (see below and Table 1 for details). No customer purchased more than once per week, so the weekly data were equivalent to basket-level data. A possible reason for why customers

[3] We analyzed at subcategory level rather than SKU level because we could not identify the specifics of the item purchased at the SKU level, i.e., we did not have a product description for each SKU. We know, however, for each SKU the corresponding subcategory, quantity, price, and brand. We note that previous research on returns has typically also used a more aggregate level than SKU (e.g., Narang and Shankar 2019; Petersen and Kumar 2009; 2015; Lewis, Singh and Fay 2006).

purchased no more than once per week is the retailer's regular flat shipping fee policy encouraged consumers to bundle their purchases to avoid paying the fee multiple times. Consumers could bundle because they purchase most of the retailer's products infrequently, so can adjust purchase timing to create bundles.

[Table 1 Goes Here]

Measuring risk. We measured the riskiness of each subcategory using independent raters (Hong and Pavlou 2014; Mitchell, Peres and Shachar 2013). Four research assistants (2 male and 2 female) coded all subcategories on three items, derived from previous research: Following Hong and Pavlou (2014), the raters evaluated (1) product fit uncertainty, and (2) product quality uncertainty, and complemented this with (3) the raters' evaluation of overall risk of a purchase in this category (Table A1 in Web Appendix A shows details). Interrater agreement was high, with an agreement percentage of 92.5% and a Cronbach's alpha of .86. Table A2 in Web Appendix A shows the descriptive statistics for each rater. We operationalized subcategory risk as its average value across the three items and across the four raters (M = 4.038, SD = .861). The results have high face validity: subcategories such as vacuum cleaner bags (1.833), storage boxes (1.917), and mirrors (2.000) are low risk; while ladies' traditional fashion (6.083), brassieres (5.833), and cosmetics (5.670) are relatively high risk. Two of the retailer's category managers confirmed the face validity of the ratings. We classify all subcategories as either low-risk or high-risk using a median split (median = 4.083). As a result, 207 subcategories are high-risk and 206 are low-risk. In the robustness checks section, we re-estimate the model with different risk categorizations.

We operationalize the expenditure (in €) for high-risk and low-risk subcategories in each purchase for customer i in week t as:

$$\mathrm{hr}_{\mathrm{it}} = \sum_{\mathrm{h}=1}^{\mathrm{H}} \mathrm{y}_{\mathrm{hit}} \quad (1)$$

$$lr_{it} = \sum_{l=1}^{L} y_{lit} \tag{2}$$

where y_{hit} is the order size (in €) of high-risk subcategory h for customer i in week t, and y_{lit} denotes order size for low-risk category l. Adding equations (1) and (2) yields y_{it}, the customer's total order size or "basket size". Return share is measured as the fraction of the basket size purchased in week t that was eventually returned. An alternative way of modeling the purchase of risky products would be an equation in which the share of risky products in a basket serves as a dependent variable instead of two separate equations for high- and low-risk spend. We opt for the two separate equations because it allows us directly to derive profit implications. In the robustness checks section we assess alternative specifications of the purchase of risky products, which support the free shipping effect on product returns (also see Web Appendix C2).

Free shipping. Given that the free shipping campaigns essentially followed the same design, we quantify free shipping by a dummy variable equal to one during each week of a free shipping campaign.

Control variables. We control for all major promotion and communication activities the company used during the observation period. We measure the number of catalog pages for all catalogs customer i received in week t.[4] We quantify coupon promotions by the value (in €) of all coupons available for customer i in week t. We also obtained expenditures in € for all online advertising activities during week t. Further, we include dummy variables for each quarter-year combination. Lastly, we capture customer heterogeneity by including customer-specific recency, frequency, and monetary value of previous orders (e.g., Fader, Hardie, and Lee 2005), customer-

[4] The company targeted customers to receive catalogs and coupons, creating potential endogeneity in these variables. These variables are not of primary interest to us, and their correlation with free shipping is small (Web Appendix B). Two robustness checks: (1) using Gaussian copulas (Park and Gupta, 2012) and (2) excluding the catalog and coupon variables, yield consistent results regarding the focal effects (Table 3 and Web Appendix C6).

specific lagged returns (Petersen and Kumar 2009), and customer-level random intercepts.

Descriptive statistics. Table 1 provides descriptive statistics (Tables B1 and B2 in Web Appendix B provide correlations). The average customer purchased in 7.5% of the 154 weeks covered by our data. Free shipping promotions were available in 15% of the weeks. The average basket size calculated across all purchases is €213.550 (SD = €242.700), €129.881 (SD = €194.397) for high-risk products, and €83.669 (SD = €154.979) for low-risk products. Return share averages 36.956%, meaning that on average 37% of a customer's shopping basket, measured in €, is returned. Model-free evidence provides initial support for the free shipping effect. Mean basket size of high-risk products during free shipping weeks is higher than in weeks without free shipping (M = €103,123, SD = €20,277 for free shipping versus M = €89,472, SD = €21,059 for non-free shipping; t = 2.880, p = .005). Mean basket size of low-risk products does not differ between free shipping and non-free shipping weeks (M = €61,819, SD = €15,143 for free shipping versus M = €58,782, SD = €14,466 for non-free shipping; t = .923, p = .358). The mean weekly return share is higher during free shipping promotions (M = .386, SD = .038 during free shipping weeks versus M = .366, SD = .030 during non-free shipping, t = 2.794, p = .006).[5]

Model Development

Customers make four decisions: (1) whether to purchase (incidence); and if so, (2) how much to spend on high-risk products, (3) how much to spend on low-risk products, and (4) how much, in terms of share of their shopping basket (high-risk + low-risk products) to return ("return share"). Since there may be unobserved factors common to these four decisions, we use a Tobit Type II model (Van Heerde, Gijbrechts, and Pauwels 2008; Danaher and Dagger, 2013). We model

[5] There are 23 weeks with free shipping and 131 weeks without free shipping.

high-risk spend, low-risk spend, and returns conditional on purchase. Purchase incidence is a probit model and the equations for high-risk spend, low-risk spend, and return percentage are regression models conditional on purchase. The model for purchase incidence is:

$$\mathrm{P\_inc}_{\mathrm{it}} = \begin{cases} 1 \text{ if } \mathrm{P\_inc}^{*}_{\mathrm{it}} > 0 \\ 0 \text{ otherwise} \end{cases}, \tag{3}$$

where $\mathrm{P\_inc}^{*}_{\mathrm{it}}$ is a latent variable:

$$\mathrm{P\_inc}^{*}_{\mathrm{it}} = \beta^{\mathrm{p}}_{0\mathrm{i}} + \delta^{\mathrm{p}}\mathrm{FS}_{\mathrm{t}} + \beta^{\mathrm{p}}\mathrm{X}_{\mathrm{it}} + \beta^{\mathrm{p}}_{\mathrm{b}}\mathrm{RFM}_{\mathrm{it}} + \mathrm{u}^{\mathrm{p}}_{\mathrm{it}}, \tag{4}$$

where FS_{t} equals 1 if a free shipping campaign was active in week *t*, and 0 otherwise. X_{it} denotes control variables. These include advertising, available coupons, catalog pages, as well as past return behavior. We operationalize past returns as the sum of return share in the 26 weeks prior to week t. We operationalize RFM as follows: Recency is the number of weeks since a customer's last purchase prior to week t. Frequency is how often the customer purchased in the 26 weeks prior to week t. Monetary value is the sum of total spend in the 26 weeks prior to week t. $\beta^{\mathrm{p}}_{0\mathrm{i}}$ is a random intercept for each customer i, and $\mathrm{u}^{\mathrm{P}}_{\mathrm{it}}$ is random error. Conditional on purchase incidence, we have regression equations for high-risk spend, low-risk spend, and return share:

$$\mathrm{hr}_{\mathrm{it}} = \beta^{\mathrm{h}}_{0\mathrm{i}} + \delta^{\mathrm{h}}\mathrm{FS}_{\mathrm{t}} + \beta^{\mathrm{h}}\mathrm{X}_{\mathrm{it}} + \beta^{\mathrm{h}}_{\mathrm{RFM}}\mathrm{RFM}^{\mathrm{h}}_{\mathrm{it}} + \mathrm{u}^{\mathrm{h}}_{\mathrm{it}} \tag{5}$$

$$\mathrm{lr}_{\mathrm{it}} = \beta^{\mathrm{l}}_{0\mathrm{i}} + \delta^{\mathrm{l}}\mathrm{FS}_{\mathrm{t}} + \beta^{\mathrm{l}}\mathrm{X}_{\mathrm{it}} + \beta^{\mathrm{l}}_{\mathrm{RFM}}\mathrm{RFM}^{\mathrm{l}}_{\mathrm{it}} + \mathrm{u}^{\mathrm{l}}_{\mathrm{it}} \tag{6}$$

$$\mathrm{rs}_{\mathrm{it}} = \beta^{\mathrm{r}}_{0\mathrm{i}} + \delta^{\mathrm{r}}\mathrm{FS}_{\mathrm{t}} + \gamma_1\mathrm{hr}_{\mathrm{it}} + \gamma_2\mathrm{lr}_{\mathrm{it}} + \beta^{\mathrm{r}}\mathrm{X}_{\mathrm{it}} + \mathrm{u}^{\mathrm{r}}_{\mathrm{it}}. \tag{7}$$

The free shipping effect is operative if $\delta^{\mathrm{h}} > \delta^{\mathrm{l}}$ and $\gamma_1 > \gamma_2$.

We express all continuous independent variables as well as high-risk and low-risk spend ($\mathrm{hr}_{\mathrm{it}}$ and $\mathrm{lr}_{\mathrm{it}}$) in logs. The control variables X_{it} are common to all equations. We identify the system of equations (4-7) using exclusion restrictions (Leeflang et al. 2000, p. 381; Ailawadi, Pauwels and Steenkamp 2008). In the high- and low-risk equations we include risk-specific RFM measures, i.e., RFM variables in the high-risk equation pertain to high-risk purchases in the previous 26 weeks, and RFM in the low-risk equation pertain to low-risk purchases in the previous 26 weeks (see Table 1). The covariates in equations (4) to (7) are consequently not identical. The covariance matrix among the error terms u_{it} is a 4×4 matrix:

$$\Sigma = \begin{bmatrix} 1 & \sigma_{ph} & \sigma_{pl} & \sigma_{pr} \\ \sigma_{ph} & \sigma_h^2 & \sigma_{hl} & \sigma_{hr} \\ \sigma_{pl} & \sigma_{hl} & \sigma_l^2 & \sigma_{lr} \\ \sigma_{pr} & \sigma_{hr} & \sigma_{lr} & \sigma_r^2 \end{bmatrix}, \tag{8}$$

where p, h, l, and r indicate the incidence, high-risk spend, low-risk spend and return share equations. As per common practice, we set the variance of the probit incidence equation to 1. We estimate the outcome equations jointly with the selection equation, which corresponds to a Tobit Type II (Danaher and Dagger 2013). We model equations (5)-(7) conditional on incidence (Minnema et al. 2016). Through cross-equation correlations, we consider unobserved factors that could affect incidence, high-risk spend, low-risk spend, and return share.

In total, we have 1,165,661 observations. This is less than 9,460 customers × 128 weeks (1,210,880) because of missing values for the RFM variables that arise if customers did not make a purchase during the 26-week initialization period. The model is estimated jointly by simulated maximum likelihood (Roodman 2011).

Model Results

The free shipping effect. Table 2, Model 1 shows the estimates of Equations (4)-(7) (see Web Appendix B, Table B3 for cross-equation correlations). The results suggest that free shipping increases purchase incidence ($p < .001$). This is neither necessary nor sufficient for the free shipping effect. However, the significant impact on purchase incidence shows that free shipping promotions, like other promotions, stimulate buying.

[Table 2 Goes Here]

More germane to our research, Table 2, Model 1 shows that free shipping has a positive impact on high-risk product spend (p < .001). The effect on low-risk product spend is much weaker and not statistically significant (p = .525). A likelihood ratio test comparing Model 1 to a model where the free shipping impact on high-risk and low-risk purchases is constrained to be equal finds a lower fit for the constrained model. This suggests that the free shipping coefficients for high-risk and low-risk purchases are statistically different ($\chi^2(1) = 199.60$, p < .001, see Web Appendix B, Table B4 for details). The returns equation shows that, all else equal, if the basket is comprised of more high-risk spend, it has higher return share (p < .001); low risk spend does not have a significant impact on return share (p = .551).

In summary, Table 2, Model 1 supports the free shipping effect on returns. Free shipping increases the spend on high-risk goods, which in turn increases return share.

Additional results. Table 2, Model 1 shows that RFM variables and past returns significantly influence high-risk and low-risk spend, meaning the observed free shipping effect is above and beyond normal customer behavior. The direct free shipping effect on returns is not significant (p = .606), i.e., there is no evidence that free shipping affects returns once we control for high- and low-risk spend. Table 2, Model 1 shows that advertising, coupons, and catalogs are associated with *both* low- and high-risk spend but do not directly affect returns.

Robustness checks. We examine the robustness of our results by estimating multiple versions of the main model (equations 3-7), summarized in Table 3. The focal results are robust across all different specifications. The details are in Web Appendix C.

Investigating the role of brands. Brands are important in the consumer's evaluation of purchase risk (Erdem and Swait 1998). We therefore explore the role of brands in the free shipping effect. We add an equation to our main model (equations 3-7) in which the dependent variable is the extent to which a customer purchases brands that she/he has not purchased in the previous 26 weeks. We label this variable "purchases of unfamiliar brands". In the added equation, it is a function of free shipping as well as other controls (see Web Appendix C5 for specifics). We also include this variable in the returns equation, and interact it with high-risk spend. In summary, this model investigates whether free shipping encourages purchase of brands that the customer has not recently purchased, and in turn whether purchase of such "unfamiliar" brands leads to more returns, especially for risky products.

Interestingly, Table 2, Model 2 shows that free shipping *does not* significantly increase the purchase of unfamiliar brands, i.e., brands that the consumer has not purchased in the past 26 weeks. However, the return share equation indicates that customers return more when they do purchase such brands. Importantly, the estimates for the original equations (3-7) still support the free shipping effect found in Model 1. A likelihood ratio test comparing Model 2 to a model where the free shipping impact on high-risk and low-risk purchases is constrained to be equal finds a lower fit for the constrained model (see Web Appendix B, Table B5), supporting Model 1's finding that free shipping influences high-risk and low-risk purchases differently. We conduct robustness tests where we vary the measurement level of brand unfamiliarity (unfamiliarity of brand based on purchases within one category instead of across all categories), and the time window (52 weeks, or all previous weeks in our data instead of 26 weeks; see Web Appendix C5).

In summary, this exploration suggests that the free shipping effect operates at the category level and not at the brand level. We discuss the possible reasons for this in the *Discussion* section.

STUDY 2 – FIELD EXPERIMENT

Design and data. The retailer ran a field experiment during August to October 2014. The 762,178 customers who purchased at least once during 2011–2013 were mailed a print catalog in August 2014. Of these, 381,379 were randomly offered a free shipping promo code they could use for purchases during September and October 2014; 380,799 customers received the catalog without the promo code. Customers could place orders online or offline through the call center – the free shipping code was valid for both channels. As previously, we excluded commissioner customers, leaving 760,395 customers – 380,551 received a free shipping promo code, while the remaining 379,844 did not.

A comparison of the test and control groups in July 2014, one month before the field experiment, shows that the mean number of purchases, basket size, spend for high-risk and low-risk products, overall returns, and returns of high-risk and low-risk products did not differ significantly between groups (see Table D1 in Web Appendix D).

Impact of free shipping. Table 4 shows that free shipping leads to higher purchase incidence ($p < .001$). Further, mean high-risk spend is larger for the test group ($p = .039$), while low-risk spend does not differ significantly between test and control ($p = .936$). This is consistent with the first part of the free shipping effect, that free shipping increases risky purchases. The return rate of high-risk products is clearly higher than for low-risk products (e.g., in the control group, .393 for high-risk vs. .216 for low-risk). As a result, and consistent with the second part of the free shipping effect, free shipping leads to a higher overall return share ($p = .001$).[6] Finally, baskets for unfamiliar and familiar brands do not differ significantly between groups ($p = .140$).

[Table 4 Goes Here]

[6] Average return share per customer.

The results are consistent with Study 1: free shipping increases purchases of high-risk products, high-risk products have higher return rates, and the overall return share increases. We note that the promotion design in the field experiment differs from that used in the observational data (Study 1). While the retailer intensively advertised the free shipping promotions in the observational data, it did not advertise the free shipping promotion in the experiment so as not to contaminate the control group. The retailer used the catalog to inform the test group customers of the free shipping promo code. Thus, the treatment was much more subtle than the usual free shipping promotion, and effect sizes in the field experiment are smaller. Nevertheless, the field experiment is randomized and replicates the free shipping effect observed in Study 1.

STUDY 3 – FIELD TEST

Studies 1 and 2 support the free shipping effect: (1) free shipping promotions increase purchases of risky products more than non-risky products, and (2) consumers are more likely to return risky products. The question is why free shipping promotions increase purchase of risky products. Earlier, we drew on Loewenstein et al.'s (2001) dual-processing theory of decision-making, which suggests that decision-making is driven by "cognitive" and "feelings" components, to identify risk premium and positive affect as potential drivers of risky purchases. In Study 3, we explore which mechanism – risk premium, positive affect, or both – underlies the ability of free shipping promotions to increase purchase of risky products.

Design and data. In collaboration with the same retailer, we conducted a field test consisting of a brief customer survey immediately after the customer clicked the "place order" button in the online store. The survey was administered to a random sample of 7% of website visitors who placed an order. The retailer ran the survey in the two weeks prior to running a free shipping promotion, and in the two weeks during which the retailer offered the promotion. An independent marketing research company administered both waves of the survey.

Like in Study 1, the timing of the free shipping campaign was unknown to customers, i.e., the campaign was not pre-announced. However, respondents were not randomly assigned to free shipping promotion versus no-promotion. Therefore, it is possible that customers self-selected into receiving or not receiving the free shipping promotion by deciding to purchase at a particular time. We did not have available the rich set of control variables we had in Study 1. However, we were able to match promotion-period with non-promotion period customers using their purchase history from the six months prior to the field test. We use these pre-treatment variables for propensity score matching (PSM; Heckman, Ichimura and Todd 1998; Huang et al. 2012) to estimate the association between free shipping promotions and customer perceptions they are being compensated for purchase risk (the risk premium mechanism) and/or their degree of positive affect (the affect mechanism). Furthermore, we verify the first component of the free shipping effect – whether free shipping is associated with purchase of risky products.

Measures. We measured affect using the positive affect items of the PANAS scale (Watson, Clark and Tellegen 1988; Web Appendix E, Table E1). This is a strong test for whether free shipping generates positive affect because the items are not purchase-specific – they simply register the customer's mood right after placing the order. To assess whether free shipping served as a risk premium, we built on the definition by Blattberg and Neslin (1990, p. 50) and asked respondents to state whether, "Given the shipping costs for this order, I feel I have nothing to lose, even if I need to return the products". For all questions, respondents indicated agreement on 7-point scales (see Web Appendix E, Table E1).

In total, 4,491 customers answered the survey – 1,561 in the no free shipping condition; 2,930 in the free shipping condition. We found that 1,464 respondents – 554 in the no free shipping condition, and 910 in the free shipping condition – purchased at least once in the 26 weeks prior to the survey. Hence, we have sufficient information about these respondents to conduct the PSM.

Results. The first step in the PSM is to estimate a probit model of whether a customer is in the free shipping or non-free shipping group. As covariates, we use all customer-specific information we have available, i.e., recency, frequency, total basket and total returned amount (in €) for high- and low-risk products ordered by each respondent in the 26 weeks prior to the survey. In addition, we use the number of high- and low-risk categories purchased in the 26 weeks prior to the survey (see Web Appendix E, Table E2). In the second step, we use a Gaussian kernel matching algorithm, and compute the bootstrapped treatment effects for affect, risk premium, high- and low-risk spend as well as return share.[7] Matching reduces differences between groups substantially, since both the pseudo-R^2 and the mean standardized bias are substantially lower after matching (Sianesi 2004; Web Appendix E, Table E3).

Table 5 displays average treatment effects for key variables after matching using PSM. Both the high-risk basket (ATT = 91.411, SE = 17.679, p = .000) and return share (ATT = .051, SE = .025, p = .039) are higher during free shipping. In addition, the ATT for spend on low-risk products is insignificant (p = .974). This means that free shipping promotions are associated with high-risk but not low-risk spending, an important requirement of the free shipping effect. Furthermore, in line with the results from Studies 1 and 2, we do not observe a free shipping effect on the spend for unfamiliar brands (ATT = 17.310, SE = 17.883, p = .333).

[Table 5 Goes Here]

[7] As a robustness check to the PSM, we also applied one-to-one nearest-neighbor matching and obtained similar results (Web Appendix E, Table E4).

We now turn to the underlying mechanism. Table 5 shows that free shipping increases affect (ATT = .273, SE = .114, p = .017) and the perception of being compensated through a risk premium (ATT = .723, SE = .164, p = .000). This suggests that the free shipping effect operates through both the feelings and the cognitive mechanisms. The results for the unmatched sample point into a similar direction and are shown in the Web Appendix, Table E5.

In summary, Study 3 provides empirical evidence that free shipping increases both positive affect and risk premium perceptions, and it replicates the high-risk spend, brand unfamiliarity, and the return effects from Studies 1 and 2. We validated these findings using a more controlled setting in Study 4.

STUDY 4 – ONLINE LAB EXPERIMENT

Study 4 provides a more detailed investigation of the possible mechanisms underlying the free shipping effect (i.e., risk premium or positive affect). Unlike Study 3, Study 4 is a controlled online lab experiment. We manipulated free shipping vs. no free shipping as well as the riskiness of the product, and assign respondents randomly to conditions. We expected free shipping to increase purchase intentions of high-risk more than low-risk products. Regarding the mechanisms, free shipping should increase the perceptions of risk premium and positive affect. We then conducted a mediation analysis to see which mechanism generates the connection between free shipping and purchase intention.

Experiment. We implemented a 2 (free shipping vs. no free shipping) × 2 (high-risk vs. low-risk) design. The setting was a fictitious online store. We asked respondents to imagine themselves purchasing a pair of running shoes. We manipulated free shipping by prominently displaying a red box that read "free shipping" in the free shipping condition; this sign was absent in the no-free shipping condition. We manipulated risk by means of user reviews. In the low-risk condition, user reviews were tightly distributed around their mean. Furthermore, we displayed the two "most helpful" reviews, both consistent with mean review scores. Mean review scores in the high-risk condition were the same as in the low-risk condition, but the distribution was more dispersed, and the two "most helpful" reviews reflected this heterogeneity – one review was extremely positive while the other was negative.

Subjects were n = 457 consumers from an online survey panel managed by a professional market research firm. The data were collected in August 2018. The firm recruited subjects who were 18–69 years old, made online purchases at least occasionally, and engaged in a sports activity at least occasionally. These criteria ensured familiarity with the focal product and with online shopping. We exposed subjects randomly to one of four hypothetical online stores reflecting our four conditions (see Web Appendix F, Figure F1). They then answered questions that served as manipulation checks, as well as questions on affect, risk premium, and purchase intention. In addition, we follow Paas and Morren (2018) and included as an attention check an item that respondents were instructed to leave unanswered. In total, 56 respondents did not pass this check and were therefore dropped from the sample, yielding a final sample of n = 401.

Measures. We used the same measures as in Study 3 to assess affect and risk premium, and we measured purchase intention for the sneakers to which the subjects were exposed.

Manipulation tests. The mean perception that shipping costs are low is larger in the free shipping condition (M = 5.084, SD = 2.112) than in the no-free shipping condition (M = 2.941, SD = 1.423), and the difference is significant (t = 12.050). We asked respondents whether they perceived purchasing of the product to be risky. The mean for this variable is larger in the high-risk condition (M = 3.803, SD = 1.810) than the low-risk condition (M = 3.158, SD = 1.753); the difference is significant (t = 3.626).

Results. The goal of this experiment is to analyze the underlying mechanism, i.e., whether the free shipping effect operates through higher affect, or through perceptions that free shipping is compensation for the risk of shopping online, i.e., a risk premium. Table 6 shows the impact of treatments on risk premium and affect perceptions (see also Figure F1.2 & F1.3 in the Appendix). An ANOVA finds that the main effect of free shipping on risk premium is significant ($p < .001$), while the main effect of product riskiness on risk premium and the interaction effect between free shipping and product riskiness on risk premium, are both insignificant. This means subjects perceived free shipping as a risk premium for both risky and not-risky products, i.e., free shipping compensates for risk regardless of whether risk is high or low. In contrast, Table 6 reveals that free shipping increases affect only in the high-risk condition. In the ANOVA, main effects of both free shipping and risk on affect are insignificant, but the interaction between risk and free shipping is marginally significant ($p = .070$). This means that free shipping induces positive affect when purchase risk is high but not when it is low, suggesting that shipping costs are more of a pain point when there is a real risk the customer will have to return the product.

[Table 6 Goes Here]

The ANOVA with purchase intention as the dependent variable shows that the main effect of free shipping is not significant ($p = .388$), while the main effect of product risk is marginally significant ($p = .088$). However, there is a positive interaction whereby free shipping increases purchase intention for the high-risk product ($p = .036$). Parallel mediation analysis of free shipping through affect and risk premium show that the direct free shipping effect is not significant, and that unconditional on product risk, the transmission through risk premium is significant, whereas the transmission through affect is not (Web Appendix F, Table F1). However, Table 6 and Figure 1.3 in Web Appendix F suggest the impact of free shipping on affect is moderated by product risk. We therefore investigate in a moderated mediation analysis whether product risk moderates the link from free shipping to purchase intent (Table 7). Results show that the cognitive path, free shipping -> risk premium -> purchase intent, is always effective (95% CI: .113 to .375 for low risk; 089 to .367 for high risk). The feelings path via positive affect, in contrast, is effective for high-risk purchases (95% CI: .026 to .647), but not for low-risk purchases (95% CI: -.362 to .234).

[Table 7 Goes Here]

The conclusion is that free shipping increases purchase intention via the risk premium mechanism – as long as there is some risk, risk premium has a role to play. In contrast, positive affect does not play a role for low-risk products, but plays a strong role for high-risk products. This suggests that the total impact of free shipping on purchase intention is stronger for high-risk than low-risk products; high-risk products include both the risk premium and affect mechanisms.

In sum, these initial experimental results suggest that both risk premium, the cognitive–evaluation side of Loewenstein et al.'s (2001) dual-process theory, and affect, the feelings side, are at work in translating free shipping into purchase of risky products.

IMPACT OF THE FREE SHIPPING EFFECT ON PROFITS

We use the model estimates in Table 2, Model 1, to calculate the incremental profitability of free shipping promotions. We analyze four scenarios: (I) free shipping promotions, (II) no free shipping promotions, (III) additional available coupon value equal to the same value as the shipping fee, and (IV) no additional available coupon value.[8] By comparing scenarios (I) and (II) we obtain the profit impact of free shipping promotions. A comparison of scenarios (III) and (IV) shows the profit impact of additional coupon availability with an equivalent economic value.

Free shipping increases the number of purchases and the spend for high-risk goods, which increases the return share. In addition, under free shipping the retailer does not earn shipping revenue and incurs higher costs, for example, in handling returns. If the increase in total order volume is large enough to offset more returns, lost shipping revenue, and higher handling costs, profits will increase; otherwise profits will decrease. To assess this, we used the estimates of Equations (3)–(8) to randomly generate for each customer in our sample a time series of purchases of high-risk products, low-risk products, and returns. For each week in our observation period, we compute each customer's purchase incidence utility using equation (4). Under free shipping, we set the free shipping variable to 1 each week. When free shipping is not operative, we set it to 0 each week. For the customers for whom $\widehat{P\_inc}_{it}^{*}$>0, we calculate their low-risk purchases, high-risk purchases, return share,[9] and the associated costs. We then take the mean across all weeks of all customers who purchase. We index results relative to the no free shipping case by dividing all numbers by a constant, such that the mean basket size in the no free shipping case equals 100. We then scale this to an illustrative base of 10,000 customers. This disguises the actual levels and preserves the firm's anonymity. We use the Euro symbol (€) to facilitate interpretation.

We account for costs of goods sold and handling costs (e.g., Stock, Speh and Shear

[8] The coupon effect is captured in the coefficient of "available coupons" in Table 2.
[9] The random variation induced by the error in this simulation leads to some return shares being negative or larger than one. However, as the profit simulation entails the comparison between two scenarios (and within an observation, the error is constant across the scenarios), the difference between scenarios, not the absolute level, is relevant. We note that in the estimation, we do not obtain negative return shares or return shares of larger than 1.

2006). First, we assume costs of goods sold is 50% of order volume. Second, while the retailer could not provide handling costs *separately* for returns and outbound orders, it provided *total* handling costs for each basket. We regressed total handling costs per basket versus basket size (in €), the free shipping dummy, the amount of available coupons, as well as the return share for each basket. The coefficients from this handling costs function enable us to identify the increase in handling costs in response to a one percentage point increase in return share, to free shipping, to a €1 increase in available coupon value, and to a €1 increase in total basket. We use these coefficients to predict the total handling costs for each simulated basket. To illustrate, for a basket of size €100 of which €25 is returned, we predict handling costs of €11.86. For a €100-basket of which €50 is returned, we predict €14.06 in handling costs, a 19% increase.

In Table 8, the left panel (A) shows the simulation for free shipping, while the right panel (B) considers coupons. Row A starts with the total order volume. Handling costs, returns, and COGS are subtracted in the rows below. Scenario I calculates the profits with free shipping promotions, while Scenario II depicts profits without free shipping promotions.

[Table 8 Goes Here]

Row H in Panel A shows a profit contribution of €12,157.07 with free shipping promotion, and €12,237.49 without, i.e., the firm incurs a slight loss from free shipping promotions of €80.42, or .7%, despite the substantial increase (11%) in total order volume. This is the result of two factors. First, handling costs increase (Row B), both per basket (+3.7%) and in total. Second, the retailer no longer earns revenue from shipping fees, which is important because, before subtracting this, free shipping promotion is profitable. These is in line with Lewis, Singh and Fay (2006), who also find that total order volume increases in response to free shipping, while profits are adversely affected because of foregone shipping revenue.

For coupons (Panel B) we apply the same simulation process as above. In Scenario III, we add to each customer's available coupon variable an amount equal to the firm's regular shipping cost (in €). In Scenario IV, we leave available coupons as it is and do not add any amount to it. Comparing Scenarios III and IV therefore shows incremental profits when we provide each customer additional coupon value equal to the same amount (in €) as the shipping costs that a customer saves under free shipping. Again, we see a substantial increase in total order volume (Row A). While the increase in total order volume due to coupons (13%) is similar to the increase in order volume for free shipping, the profit implications are quite different. We saw a slightly negative profit for the free shipping promotion, while, in contrast, adding coupon value equal to the regular shipping fee is profitable. This also applies when we use the estimates from the robustness check that corrects for potential endogeneity of coupons by Gaussian copulas (Web Appendix C, Table C6.1). The reason is that the increase in order volume during a free shipping promotion is driven by an increase in high-risk purchases, while the increase in order volume from coupons is driven by an increase in *both* high-risk and low-risk purchases. From the data (not reported in the table), we computed that, during a free shipping promotion, the share of high-risk sales increases from 62.8% to 65.2%, while this share remains essentially unchanged in the case of additional couponing. This increase in the share of high-risk products leads to a higher overall return rate in the case of free shipping, which reduces the profitability of the free shipping promotion relative to additional couponing of the same economic value.

DISCUSSION

General Discussion

Free shipping promotions and product returns have each attracted significant attention from both managers and researchers. This has generated a considerable number of studies that consider these phenomena separately (e.g., Narang and Shankar 2019, Petersen and Kumar 2015, 2009; Lewis, Singh and Fay 2006). We contribute to the literature by considering both phenomena together and assessing the extent to which free shipping increases product returns, why it does so, and how this affects the profitability of free shipping promotions. We have demonstrated that free shipping promotions are associated with consumers returning a higher share of their shopping basket. Our results suggest that this happens because: (1) free shipping encourages more purchases of risky products; and (2) risky products have an inherently higher return rate than low risk products. We call this the "free shipping effect" on product returns.

Our theoretical framework builds upon dual-processing theories of decision-making (e.g., Kahnemann 2003). In particular, we draw upon Loewenstein et al.'s (2001) theory, which identifies two components of decision-making under uncertainty: "cognitive" and "feelings." Loewenstein et al. (2001) discuss "expected utility" as an example of the cognitive component, while emotions and affect are examples of the feelings component. We draw upon expected utility, particularly the risk premium, to represent the cognitive component, and affect to represent the feelings component. We theorize that consumers can view free shipping as a risk premium that compensates them for taking a risk (cognitive component); free shipping can also generate positive affect (feelings component). Both mechanisms can lead consumers to make riskier purchases, and hence increase returns. Consequently, free shipping promotions increase the share of the basket consumers return, a downside one must consider to evaluate the full impact of free shipping promotions on profitability.

We analyze the free shipping effect in four studies. Study 1 uses longitudinal data of a random sample of 9,460 customers over 3 years. We estimate a model of the impact of free shipping on purchase incidence, low-risk spend, high-risk spend, and return share. The results support the free shipping effect, which we replicate in a randomized field experiment (Study 2) and a field test (Study 3). Studies 3 and 4 suggest that both risk premium and affect mechanisms are at work. The net result is that free shipping promotions increase high-risk spend more than low-risk spend. A simulation shows that free shipping promotions increase total order volume, but the higher returns, as well as lost shipping revenue, can render free shipping promotions unprofitable. Other promotions, for example, coupons, appear similar because they also increase total order volume. However, in contrast to free shipping, which primarily increases the spend for high-risk products, the increase in order volume from coupon promotions is driven by a higher spend for both high- and low-risk products. Consequently, in the empirical setting that we study, coupon promotions do not lead to similar increases in product returns. Coupon promotions are thus profitable while free shipping promotions are not.

This work advances three central themes. First, we link the literature on shipping (e.g., Lewis, Singh and Fay 2006) and product returns (e.g., Petersen and Kumar 2009; Minnema et al. 2016; Schulz, Shehu and Clement 2019). By investigating free shipping promotions, we answer Minnema et al.'s (2018, p. 114) call for research that links promotional activities to product returns. Our work also adds to the literature on perceived risk and product returns. For example, Petersen and Kumar (2015) consider the *time* aspect of risk and how that relates to optimal targeting based on customer value. They show how to account for the risk of losing future customer transactions because the customer will have to return the product. Our study focuses on the *cross-product* aspect of risk. We measure how free shipping promotions at a given time influence the mix of high- versus low-risk products in the basket, ultimately affecting product returns. We therefore complement Petersen and Kumar (2015).

Second, we add to the promotions literature (Davis and Bagchi 2018, Guha et al. 2018), especially regarding online promotions (Vana, Lambrecht and Bertini 2018). For example, free shipping, in contrast to traditional coupons, increases the high-risk spend, but not the low-risk spend, leading to a higher return rate. This, and the lost revenue from shipping fees, makes free shipping promotions in our setting unprofitable. This highlights the relevance of fully understanding the free shipping effect because, on the surface, free shipping promotions appear to be similar to other promotions, since they increase total order volume. At the same time, we show that they lead to riskier purchases and more returns, which is not apparent without a detailed analysis. The findings suggest that the relatively small discount that consumers receive during a free shipping promotion triggers considerations of risk and feelings of affect that are more nuanced than previously thought. This in turn shifts the composition of the basket to a degree that makes the promotion less profitable or even unprofitable.

Finally, we reinforce the trend in quantitative marketing research to combine statistical analysis and field or lab experiments (e.g., Lambrecht and Tucker 2013; Montaguti, Neslin, and Valentini 2016). Statistical analyses will always be subject to critiques related to causality. Field experiments address causality but are subject to critiques regarding the uniqueness of the treatments and of the difficulty teasing out temporal mechanisms from what are often short-term results provided by the experiment. Together, these methods offset the flaws of the other and yield a deeper understanding of how marketing works.

We summarize the key implications and points of discussion below.

Free shipping promotions increase return rates. This “free shipping effect” reduces the profitability of free shipping promotions. Profitability decreases because the final sales gain from a free shipping promotion will be less than the immediate sales gain. Environmentally, shipments with returned products waste natural resources. Furthermore, it often is not possible for retailers to re-sell returned merchandise, and a non-trivial share of returned merchandise is reportedly destroyed (*New York Times* 2015). The free shipping effect suggests that less reliance on free shipping promotions can not only increase the profitability of an online retailer's promotional mix but also contribute to a more efficient use of natural resources.

The free shipping effect most acutely affects online retailers who sell "risky" products. Free shipping promotions encourage consumers to buy risky products – those whose quality consumers cannot easily assess in advance – by serving as a risk premium and increasing consumer affect. Retailers who rely disproportionately on the sales of risky products – e.g., apparel – will particularly be vulnerable to high return rates generated by the free shipping effect.

Retailers need to trade off the upside and downside of free shipping promotions before implementing them. Our results show that free shipping promotions generate more sales, but at the same time lead to more returns. Managers must balance these two forces by measuring the impact of free shipping on purchasing incidence and returns. Perhaps reassuringly, there is evidence that product returns enhance future buying behavior (Petersen and Kumar 2009). However, retailers may be able to increase immediate profits through other promotions. For example, our analysis (Table 8) found that a coupon promotion of the same monetary value as a free shipping promotion was more profitable because – even though it generated less sales – it also generated fewer returns. This, of course, is specific to our particular retailer, but illustrates the trade-offs retailers need to assess.

Certain retailers may find free shipping promotions attractive. While we find that free promotions are negative for our retailer, other retailers may benefit from these promotions. Our analyses suggest the following types of retailers may find free shipping promotions attractive. (1) The retailer's *return rates* are naturally low, for example if it sells mostly low-risk search goods, or if it has high baseline return rates but can decrease them by using tactics such as online chat, product page videos, or user recommendations. Multichannel retailers may be able to turn product returns into profitable exchanges by routing returns to the physical store (Pauwels and Neslin 2015). (2) The retailer's *regular shipping fees* are low. In that case, waiving the shipping fee leads to less decline in revenue. For example, the retailer may sell merchandise that is inexpensive to ship, or it has low shipping fees by not incorporating production costs in these fees. (3) The retailer has low *returns handling costs*, or can decrease them through efficient operations (Guide et al. 2006). In summary, the ideal retailer for free shipping promotions has low return rates, low regular shipping fees, and low returns handling costs. Other retailers should think twice before implementing free shipping promotions. Our paper illustrates the methods and calculations for retailers to determine how well they fit the ideal.

The free shipping effect is a product category phenomenon. Our results indicate that free shipping promotions encourage consumers to purchase more risky products. While our work has focused on the riskiness of the product category (e.g., apparel is risky; laptop computers are less risky), we also considered the role of brands. We measured whether a customer had purchased the brand within the previous 26 weeks, and labeled this variable "purchases of unfamiliar brands." Our motivation was that "unfamiliar" brands are riskier, and hence the free shipping effect may apply to them, as well as to risky categories. Interestingly, we did not find evidence that free shipping increased purchases of unfamiliar brands, although consumers were more likely in general to return these purchases. We proffer three possible explanations. (1) *Preference* *versus familiarity*: the absence of a brand purchase in the previous 26 weeks might not be because a customer is unfamiliar with the brand, but because this customer has low preference for it based on, e.g., its attributes and reputation. However, if the customer does buy that brand (e.g., as a result of advertising), it is less likely to fulfil the customer's needs and more likely to be returned. (2) *Free shipping promotion is not brand-specific*: brands often run promotions to induce brand switching (Neslin 2002). The free shipping promotions that we have studied, however, are not brand-specific; rather, they apply to all brands. Hence, there is no need for customers to switch from a high-preference brand to obtain free shipping. (3) *Consumers can address brand risk without a free shipping promotion:* one can think of the purchase risk as the sum of product category risk plus brand risk. Free shipping addresses category risk, while the consumer can address brand risk even without a free shipping promotion by focusing on a familiar or preferred brand. Therefore, the free shipping effect operates at the category level, not brand level.

Future Research and Limitations

There are limitations to our study that open the door for future research. First, similar to other CRM studies, our data are only for one retailer. We could not study the impact of this retailer's free shipping promotions on its competitors, and whether free shipping promotions are a prisoner's dilemma. Second, while we compared the free shipping effect to coupon promotions, we have not established the extent to which this effect is generalizable to other types of promotion. Third, our focal retailer's current shipping policy was a non-volume-related fee for outgoing shipping, but free shipping for returns. Other policies, e.g., charging fees for outbound *and* return shipping, would provide additional contexts for studying the impact of free shipping promotions. Fourth, our study addresses free shipping *promotions*, and not the impact of moving to a permanent free shipping policy. While free shipping promotions are omnipresent, some firms implement permanent free shipping policies (Bower and Maxham 2013) or “free shipping” in return for a monthly fee like Amazon Prime. Fifth, our study involves durable goods. Future studies could analyze how these effects may vary for different types of products and services. Sixth, there is the important question of the potential long-term implications of free shipping promotions. Several possibilities are conceivable. (1) Free shipping promotions may become less effective over time. (2) Consumers who return items may learn over time, thereby reducing their need to return items in the future. (3) The free shipping effect may carry over to the future and make future purchases more likely. Our results from Study 1 (Web Appendix C, Table C1) and Study 2 (Web Appendix D, Table D2) suggest that free shipping does not induce stockpiling. However, there could be longer-term carry-over driven by customer satisfaction. Seventh, our data do not allow us to examine whether consumers order different colors and/or sizes of the same product and keep only the best match. Finally, due to data availability constraints, we could not compare online to offline purchases, an important topic for future studies. In sum, our work suggests that managers who make promotion decisions in an online environment must consider the magnitude of product returns. We believe our work therefore moves the field forward, and we trust that it will encourage more work to analyze and understand this important issue.

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TABLES

Table 1: Variables, Measures, and Descriptive Statistics (Study 1)

Variable	Description	Mean	SD	Min	Max
Purchasing incidence$_{it}$	= 1 if customer i makes a purchase in week t	.075	.263	.000	1.000
Free shipping$_{t}$	= 1 if free shipping is offered in week t	.149	.356	.000	1.000
Basket size$_{it}$*	Order size (in €) of all purchases of customer i in week t	213.550	242.700	.000	6,574.910
High-risk$_{it}$*	Order size (in €) of high-risk subcategories purchases of customer i in week t	129.881	194.397	.000	4,399.970
Low-risk$_{it}$*	Order size (in €) of low-risk subcategories purchases of customer i in week t	83.669	154.979	.000	6,574.910
Return share$_{it}$*	Percentage of a shopping basket (% of €) returned by customer i for purchases in week t	.369	.387	.000	1.000
Advertising$_{t}$	Online advertising expenditure (in €1,000) in week t	121.093	219.837	94.669	2,475.068
Available coupons$_{it}$	Value of coupons (in €) available to customer i in week t	1.944	3.194	.000	16.119
Catalog pages$_{it}$	Total number of catalog pages delivered to customer i in week t	16.842	109.751	.368	1,717.629
Recency$_{it}$	Number of weeks since previous purchase of customer i in week t	13.436	13.162	2.000	108.000
Frequency$_{it}$	Number of purchases of customer i in the 26 weeks prior to week t	2.215	2.364	.000	25.000
Monetary$_{it}$	Sum of basket (in €) for high-risk goods of customer i in the 26 weeks prior to week t	521.428	625.301	.000	12,185.700
Recency$_{it\ (low)}$	Number of weeks since previous low-risk product purchase of customer i in week t	17.969	18.008	1.000	150.000
Frequency$_{it\ (low)}$	Number of low-risk purchases of customer i in the 26 weeks prior to week t	1.740	1.749	.000	25.000
Monetary$_{it\ (low)}$	Sum of low-risk basket (in €) for high-risk goods of customer i in the 26 weeks prior to week t	319.490	452.879	.000	12,115.710
Recency$_{it\ (high)}$	Number of weeks since previous high-risk purchase of customer i in week t	17.445	17.670	1.000	144.000
Frequency$_{it\ (high)}$	Number of high-risk purchases of customer i in the 26 weeks prior to week t	1.901	1.909	.000	21.000
Monetary$_{it\ (high)}$	Sum of high-risk basket (in €) for high-risk goods of customer i in the 26 weeks prior to week t	201.937	314.067	.000	7,234.840
Past returns$_{it}$	Sum of return share for customer i in the 26 weeks prior to week t	.717	.990	.000	13.572

Note: * indicates that the descriptive statistics of these variables are calculated for observations with positive purchasing incidence. We report statistics for the variables in their original non-log scale.

Table 2: Estimation Results (Study 1)

	Model 1								Model 2									
	Incidence		High-risk		Low-risk		Return share		Incidence		High-risk		Low-risk		Brand unfamiliarity		Return share	
	β (se)	*p*	β (se)	*p*	β (se)	*p*	β (se)	*p*	β (se)	*p*	β (se)	*p*	β (se)	*p*	β (se)	*p*	β (se)	*p*
Free shipping	.042	.000	.123	.000	.018	.525	.003	.606	.042	.000	.159	.000	.046	.009	.022	.175	.004	.556
	(.007)		(.032)		(.028)		(.006)		(.004)		(.019)		(.017)		(.017)		(.006)	
High-risk spend							.053	.000									.036	.000
							(.001)										(.002)	
Low-risk spend							-.001	.551									-.006	.000
							(.001)										(.001)	
Brand unfamiliarity																	.005	.021
																	(.002)	
High-risk × unfamiliarity																	.001	.075
																	(.000)	
Advertising	.424	.000	.701	.000	1.014	.000	-.025	.315	.415	.000	1.075	.000	1.437	.000	.813	.000	-.022	.410
	(.028)		(.129)		(.113)		(.025)		(.014)		(.076)		(.071)		(.067)		(.026)	
Available coupons	.028	.000	.056	.000	.053	.000	-.001	.563	.029	.000	.076	.000	.086	.000	.060	.000	.000	.815
	(.002)		(.009)		(.008)		(.002)		(.001)		(.005)		(.005)		(.005)		(.002)	
Catalog pages	.010	.000	.022	.000	.015	.002	.000	.852	.011	.000	.032	.000	.027	.000	.019	.000	.000	.969
	(.001)		(.006)		(.005)		(.001)		(.001)		(.003)		(.003)		(.003)		(.001)	
Recency*	.273	.000	.689	.000	.702	.000			.167	.000	.672	.000	.610	.000	.561	.000		
	(.004)		(.018)		(.015)				(.002)		(.011)		(.01)		(.021)			
Frequency*	.391	.000	.525	.000	.758	.000			.356	.000	.927	.000	1.006	.000	.817	.000		
	(.009)		(.047)		(.04)				(.004)		(.028)		(.025)		(.009)			
Monetary*	-.010	.000	.065	.000	.056	.000			-.012	.000	.060	.000	.044	.000	.099	.000		
	(.002)		(.009)		(.009)				(.001)		(.005)		(.005)		(.004)			
Past returns	.051	.000	.177	.000	.037	.000	.012	.000	.058	.000	.262	.000	.126	.000	.125	.000	.010	.000
	(.003)		(.013)		(.010)		(.002)		(.001)		(.007)		(.006)		(.005)		(.002)	
Constant	-8.520	.000	-12.566	.000	-17.648	.000	.560	.130	-8.089	.000	-2.126	.000	-25.889	.000	-14.287	.000	.537	.164
	(.408)		(1.901)		(1.673)		(.369)		(.21)		(1.121)		(1.044)		(.992)		(.386)	
N	1,165,661								1,165,661									
Log-likelihood	-706,584.200								-874,649.15									

Note: * to conserve space we collapse the *reporting* for the equation-specific measures for recency, frequency, and monetary value into three common rows. The coefficients represent the effects of the equation-specific measures, as defined in Equations (4)–(6) and in Table 1.

Table 3: Overview of Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Specification	Add lagged free shipping variable	Binary classification of risk based on mean rather than median	Continuous measure for riskiness	Share of high-risk products rather than binary classification	Share of high-risk products and share of unfamiliar brands rather than binary classifications	Add lagged catalog variable	Omit random customer intercepts
Focal results							
FS effect on high-risk spend supported?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
High-risk spend effect on returns supported?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional results	Lagged FS effect insignificant		Riskiness score of purchases increases under FS, leading to more returns	Share of high-risk purchases increases under FS, leading to more returns	Share of high-risk purchases increases under FS, but not the share of unfamiliar brands	Catalog shows significant lagged effects	
Detailed results	Table C1	Table C2.1	Table C2.2	Table C2.3	Table C2.4	Table C3	Table C4
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Specification	Add equation for purchases of unfamiliar brands (last 52 weeks)	Add equation for purchases of unfamiliar brands (all previous weeks)	Add equation for purchases of unfamiliar brands in subcategory (last 26 weeks)	Add equation for purchases of unfamiliar brands in subcategory (last 52 weeks)	Add equation for purchases of unfamiliar brands in subcategory (all previous weeks)	Add Gaussian copula terms for catalogs and coupons	Exclude catalogs and coupons from model specification
Focal results							
Effect of *FS on high-risk spend* supported?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
High-risk spend effect on returns supported?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional results	FS does not significantly increase purchases of unfamiliar brands						
Detailed results	Table C5.1	Table C5.2	Table C5.3	Table C5.4	Table C5.5	Table C6.1	Table C6.2

Table 4: Comparison of Test and Control Groups for the Free Shipping Field Experiment (Study 2)

		N	M	SD	*p* *(diff = 0)*
Purchase Incidence					
	Control group	379,844	.397	.489	.000
	Test group	380,551	.404	.491	
Basket size					
	Control group	150,965	335.888	315.034	.083
	Test group	153,745	337.868	316.212	
High-risk spend					
	Control group	150,965	242.727	271.680	.039
	Test group	153,745	244.758	272.320	
Low-risk spend					
	Control group	150,965	93.161	171.919	.936
	Test group	153,745	93.111	172.912	
Return share for high-risk products					
	Control group	132,154	.393	.351	.014
	Test group	129,151	.390	.351	
Return share for low-risk products					
	Control group	94,056	.216	.345	.430
	Test group	92,493	.215	.345	
Overall return share					
	Control group	150,965	.333	.350	.001
	Test group	153,745	.337	.357	
Unfamiliar brand spend					
	Control group	150,965	202.454	232.626	.140
	Test group	153,745	203.701	233.217	
Familiar brand spend					
	Control group	150,965	133.415	132.508	.282
	Test group	153,745	134.118	133.121	

Table 5: Average Treatment Effects (ATT) of Free Shipping (Study 3)

Dependent variable	ATT	SE	t	*p*	2.5%	97.5%
Affect	.273	.114	2.400	.017	.005	.496
Risk premium	.723	.164	4.400	.000	.401	1.045
Basket size	113.118	32.317	3.500	.000	49.780	176.459
High-risk spend	91.411	17.679	5.170	.000	56.760	126.062
Low-risk spend	-.745	23.207	.030	.974	-46.231	44.741
Overall return share	.051	.025	2.060	.039	.003	.099
Unfamiliar brand spend	17.310	17.883	.970	.333	-17.740	52.359
Familiar brand spend	101.843	28.843	3.530	.000	45.313	158.374
N=1,464						

Note: We report the results based on a Gaussian Kernel.
Standard errors are computed via bootstrapping with 500 replications.

Table 6: Descriptive Statistics (Study 4)

Affect		Free shipping	
		Yes	No
Risk	High	3.031	2.586
		(1.547)	(1.389)
		n=113	*n=85*
	Low	2.882	2.958
		(1.371)	(1.452)
		n=102	*n=101*

Risk premium		Free shipping	
		Yes	No
Risk	High	3.779	2.694
		(2.108)	(1.711)
		n=113	*n=85*
	Low	4.108	2.921
		(1.914)	(1.869)
		n=102	*n=101*

Purchase intent		Free shipping	
		Yes	No
Risk	High	2.757	2.247
		(1.744)	(1.469)
		n=113	*n=85*
	Low	2.691	2.881
		(1.549)	(1.807)
		n=102	*n=101*

Table 7: Moderated Mediation Results (Study 4)

	Risk premium					Affect					Purchase intent (PI)				
	coeff	se	*p*	2.5%	97.5%	coeff	se	*p*	2.5%	97.5%	coeff	se	*p*	2.5%	97.5%
Free shipping (FS)	1.187	.269	.000	.657	1.716	-.076	.203	.708	-.475	.323	-.042	.126	.046	-.423	-.003
High-risk (HR)	-.227	.283	.423	-.782	.329	-.372	.213	.081	-.791	.046					
FS × HR	-.102	.385	.790	-.860	.655	.522	.290	.073	-.049	1.093					
Risk premium											.196	.031	.000	.134	.258
Affect											.747	.041	.000	.664	.829
Constant	2.921	.191	.000	2.545	3.296	2.958	.144	.000	2.674	3.241	-.402	.126	.739	-.290	.206
Indirect effects															
FS->RP->PI															
HR=0											.232	.066		.113	.375
HR=1											.212	.070		.089	.367
FS->affect->PI															
HR=0						-.076	.203	.708	-.475	.323	-.056	.151		-.362	.234
HR=1						.446	.207	.032	.038	.854	.333	.159		.026	.647
N	401					401					401				
F (*p*)	12.010 (.000)					1.680 (.170)					224.318 (.000)				

Table 8: Profit Impact of Proposed Mechanism

	A: Free shipping		B: Coupons	
	Scenario			
	I. Free shipping promotion	II. No free shipping promotion	III. Additional coupon value	IV. No additional coupon value
Customer Base	10,000	10,000	10,000	10,000
Number of Purchases	719	666	700	638
Average per Customer Basket Size	103.23 €	100.00 €	103.41 €	100.00 €
(A) Total Order Volume	74,209.39 €	66,603.41 €	72,371.78 €	63,772.40 €
(B) Handling Costs	6,255.80 €	5,589.72 €	6,058.03 €	5,357.37 €
(C) Net Order Volume {(A) – (B)}	67,953.59 €	61,013.69 €	66,313.76 €	58,415.03 €
(D) Return Volume	35,503.99 €	30,948.99 €	33,799.58 €	29,724.58 €
(E) Profit Contribution {(C) – (D)}	32,449.60 €	30,064.71 €	32,514.18 €	28,690.45 €
(F) Gross Profit {(E) – [(A) – (D)]×0.50}	13,096.90 €	12,237.49 €	13,228.08 €	11,666.54 €
(G) Total Cost of Promotion (Lost Shipping Fees / Coupon Costs)	939.83 €		859.55 €	
(H) Net Profit {(F) – (G)}	12,157.07 €	12,237.49 €	12,368.53 €	11,666.54 €
(I) Incremental Profit vs. Baseline	-80.42 €		701.99 €	
(J) % Profit Change (vs. Baseline)	-.7%		6.0%	

Note: All numbers are scaled by a constant such that the average basket size under the no-free-shipping (no-coupon) scenario is indexed as 100. Therefore, the upper-left number €103.23 in Row A means that the average basket size is 3.23% higher when free shipping is implemented and the proposed mechanism is operative.

WEB APPENDIX

WEB APPENDIX A: RISK MEASUREMENT STUDY 1

Table A1: Risk measurement items based on Hong and Pavlou (2014)

When making a purchase in this category, you cannot be certain that the product would perform as expected.	1=”strongly disagree”/7=”strongly agree”
When making a purchase in this category, you cannot be certain that the product would match my requirements (e.g., size, taste, style, appearance)	1=”strongly disagree”/7=”strongly agree”
Making a purchase in this category feels risky	1=”strongly disagree”/7=”strongly agree”

Table A2: Descriptive statistics of risk evaluations

Variable	N	M	SD	Min	Max
Rater 1	413	3.75	1.01	1.00	7.00
Rater 2	413	4.36	1.42	1.00	6.33
Rater 3	413	3.95	1.04	1.00	6.67
Rater 4	413	4.11	1.22	1.00	7.00

WEB APPENDIX B: ADDITIONAL RESULTS PERTAINING TO MODEL 1 OF STUDY 1

Table B1: Correlation matrix for all observations (N = 1,210,880)

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	Incidence	1.00																	
2	High-risk spend	.79	1.00																
3	Low-risk spend	.83	.52	1.00															
4	Return share	.68	.49	.69	1.00														
5	Free shipping	.01	.01	.01	.01	1.00													
6	Advertising	.02	.02	.01	.00	.05	1.00												
7	Available coupons	.03	.02	.02	.02	.05	.09	1.00											
8	Catalog pages	.01	.01	.01	.00	-.07	-.08	-.01	1.00										
9	Recency	.02	.02	.02	.01	-.01	.00	-.07	-.02	1.00									
10	Frequency	.04	.03	.03	.03	.00	-.03	.08	.05	-.65	1.00								
11	Monetary value	.08	.05	.06	.06	.00	-.03	.10	.05	-.68	.82	1.00							
12	Recency (low risk)	-.01	.00	-.01	-.01	.00	.02	-.07	-.04	.77	-.55	-.59	1.00						
13	Frequency (low-risk)	.07	.06	.05	.05	.00	-.04	.08	.06	-.56	.68	.82	-.74	1.00					
14	Monetary (low-risk)	.04	.04	.03	.03	.00	-.04	.07	.05	-.52	.75	.69	-.72	.88	1.00				
15	Recency (high-risk)	-.01	.00	.00	-.01	.00	.01	-.07	-.05	.80	-.58	-.60	.52	-.41	-.34	1.00			
16	Frequency (low-risk)	.08	.04	.07	.07	-.01	-.03	.09	.07	-.57	.72	.84	-.42	.58	.45	-.74	1.00		
17	Monetary (high-risk)	.04	.03	.05	.04	-.01	-.03	.07	.06	-.53	.81	.70	-.36	.47	.42	-.72	.87	1.00	
18	Past returns	.08	.08	.05	.12	.00	-.01	.06	.03	-.38	.45	.63	-.32	.49	.34	-.43	.66	.49	1.00

Table B2: Correlation matrix for positive purchase incidence observations (N = 92,948)

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	High-risk spend	1.00																
2	Low-risk spend	-.39	1.00															
3	Return share	-.11	.30	1.00														
4	Free shipping	-.01	.01	.02	1.00													
5	Advertising	.02	-.02	-.04	.04	1.00												
6	Available coupons	.01	.00	-.01	.04	.09	1.00											
7	Catalog pages	.00	.02	.00	-.09	-.08	-.01	1.00										
8	Recency	.06	.05	.01	.02	.01	-.05	-.03	1.00									
9	Frequency	-.02	.01	.03	-.02	-.02	.06	.04	-.66	1.00								
10	Monetary value	-.07	-.05	.01	-.02	-.02	.07	.03	-.70	.82	1.00							
11	Recency (low risk)	.08	.02	.00	.01	.02	-.05	-.04	.74	-.58	-.62	1.00						
12	Frequency (low-risk)	.01	-.05	.01	-.01	-.03	.07	.04	-.59	.70	.84	-.73	1.00					
13	Monetary (low-risk)	.04	-.04	.00	-.02	-.03	.06	.03	-.55	.77	.71	-.71	.87	1.00				
14	Recency (high-risk)	.05	.04	-.03	.01	.02	-.05	-.05	.77	-.60	-.63	.50	-.47	-.40	1.00			
15	Frequency (low-risk)	-.08	.04	.08	-.01	-.02	.07	.05	-.60	.72	.87	-.48	.63	.49	-.73	1.00		
16	Monetary (high-risk)	-.04	.07	.08	-.02	-.02	.06	.05	-.56	.83	.72	-.42	.51	.48	-.71	.86	1.00	
17	Past returns	.06	-.06	.23	.00	-.01	.04	.00	-.40	.45	.66	-.35	.52	.36	-.43	.68	.49	1.00

Table B3: Cross-equation correlations

	Incidence	Low-risk	High-risk
Low-risk	.836		
High-risk	.818	.100	
Return share	-.026	.013	-.072

Note: all correlations are significant with p<.05

Table B4: Estimates of restricted model (equal free shipping coefficients for high- and low-risk spend)

	Incidence		Low-risk spend		High-risk spend		Return share	
	β (se)	*p*	β (se)	*p*	β (se)	*p*	β (se)	*p*
Free shipping	.042	.000	.071	.001	.071	.001	.004	.502
	(.007)		(.021)		(.021)		(.006)	
High-risk spend							.051	.000
							(.001)	
Low-risk spend							.011	.000
							(.002)	
Advertising	.423	.000	.996	.000	.781	.000	-.026	.302
	(.027)		(.111)		(.127)		(.025)	
Available coupons	.028	.000	.055	.000	.056	.000	-.001	.623
	(.002)		(.008)		(.009)		(.002)	
Catalog pages	.010	.000	.018	.000	.021	.000	.000	.873
	(.001)		(.005)		(.006)		(.001)	
Recency	.269	.000	.707	.000	.697	.000		
	(.004)		(.015)		(.018)			
Frequency	.403	.000	.769	.000	.563	.000		
	(.008)		(.039)		(.047)			
Monetary	-.012	.000	.057	.000	.063	.000		
	(.002)		(.009)		(.009)			
Past returns	.050	.000	.044	.000	.184	.000	.565	.123
	(.003)		(.009)		(.013)		(.367)	
Constant	-8.499	.000	-17.540	.000	-13.889	.000	-13.889	.000
	(.395)		(1.64)		(1.867)		(1.867)	
N				1,165,661.000				
log likelihood				-706,684.000				

Comparison of the unconstrained (Table 2, Model 1) and constrained models by Likelihood-Ratio test:

$$\text{LR-Chi}^2(1) = -2\ln(L_{constrained}/L_{unconstrained}) = 2(LL_{unconstrained} - LL_{constrained}) =$$
$$2\times(-706584.2+706684.00)=199.60;\ p=.000$$

Table B5: Estimates of restricted model with brand unfamiliarity (equal free shipping coefficients for high- and low-risk spend)

	Incidence		Low-risk spend		High-risk spend		Unfamiliarity with brand		Return share	
	β (se)	*p*	β (se)	*p*	β (se)	*p*	β (se)	*p*	β (se)	*p*
Free shipping	.043	.000	.102	.000	.102	.000	.019	.269	.004	.529
	(.004)		(.013)		(.013)		(.017)		(.006)	
High-risk spend									.036	.000
									(.002)	
Low-risk spend									-.006	.000
									(.001)	
Unfamiliarity									.005	.018
									(.002)	
High-risk × Unfamiliarity									.001	.094
									(.000)	
Advertising	.414	.000	1.392	.000	1.124	.000	.816	.000	-.021	.430
	(.015)		(.071)		(.076)		(.068)		(.026)	
Available	.029	.000	.085	.000	.076	.000	.060	.000	.000	.868
	(.001)		(.005)		(.005)		(.005)		(.002)	
Catalog pages	.011	.000	.028	.000	.030	.000	.019	.000	.000	.934
	(.001)		(.003)		(.003)		(.003)		(.001)	
Recency	.168	.000	.610	.000	.673	.000	.554	.000		
	(.002)		(.01)		(.011)		(.021)			
Frequency	.349	.000	1.001	.000	.915	.000	.815	.000		
	(.005)		(.026)		(.029)		(.009)			
Monetary	-.011	.000	.043	.000	.059	.000	.098	.000		
	(.001)		(.006)		(.006)		(.004)			
Past returns	.060	.000	.126	.000	.263	.000	.127	.000	.009	.000
	(.001)		(.006)		(.007)		(.006)		(.002)	
Constant	-8.080	.000	-25.216	.000	-2.816	.000	-14.308	.000	.522	.179
	(.21)		(1.051)		(1.126)		(1.008)		(.388)	
N						1,165,661.000				
log likelihood						-874,649.150				

Comparison of the unconstrained (Table 2, Model 2) and constrained models by Likelihood-Ratio test:

$$\text{LR-Chi}^2(1)=-2\ln(L_{constrained}/L_{unconstrained})=2(LL_{unconstrained}-LL_{constrained})=$$
$$2\times(-874590+874649)=118.30;\ p=.000$$

WEB APPENDIX C: ROBUSTNESS ESTIMATIONS STUDY 1

We conduct 14 robustness checks, which we display and explain below:

(1) *Add lagged free shipping variable:* We investigate whether free shipping promotions influences sales beyond their expiration. We find free shipping promotions have no impact beyond their immediate impact (Web Appendix C1).

(2) *Binary classification based on mean rather than median:* We investigate whether the results hold up with we use a mean split to define high- vs. low-risk instead of a median split. The results hold up (Web Appendix C2, Table C2.1).

(3) *Continuous measure for riskiness:* Rather than splitting into high- vs. low-risk, we model a continuous measure of basket riskiness. This is positively affected by free shipping, and the continuous measure is positively associated with return share (Web Appendix C2, Table C2.2).

(4) *Share of high-risk products rather than binary classification:* Instead of a binary risk classification, we use the share of high-risk products in the basket. Again, we find that this measure is positively affected by free shipping, and it increases return share (Web Appendix C2, Table C2.3).

(5) *Share of high-risk products and share of unfamiliar brands rather than binary classifications*: We use the share of high-risk products in the basket instead of a binary classification. Similarly, we use the share of basket spent for unfamiliar brands instead of a binary classification. We find that free shipping positively affects the share of basket spent for high-risk products, but not the share of basket spent for unfamiliar brands consistent to the results of Model 2 in Table 2 of the main text (Web Appendix C2, Table C2.4).

(6) *Add lagged catalog variable:* We investigate whether catalogs have impact on sales beyond the week they are mailed, which we find to be the case. However, the focal results remain robust (Web Appendix C3).

(7) *Omit random customer intercepts:* Random intercepts are commonly used to control for unobserved heterogeneity. We estimate the model without random intercepts and the free shipping effect estimates are unchanged (Web Appendix C4).

(8) *Add equation for purchases of unfamiliar brands (last 52 weeks):* We re-estimate Model 2 in Table 2 of the main text, using a time window of 52 weeks instead of 26 weeks to define unfamiliar brands. Brands that are purchased in week *t* but not in the 52 previous weeks are defined as unfamiliar brands. The focal results remain unchanged, i.e. free shipping increases high-risk spend, but not the unfamiliar brands spend. High-risk products increase returns (Web Appendix C5, Table C5.1).

(9) *Add equation for purchase of unfamiliar brands (all previous weeks):* We define brand unfamiliarity based on all purchases previous to week *t*. Brands, which are purchased in week *t*, but not in any of the weeks covered by our data, are defined as unfamiliar brands. The focal results remain unchanged, i.e., free shipping increases high-risk spend, but not the spend for unfamiliar brands. High-risk products increase returns (Web Appendix C5, Table C5.2).

(10) *Add equation for purchase of unfamiliar brands in subcategory (last 26 weeks):* We measure brand unfamiliarity for each subcategory, instead of across subcategories. In other words, we now look whether a customer purchases Adidas sport shoes in the past, instead of Adidas in general. We use a time window of 26 weeks to determine unfamiliarity, and re-estimate Model 2 from the paper. All focal results remain unchanged, i.e., free shipping increases high-risk spend, but not spend for unfamiliar brands, and high-risk spend increases return share (Web Appendix C5, Table C5.3).

(11) *Add equation for purchase of unfamiliar brands in subcategory (last 52 weeks):* We re-estimate the model as described in (10) using a time window of 52 weeks instead of 26 weeks for brand-subcategory unfamiliarity. All focal results remain unchanged. (Web Appendix C5, Table C5.4)

(12) *Add equation for purchases of unfamiliar brands in subcategory (all previous weeks):* We re-estimate the model described in (10) using all weeks previous to week *t* to define brand-subcategory unfamiliarity. All focal results remain unchanged (Web Appendix C5, Table C5.5).

(13) *Add Gaussian copula terms for catalogs and coupons:* We include two copula terms for catalogs and coupons to control for potential endogeneity (Park and Gupta 2012). Although the coefficients for catalogs and coupons change, all focal results remain robust (Web Appendix C6, Table C6.1).

(14) *Exclude catalogs and coupons from model specification:* We re-estimate Model 1 from the main text excluding catalogs and coupons to control for potential endogeneity biases. All focal results remain robust (Web Appendix C6, Table C6.2).

Web Appendix C1: Robustness estimation with lagged free shipping variable

First, we assess whether the free shipping may show effects, which go beyond the current period of the promotion, and include a lagged free shipping variable on incidence, low- and high-risk spend and return share equations (4) to (7). Table C1 presents the results and shows no significant effects of the lagged free shipping variable on incidence, low- or high-risk spend, or return share. More importantly, all short-term free shipping effects remain consistent.

Table C1: Estimation results with lagged free shipping variable

	Incidence		Low-risk spend		High-risk spend		Return share	
	β (se)	*p*	β (se)	*p*	β (se)	*p*	β (se)	*p*
Free shipping	.049	.000	.051	.146	.132	.001	-.001	.886
	(.009)		(.035)		(.04)		(.008)	
Lagged free shipping	-.012	.164	-.053	.119	-.016	.685	.007	.360
	(.008)		(.034)		(.039)		(.008)	
High-risk spend							.053	.000
							(.001)	
Low-risk spend							-.001	.455
							(.001)	
Advertising	.424	.000	1.002	.000	.703	.000	-.024	.327
	(.028)		(.114)		(.129)		(.025)	
Available coupons	.028	.000	.052	.000	.055	.000	-.001	.539
	(.002)		(.008)		(.009)		(.002)	
Catalog pages	.010	.000	.015	.002	.022	.000	.000	.813
	(.001)		(.005)		(.006)		(.001)	
Recency	.273	.000	.700	.000	.689	.000		
	(.004)		(.016)		(.018)			
Frequency	.389	.000	.752	.000	.514	.000		
	(.009)		(.04)		(.047)			
Monetary	-.010	.000	.055	.000	.066	.000		
	(.002)		(.009)		(.009)			
Past returns	.389	.000	.038	.000	.177	.000	.012	.000
	(.009)		(.01)		(.013)		(.002)	
Constant	.051	.000	-17.437	.000	-12.581	.000	.547	.138
	(.003)		(1.678)		(1.903)		(.369)	
N	1,165,661.000							
log likelihood	-702,262.270							

Web Appendix C2: Robustness estimations with different high-risk measurements

Second, we test the robustness of the results with respect to the operationalization of high-risk spend. In our main model, our operationalization of purchases for high-risk goods is based on a binary classification of 413 subcategories into high- and low-risk. We classified subcategories as high-risk if their score was higher than the median value for all subcategories; subcategories with a lower or equal score than the median value are classified as low-risk. While this classification has high face validity, we assess whether the free shipping effects from the main model are robust to this classification. First, we estimate a model where we use the average value instead of the median value as cut off for the categorization of categories into high- and low-risk.

Table C2.1: Estimation results based on mean risk value

	Incidence		Low-risk spend		High-risk spend		Return share	
	β (se)	*p*	β (se)	*p*	β (se)	*p*	β (se)	*p*
Free shipping	.040	.000	.038	.039	.128	.000	.002	.748
	(.004)		(.018)		(.022)		(.006)	
High-risk spend							.046	.000
							(.001)	
Low-risk spend							-.014	.000
							(.001)	
Advertising	.417	.000	1.546	.000	.666	.000	-.020	.439
	(.015)		(.075)		(.09)		(.026)	
Available coupons	.030	.000	.099	.000	.046	.000	.000	.819
	(.001)		(.005)		(.006)		(.002)	
Catalog pages	.011	.000	.023	.000	.027	.000	.000	.858
	(.001)		(.003)		(.004)		(.001)	
Recency	.165	.000	.438	.000	.633	.000		
	(.002)		(.01)		(.012)			
Frequency	.327	.000	.781	.000	.755	.000		
	(.005)		(.027)		(.032)			
Monetary	-.009	.000	.037	.000	.039	.000		
	(.001)		(.006)		(.006)			
Past returns	.065	.000	.188	.000	.167	.000	.007	.001
	(.001)		(.006)		(.009)		(.002)	
Constant	-8.111	.000	-28.314	.000	-11.208	.000	.516	.179
	(.219)		(1.1)		(1.324)		(.384)	
N	1,165,661.000							
log likelihood	-688,978.130							

Second, we build a continuous riskiness score for each basket purchased by each customer. Specifically, we sum up the raters' experience score of each subcategory contained in a basket, weighted by the share of this subcategory of the total basket:

$$\text{risk\_score}_{\text{it}} = \sum_{\text{n}=1}^{\text{N}} \text{risk}_{\text{n}} \times \left(\frac{\text{y}_{\text{nit}}}{\text{y}_{\text{it}}}\right), \tag{C1}$$

where $\text{risk\_score}_{\text{n}}$ is the average risk score provided by the four raters for each subcategory n (=1,…, N, with N total number of subcategories contained in a basket purchased by customer i in week t). y_{nit} is the basket size for subcategory n and y_{it} is the total basket size purchased by customer i in week t. Higher values of this index indicate that a basket is dominated by high-risk goods. The index ranges from 1.833 to 6.083 (M = 4.449; SD = .731).

We estimate a four-equation model with this continuous risk index. The model consists of the incidence equation specified as in equations (3) and (4) of the main manuscript. We specify the other three equations for experience score, total basket size and return share as follows:

$$\text{total\_basket}_{\text{it}} = \beta_{0\text{i}}^{\text{tb}} + \delta^{\text{tb}}\text{FS}_{\text{t}} + \beta^{\text{tb}}\text{X}_{\text{it}} + \beta_{\text{RFM}}^{\text{tb}}\text{RFM}_{\text{it}}^{\text{tb}} + \text{u}_{\text{it}}^{\text{tb}} \tag{C2}$$

$$\text{risk\_score}_{it} = \beta_{0i}^{r} + \delta^{r}\text{FS}_{t} + \beta^{r}\text{X}_{it} + \beta_{b}^{r}\text{risk\_score\_base}_{it} + \text{u}_{it}^{r} \quad \text{(C3)}$$

$$\text{rs}_{it} = \beta_{0i}^{rs} + \delta^{rs}\text{FS}_{t} + \gamma_{1}\text{risk\_score}_{it} + \gamma_{2}\text{total\_basket}_{it} + \beta^{rs}\text{X}_{it} + \text{u}_{it}^{rs}, \quad \text{(C4)}$$

where the base variables for risk score and total basket size are the sum of the respective measures in the 26 weeks prior to week t. We use natural logarithms of total basket and risk score as dependent variables in equations (C2) and (C3). The control variables are identical to our main model. We estimate all four equations simultaneously with correlated error terms across the equations.

Table C2.2 shows that the results are in line with the free shipping effect. Free shipping increases high-risk spend measured by the continuous risk score (p=.018). This implies that consumers respond to free shipping by purchasing riskier baskets than baskets they usually buy. Further, the return equation (C4) shows that the experience score increases return share (p<.001), i.e., riskier baskets have more returns. This effect goes beyond the mere basket effect on returns, since we control for the basket size in the returns equation. In sum, a model based on a continuous measurement of experience goods leads to the same conclusions regarding the free shipping effect as our focal model (Table 2). Interestingly, we see a negative free shipping effect on the total basket, which is line with previous literature (e.g., Lewis 2006).

Table C2.2: Estimation results of model with riskiness score

	Incidence		Total basket		Riskiness		Return share	
	β (se)	*p*	β (se)	*p*	β (se)	*p*	β (se)	*p*
Free shipping	.041	.000	-.038	.012	.025	.018	-.003	.617
	(.008)		(.015)		(.011)		(.006)	
Riskiness							.431	.000
							(.038)	
Total basket							.055	.000
							(.004)	
Advertising	.430	.000	.109	.077	-.090	.031	.012	.612
	(.033)		(.062)		(.042)		(.023)	
Available coupons	.027	.000	.000	.928	.004	.152	-.001	.403
	(.002)		(.004)		(.003)		(.002)	
Catalog pages	.008	.000	-.002	.354	.004	.037	-.001	.201
	(.001)		(.003)		(.002)		(.001)	
Recency	.289	.000	.038	.000	.689	.000		
	(.005)		(.009)		(.018)			
Frequency	.405	.000	.046	.000	.525	.000		
	(.011)		(.004)		(.047)			
Monetary	-.025	.000	-.325	.000	.065	.000		
	(.002)		(.018)		(.009)			
Baseline riskiness						-.002	.001	
						(.001)		
Past returns	.042	.000	.038	.000	.030	.003	.009	.003
	(.003)		(.005)		(.01)		(.003)	
Constant	-8.596	.000	3.666	.000	5.705	.000	-1.985	.000
	(.494)		(.911)		(.615)		(.385)	
N				1,165,661.000				

log likelihood	-555,253.990

Third, we estimate a model where we use the share of basket comprised of high-risk spend instead of two dedicated equations for high- and low-risk. The results show that in line with our proposed mechanism, free shipping increases the share of the high-risk spend, and the share of high-risk spend increases returns.

Table C2.3: Estimation results of model with share of risky basket instead of dedicated high- and low-risk spends

	Incidence		Share of high-risk spend		Return share	
	β (se)	*p*	β (se)	*p*	β (se)	*p*
Free shipping	.041	.000	.017	.001	.003	.634
	(.009)		(.005)		(.006)	
Share of high-risk spend					.277	.000
					(.005)	
Advertising	.431	.000	.025	.250	-.011	.673
	(.034)		(.022)		(.026)	
Available coupons	.027	.000	.004	.007	.000	.879
	(.002)		(.002)		(.002)	
Catalog pages	.008	.000	.002	.033	.000	.949
	(.001)		(.001)		(.001)	
Recency	.294	.000	.080	.000		
	(.005)		(.003)			
Frequency	.387	.000	.134	.000		
	(.011)		(.008)			
Monetary	-.021	.000	-.012	.000		
	(.002)		(.003)			
Past returns	.043	.000	.021	.000	.007	.000
	(.003)		(.002)		(.002)	
Constant	-8.628	.000	-.391	.228	.365	.342
	(.507)		(.324)		(.385)	
N			1,162,833.000			
log likelihood			-714,675.550			

Last, we estimate a four-equation model with the purchase incidence equation, a second equation with the share of high-risk spend as in C2.3, a third equation with the share of unfamiliar brand spend to total basket (instead of the spend for unfamiliar brands as in the main text), and finally the return share equation. Results are consistent: Free shipping increases the share of basket spent for high-risk product categories, but not the share of the basket spent for unfamiliar brands.

Table C2.4: Estimation results of model with share of risky basket instead of dedicated high- and low-risk spend, and share of brand unfamiliarity

	Incidence		Share of high-risk spend		Share of unfamiliar brands spend		Return share	
	β (se)	*p*	β (se)	*p*	β (se)	*p*	β (se)	*p*
Free shipping	.041	.000	.018	.001	.000	.970	.003	.630
	(.008)		(.005)		(.004)		(.007)	
High-risk spend share							.251	.000
							(.01)	
Unfamiliar brands share							.070	.000
							(.009)	
High-risk × Unfamiliarity							.023	.086
							(.013)	
Advertising	.431	.000	.028	.207	.054	.000	-.011	.666
	(.033)		(.022)		(.015)		(.026)	
Available coupons	.027	.000	.004	.005	.005	.000	.000	.869
	(.002)		(.002)		(.001)		(.002)	
Catalog pages	.008	.000	.002	.024	.001	.025	.000	.997
	(.001)		(.001)		(.001)		(.001)	
Recency	.307	.000	.082	.000	.127	.000		
	(.005)		(.003)		(.006)			
Frequency	.413	.000	.137	.000	.137	.000		
	(.01)		(.008)		(.002)			
Monetary	-.019	.000	-.012	.000	.006	.001		
	(.002)		(.003)		(.002)			
Past returns	.045	.000	.021	.000	-.016	.000	.010	.000
	(.003)		(.002)		(.001)		(.002)	
Constant	-8.693	.000	-.462	.160	-.832	.000	.537	.164
	(.485)		(.329)		(.216)		(.386)	
N	1,165,661.000							
log likelihood	-415,415.540							

Web Appendix C3: Robustness estimation with lagged catalog variable

We test whether the free shipping effect may be affected by the long-term catalogue effect. To this end, we add a lagged catalog variable in all equations (3)-(7) and estimate the extended model. Results show that, indeed, the lagged catalog variable influences incidence, low- and High-risk spend positively, i.e., catalogs show the expected long-term effect. However, all free shipping effects are consistent with the main model.

Table C3: Results of main model with lagged catalog variable

	Incidence		Low-risk spend		High-risk spend		Return share	
	β (se)	*p*	β (se)	*p*	β (se)	*p*	β (se)	*p*
Free shipping	.061	.000	.057	.046	.183	.000	.003	.670
	(.007)		(.028)		(.032)		(.006)	
High-risk spend							.053	.000
							(.001)	
Low-risk spend							-.001	.330
							(.001)	
Advertising	.374	.000	.900	.000	.559	.000	-.022	.379
	(.028)		(.115)		(.132)		(.025)	
Available coupons	.026	.000	.047	.000	.047	.000	-.001	.562
	(.002)		(.008)		(.009)		(.002)	
Catalog pages	.019	.000	.036	.000	.052	.000	.000	.693
	(.001)		(.005)		(.006)		(.001)	
Lagged catalog pages	.023	.000	.051	.000	.073	.000	.000	.719
	(.001)		(.005)		(.006)		(.001)	
Recency	.273	.000	.693	.000	.682	.000		
	(.004)		(.016)		(.018)			
Frequency	.389	.000	.697	.000	.505	.000		
	(.009)		(.039)		(.05)			
Monetary	-.011	.000	.058	.000	.062	.000		
	(.002)		(.009)		(.009)			
Past returns	.050	.000	.046	.000	.178	.000	.009	.000
	(.003)		(.009)		(.012)		(.002)	
Constant	-7.780	.000	-15.858	.000	-1.362	.000	.514	.168
	(.418)		(1.7)		(1.946)		(.373)	
N				1,158,653.000				
log likelihood				-701,878.340				

Web Appendix C4: Robustness estimation without random intercepts

We estimate the model without customer-specific random intercepts. All free shipping effects are robust to those from the main model.

Table C4: Results of main model without random intercepts

	Incidence		Low-risk		High-risk		Return share	
	β	*p*	β	*p*	β	*p*	β	*p*

	(se)		(se)		(se)		(se)	
Free shipping	.042	.000	.042	.085	.158	.000	.008	.030
	(.005)		(.024)		(.025)		(.004)	
High-risk spend							.048	.000
							(.001)	
Low-risk spend							.003	.027
							(.001)	
Advertising	.415	.000	1.462	.000	1.122	.000	-.009	.533
	(.021)		(.098)		(.1)		(.014)	
Available coupons	.028	.000	.085	.000	.075	.000	-.007	.000
	(.001)		(.007)		(.007)		(.001)	
Catalog pages	.011	.000	.026	.000	.033	.000	-.002	.003
	(.001)		(.004)		(.004)		(.001)	
Recency	.170	.000	.629	.000	.674	.000		
	(.002)		(.01)		(.01)			
Frequency	.456	.000	1.159	.000	1.065	.000		
	(.005)		(.025)		(.029)			
Monetary	-.024	.000	.050	.000	.071	.000		
	(.001)		(.005)		(.006)			
Past returns	.044	.000	.096	.000	.233	.000	.063	.000
	(.002)		(.008)		(.008)		(.001)	
Constant	-8.118	.000	-26.445	.000	-21.084	.000	.231	.280
	(.305)		(1.443)		(1.482)		(.214)	
N	1,165,661.000							
log likelihood	-711,938.970							

Web Appendix C5: Robustness estimation with brand unfamiliarity

We conduct extensive sensitivity analysis of the brand unfamiliarity effect: (1) we vary the time window used to define unfamiliarity: 52 weeks as well as all weeks before week *t* (instead of 26 weeks as in the main text); (2) we use brand unfamiliarity at the subcategory level instead of brand unfamiliarity across all categories. In other words, we look whether a customer, for example, bought Polo brand shirts in the 26 weeks prior to week *t*, instead of just any Polo product. Tables C5.1-C5.5 provide the results.

Overall, these results show that (1) free shipping effect on risky purchases is manifested by higher purchases in high-risk categories, but not by purchases of unfamiliar brands; and (2) the effects of both models in Table 2 remain robust even after controlling for different operationalizations of brand familiarity.

Table C5.1: Estimation of model with brand unfamiliarity (time window is 52 weeks)

	Incidence		Low-risk		High-risk		Unfamiliarity with brand		Return share	
	β (se)	*p*	β (se)	*p*	β (se)	*p*	β (se)	*p*	β (se)	*p*
Free shipping	.054	.000	.003	.918	.101	.000	-.072	.000	.002	.726
	(.007)		(.027)		(.028)		(.019)		(.006)	
High-risk spend									.053	.000
									(.002)	
Low-risk spend									.014	.000
									(.001)	
Unfamiliarity									-.010	.000
									(.002)	
High-risk × Unfamiliarity									.001	.238
									(.000)	
Advertising	.354	.000	.583	.000	.232	.047	.442	.000	-.027	.284
	(.029)		(.113)		(.117)		(.077)		(.025)	
Available coupons	.029	.000	.039	.000	.028	.000	.021	.000	-.001	.593
	(.002)		(.008)		(.008)		(.005)		(.002)	
Catalog pages	.010	.000	.008	.105	.016	.002	.011	.001	.000	.800
	(.001)		(.005)		(.005)		(.003)		(.001)	
Recency	.284	.000	.420	.000	.366	.000	-.566	.000		
	(.004)		(.015)		(.016)		(.024)			
Frequency	.485	.000	.305	.000	.068	.123	.760	.000		
	(.009)		(.039)		(.044)		(.054)			
Monetary	-.024	.000	.054	.000	.080	.000	.065	.000		
	(.002)		(.008)		(.008)		(.005)			
Past returns	.047	.000	-.026	.005	.124	.000	.045	.000	.011	.000
	(.003)		(.009)		(.011)		(.006)		(.002)	
Constant	-7.489	.000	-8.028	.000	-2.747	.112	-6.704	.000	.517	.164
	(.433)		(1.662)		(1.726)		(1.189)		(.372)	
N	1,165,661.000									
log likelihood	-882,911.380									

Table C5.2: Results with brand unfamiliarity (time window is all previous weeks)

	Incidence		Low-risk		High-risk		Unfamiliarity with brand		Return share	
	β (se)	*p*	β (se)	*p*	β (se)	*p*	β (se)	*p*	β (se)	*p*
Free shipping	.046	.000	.041	.085	.159	.000	.001	.947	.003	.577
	(.006)		(.024)		(.025)		(.018)		(.006)	
High-risk spend									.043	.000
									(.002)	
Low-risk spend									.005	.000
									(.001)	
Unfamiliarity									-.022	.000
									(.002)	
High-risk × Unfamiliarity									.001	.237
									(.000)	
Advertising	.388	.000	1.233	.000	1.083	.000	.868	.000	-.014	.578
	(.022)		(.097)		(.103)		(.074)		(.025)	
Available coupons	.028	.000	.073	.000	.067	.000	.041	.000	-.001	.738
	(.002)		(.007)		(.007)		(.005)		(.002)	
Catalog pages	.010	.000	.021	.000	.029	.000	.019	.000	.000	.896
	(.001)		(.004)		(.004)		(.003)		(.001)	
Recency	.213	.000	.584	.000	.582	.000	-.234	.000		
	(.003)		(.013)		(.014)		(.023)			
Frequency	.368	.000	.769	.000	.597	.000	.305	.000		
	(.007)		(.034)		(.037)		(.058)			
Monetary	-.012	.000	.049	.000	.060	.000	.031	.000		
	(.001)		(.007)		(.007)		(.005)			
Past returns	.054	.000	.059	.000	.273	.000	.108	.000	.010	.000
	(.002)		(.007)		(.01)		(.006)		(.002)	
Constant	-7.841	.000	-21.502	.000	-19.460	.000	-13.197	.000	.453	.222
	(.329)		(1.434)		(1.521)		(1.156)		(.371)	
N					1,165,661.000					
log likelihood					-874,649.150					

Table C5.3: Results with brand unfamiliarity at the subcategory level (time window is 26 weeks)

	Incidence		Low-risk		High-risk		Unfamiliarity with brand		Return share	
	β (se)	*p*	β (se)	*p*	β (se)	*p*	β (se)	*p*	β (se)	*p*
Free shipping	.042	.000	.045	.008	.158	.000	.006	.720	.004	.559
	(.003)		(.017)		(.018)		(.016)		(.006)	
High-risk spend									.035	.000
									(.002)	
Low-risk spend									-.006	.000
									(.001)	
Unfamiliarity									.006	.004
									(.002)	
High-risk × Unfamiliarity									.001	.054
									(.000)	
Advertising	.414	.000	1.442	.000	1.079	.000	.878	.000	-.021	.413
	(.014)		(.069)		(.075)		(.067)		(.026)	
Available coupons	.029	.000	.087	.000	.076	.000	.060	.000	.000	.832
	(.001)		(.005)		(.005)		(.005)		(.002)	
Catalog pages	.011	.000	.027	.000	.032	.000	.020	.000	.000	.964
	(.001)		(.003)		(.003)		(.003)		(.001)	
Recency	.163	.000	.598	.000	.656	.000	.828	.000		
	(.002)		(.009)		(.01)		(.009)			
Frequency	.347	.000	.970	.000	.873	.000	.489	.000		
	(.004)		(.024)		(.027)		(.022)			
Monetary	-.012	.000	.045	.000	.059	.000	.119	.000		
	(.001)		(.005)		(.005)		(.005)			
Past returns	.061	.000	.135	.000	.281	.000	.160	.000	.011	.000
	(.001)		(.006)		(.007)		(.006)		(.002)	
Constant	-8.062	.000	-25.919	.000	-2.100	.000	-15.158	.000	.527	.164
	(.208)		(1.024)		(1.109)		(.988)		(.379)	
N	1,165,661.000									
log likelihood	-872,700.500									

Table C5.4: Results with brand unfamiliarity at the subcategory level (time window is 52 weeks)

	Incidence		Low-risk		High-risk		Unfamiliarity with brand		Return share	
	β (se)	*p*	β (se)	*p*	β (se)	*p*	β (se)	*p*	β (se)	*p*
Free shipping	.042	.000	.046	.008	.157	.000	-.010	.561	.004	.577
	(.004)		(.017)		(.019)		(.016)		(.006)	
High-risk spend									.043	.000
									(.002)	
Low-risk spend									-.003	.028
									(.001)	
Unfamiliarity									-.001	.680
									(.002)	
High-risk × Unfamiliarity									.000	.287
									(.000)	
Advertising	.414	.000	1.427	.000	1.056	.000	.605	.000	-.019	.469
	(.014)		(.07)		(.077)		(.065)		(.026)	
Available coupons	.029	.000	.087	.000	.077	.000	.050	.000	.000	.871
	(.001)		(.005)		(.005)		(.004)		(.002)	
Catalog pages	.011	.000	.027	.000	.032	.000	.025	.000	.000	.928
	(.001)		(.003)		(.003)		(.003)		(.001)	
Recency	.152	.000	.488	.000	.512	.000	.862	.000		
	(.002)		(.01)		(.011)		(.074)			
Frequency	.331	.000	.870	.000	.731	.000	-.272	.000		
	(.004)		(.025)		(.028)		(.022)			
Monetary	-.012	.000	.031	.000	.043	.000	.035	.000		
	(.001)		(.005)		(.005)		(.005)			
Past returns	.062	.000	.136	.000	.282	.000	.139	.000	.009	.000
	(.001)		(.006)		(.008)		(.005)		(.002)	
Constant	-8.018	.000	-25.271	.000	-19.119	.000	-11.296	.000	.505	.193
	(.208)		(1.034)		(1.136)		(1.08)		(.388)	
N					1,165,661.000					
log likelihood					-873,728.950					

Table C5.5: Results with brand unfamiliarity at the subcategory level (time window is all previous weeks)

	Incidence		Low-risk		High-risk		Unfamiliarity with brand		Return share	
	β (se)	*p*	β (se)	*p*	β (se)	*p*	β (se)	*p*	β (se)	*p*
Free shipping	.042	.000	.044	.006	.159	.000	.007	.703	.004	.569
	(.003)		(.016)		(.018)		(.018)		(.006)	
High-risk spend									.038	.000
									(.002)	
Low-risk spend									-.005	.000
									(.001)	
Unfamiliarity									-.001	.795
									(.002)	
High-risk × Unfamiliarity									.001	.135
									(0)	
Advertising	.413	.000	1.444	.000	1.075	.000	.960	.000	-.019	.471
	(.014)		(.067)		(.072)		(.072)		(.026)	
Available coupons	.029	.000	.087	.000	.076	.000	.055	.000	.000	.876
	(.001)		(.005)		(.005)		(.005)		(.002)	
Catalog pages	.011	.000	.027	.000	.033	.000	.019	.000	.000	.939
	(.001)		(.003)		(.003)		(.003)		(.001)	
Recency	.141	.000	.432	.000	.453	.000	-.160	.000		
	(.002)		(.009)		(.01)		(.023)			
Frequency	.323	.000	.820	.000	.702	.000	.345	.000		
	(.004)		(.024)		(.026)		(.06)			
Monetary	-.012	.000	.029	.000	.039	.000	.030	.000		
	(.001)		(.005)		(.005)		(.005)			
Baseline returns	.062	.000	.137	.000	.286	.000	.155	.000	.009	.000
	(.001)		(.006)		(.007)		(.006)		(.002)	
Constant	-7.963	.000	-25.352	.000	-19.266	.000	-14.755	.000	.508	.189
	(.2)		(.982)		(1.068)		(1.139)		(.386)	
N	1,165,661.000									
log likelihood	-878,258.220									

Web Appendix C6: Robustness estimation regarding endogeneity of coupons and catalogs

The retailer decides on the mailing of catalogs and coupons based on a customer's purchase history, e.g., how much the customer has purchased in the past, and in which categories. Much of these aspects are covered in the RFM variables that we include in our model. Therefore, most of the targeting that takes place is not unobserved to our model, and beyond these basic metrics, the retailer does not do any targeting. To alleviate potential concerns with regard to these variables, we conduct two robustness estimations. First, we re-estimate the main model including Gaussian copulas (Park and Gupta 2012) for catalogs and coupons (Table C6.1 in Web Appendix C). A Shapiro-Wilk test shows that neither of the two variables is normally distributed (z = 24.411 for coupons and z = 23.802 for catalogs, $p < .001$).

Table C6.1: Robustness estimation with copulas for coupons and catalogs

	Incidence		Low-risk		High-risk		Return share	
	β (se)	*p*	β (se)	*p*	β (se)	*p*	β (se)	*p*
Free shipping	.042	.000	.020	.465	.124	.000	.004	.558
	(.007)		(.027)		(.031)		(.006)	
High-risk spend							.051	.000
							(.001)	
Low-risk spend							.000	.835
							(.001)	
Advertising	.422	.000	1.039	.000	.733	.000	-.026	.305
	(.027)		(.112)		(.128)		(.025)	
Available coupons	.023	.000	.024	.108	.051	.003	-.002	.599
	(.004)		(.015)		(.017)		(.003)	
Catalog pages	.009	.000	.020	.004	.025	.002	.000	.778
	(.002)		(.007)		(.008)		(.002)	
Copula term coupons	.007	.108	.043	.018	.007	.751	.001	.753
	(.004)		(.018)		(.021)		(.004)	
Copula term catalogs	.003	.431	-.009	.516	-.008	.599	-.002	.573
	(.003)		(.014)		(.016)		(.003)	
Recency	.269	.000	.707	.000	.697	.000		
	(.004)		(.015)		(.018)			
Frequency	.404	.000	.770	.000	.563	.000		
	(.008)		(.039)		(.047)			
Monetary	-.012	.000	.057	.000	.063	.000		
	(.002)		(.009)		(.009)			
Past returns	.050	.000	.044	.000	.184	.000	.011	.000
	(.003)		(.009)		(.013)		(.002)	
Constant	-8.487	.000	-18.149	.000	-13.189	.000	.565	.124
	(.395)		(1.658)		(1.894)		(.367)	
N	1,165,661.000							
log likelihood	-706,666.090							

Second, we re-estimate the main model and exclude the variables for catalogs and advertising in order to show the robustness of the focal estimates. Again, this leaves the focal coefficients essentially unchanged (Table C6.2 in Web Appendix C).

Table C6.2: Model without coupons and catalogs

	Incidence		Low-risk		High-risk		Return share	
	β (se)	*p*	β (se)	*p*	β (se)	*p*	β (se)	*p*
Free shipping	.040	.000	.019	.485	.118	.000	.003	.643
	(.006)		(.027)		(.031)		(.006)	
High-risk spend							.052	.000

							(.001)	
Low-risk spend							-.001	.194
							(.001)	
Advertising	.432	.000	1.064	.000	.748	.000	-.023	.345
	(.026)		(.11)		(.126)		(.024)	
Recency	.267	.000	.710	.000	.700	.000		
	(.004)		(.015)		(.018)			
Frequency	.420	.000	.803	.000	.618	.000		
	(.008)		(.039)		(.046)			
Monetary	-.013	.000	.058	.000	.061	.000		
	(.002)		(.008)		(.009)			
Past returns	.051	.000	.045	.000	.175	.000	.011	.000
	(.003)		(.01)		(.013)		(.002)	
Constant	-8.611	.000	-18.585	.000	-13.414	.000	.527	.142
	(.382)		(1.619)		(1.864)		(.359)	
N	1,165,661.000							
log likelihood	-706,584.200							

WEB APPENDIX D: ADDITIONAL RESULTS STUDY 2

Table D1: Comparison of test and control groups before the free shipping field experiment*

	N	M	SD	*p* *(diff=0)*
Number of purchases				
Control group	379844	.230	.421	.946
Test group	380551	.230	.421	
Basket size				
Control group	87398	193.619	16.112	.154
Test group	87536	194.714	161.751	
High-risk spend				
Control group	87398	111.996	127.988	.516
Test group	87536	111.393	127.835	
Low-risk spend				
Control group	87398	82.684	112.462	.200
Test group	87536	83.382	115.569	
Overall return share				
Control group	87398	.423	.386	.256
Test group	87536	.425	.388	
Return share high-risk				
Control group	87398	.376	.411	.116
Test group	87536	.379	.412	
Return share low-risk				
Control group	87398	.240	.365	.689
Test group	87536	.239	.365	

Note: All statistics are based on observations from the month prior to the field experiment (July 2014)

One potential alternative explanation for our findings is consumer stockpiling (Neslin 2002), which can manifest itself in accelerated timing or multiple purchases of the same item. Either behavior would lead to a "post-promotion dip" after the promotion expired. The robustness check with lagged free shipping (Web Appendix C1) does not support stockpiling in Study 1. We arrive at a similar conclusion in the field experiment because a comparison between test vs. control group in the 6 months after the field experiment shows no significant differences for the key variables purchase incidence and purchase volume of high-risk products (Table D2).

Table D2: Post-Experimental comparison of test and control groups to estimate potential stockpiling*

	Incidence					Basket size			High-risk spend			Low-risk spend			Overall return share		
	N_{total}	M	SD	*p*	$N_{purchase}$	M	SD	*p*	M	SD	*p*	M	SD	*p*	M	SD	*p*
t+1																	
Control	379844	.268	.267	.943	101847	254.600	285.600	.405	140.129	207.044	.956	114.615	194.992	.218	.329	.389	.111
Test	380551	.268	.267		102064	255.669	293.994		140.075	211.435		115.691	199.622		.326	.382	
t+2																	
Control	379844	.229	.227	.597	86867	254.130	296.577	.546	143.093	224.929	.766	111.039	197.569	.217	.302	.373	.444
Test	380551	.228	.227		86835	254.991	298.022		142.772	222.647		112.217	200.001		.300	.394	
t+3																	
Control	379844	.230	.228	.843	87237	265.676	305.478	.784	140.648	216.043	.691	124.857	221.444	.999	.344	.423	.916
Test	380551	.230	.229		87472	265.273	307.108		140.235	218.367		124.859	219.900		.344	.390	
t+4																	
Control	379844	.198	.197	.710	75398	259.180	290.741	.421	140.864	206.255	.208	118.280	207.689	.013	.359	.386	.114
Test	380551	.198	.197		75409	257.977	289.628		142.219	211.766		115.703	196.076		.362	.382	
t+5																	
Control	379844	.281	.280	.340	106710	271.976	292.156	.601	154.037	206.638	.245	117.336	198.287	.753	.381	.370	.013
Test	380551	.282	.280		107283	272.653	307.199		155.080	208.712		117.551	219.054		.385	.378	
t+6																	
Control	379844	.258	.257	.870	98038	249.831	276.900	.339	141.559	195.312	.380	107.677	188.719	.569	.371	.396	.422
Test	380551	.258	.257		98283	251.036	281.112		142.332	194.967		108.170	195.382		.369	.392	

* Results are for the period November 2014-April 2015

WEB APPENDIX E: ADDITIONAL RESULTS STUDY 3

Table E1: Items used to measure affect and risk premium

Affect (Watson, Clark and Tellegen 1988)	Please indicate to what extent you feel … at this moment	1=”not at all”/7=”extremely”
	...interested	
	…excited	
	…elated	
	…enthusiastic	
	…strong	
Risk Premium (Blattberg and Neslin 1990)	Because of the shipping fee for today’s order, I feel I have nothing to lose even if I would need to return the product(s).	1=”strongly disagree”/7=”strongly agree”

Table E2: Descriptive statistics of purchase history prior to the study (pre-matching)

	FS			No FS				
	N	M	SD	N	M	SD	t	*p*
Recency (months)	910	4.423	1.412	554	3.792	1.732	7.593	.000
Frequency	910	2.570	1.760	554	2.646	1.839	.787	.431
High-risk spend	910	391.763	803.347	554	506.320	828.836	2.610	.009
Low-risk spend	910	325.219	709.151	554	412.433	833.973	2.133	.003
High-risk returns	910	141.799	312.066	554	191.051	411.795	2.588	.009
Low-risk returns	910	61.866	165.446	554	96.211	241.345	3.225	.001
Number of high-risk subcategories	910	5.660	9.735	554	6.327	10.429	1.236	.217
Number of low-risk subcategories	910	5.230	10.402	554	5.958	10.157	1.319	.187

Table E3: Estimation results of probit model

FS	coeff	se	t	*p*
Recency	.213	.025	8.670	.000
Frequency	-.075	.022	-3.500	.000
High-risk spend	-.000	.000	-1.320	.186
Low-risk spend	-.000	.000	-.540	.591
High-risk returns	-.000	.000	-1.170	.242
Low-risk returns	-.000	.000	-1.650	.099
Number of high-risk subcategories	.008	.008	.970	.330
Number of low-risk subcategories	.002	.007	.230	.816
Constant	-.308	.097	-3.160	.002
N	1464.000			
LL	-923.640			
LR Chi2 (*p*) before	94.810 (.000)			
LR Chi2 (*p*) after	11.080 (.197)			
Pseudo-R^2 before	.049			
Pseudo-R^2 after	.004			
Mean standardized bias before	14.100			
Mean standardized bias after	6.700			

Table E4: Bootstrapped free shipping effects (one-to-one nearest neighbor matching)

	ATT	SE	t	*p*	2.5%	97.5%
Affect	.325	.087	3.750	.000	.155	.495
Risk premium	.643	.111	5.760	.000	.424	.861
Basket	80.347	25.218	3.190	.001	30.921	129.773
High-risk spend	90.663	17.147	5.290	.000	57.056	124.270
Low-risk spend	-10.316	17.200	.600	.549	-44.026	23.395
Return share	.056	.020	2.83	.001	.017	.094
Unfamiliar brand spend	6.648	15.220	.440	.660	-23.144	36.517
Familiar brand spend	73,167	21.634	3.380	.001	30.763	115.569

Note: Standard errors are computed via bootstrapping with 500 replications

Table E5: Descriptive statistics for free shipping and no-free shipping groups – pre-matching (Study 3)

	Group	N	M	SD	t	*p*
Affect	No FS	554	4.513	1.440	4.482	.000
	FS	910	4.845	1.335		
Risk premium	No FS	554	4.903	1.948	6.712	.000
	FS	910	5.556	1.715		
Basket size	No FS	554	340.071	389.584	2.645	.008
	FS	910	404.356	484.720		
High-risk spend	No FS	554	160.337	195.904	4.345	.000
	FS	910	233.460	365.426		
Low-risk spend	No FS	554	179.733	312.981	.555	.579
	FS	910	170.896	284.052		
Overall return share	No FS	554	.211	.301	2.153	.032
	FS	910	.248	.334		
Unfamiliar brand spend	No FS	554	168.530	229.822	.385	.701
	FS	910	173.634	255.600		
Familiar brand spend	No FS	554	181.904	356.772	2.836	.005
	FS	910	246.731	459.546		

Table E5 shows the means for the focal variables for the free shipping vs. no free shipping groups before matching. We see that, on average, customers in the free shipping condition show significantly higher affect compared to those in the no-free shipping condition, and they have a stronger perception of being compensated for the risk of making a purchase (risk premium). In addition, the average order size, the average high-risk spend and the average return share are significantly higher. This is initial support for the hypothesis that free shipping is associated with perceptions of positive affect and risk premium, and more purchases of high-risk products.

WEB APPENDIX F: ADDITIONAL RESULTS STUDY 4

Figure F1.1: Stimuli used in Study 4

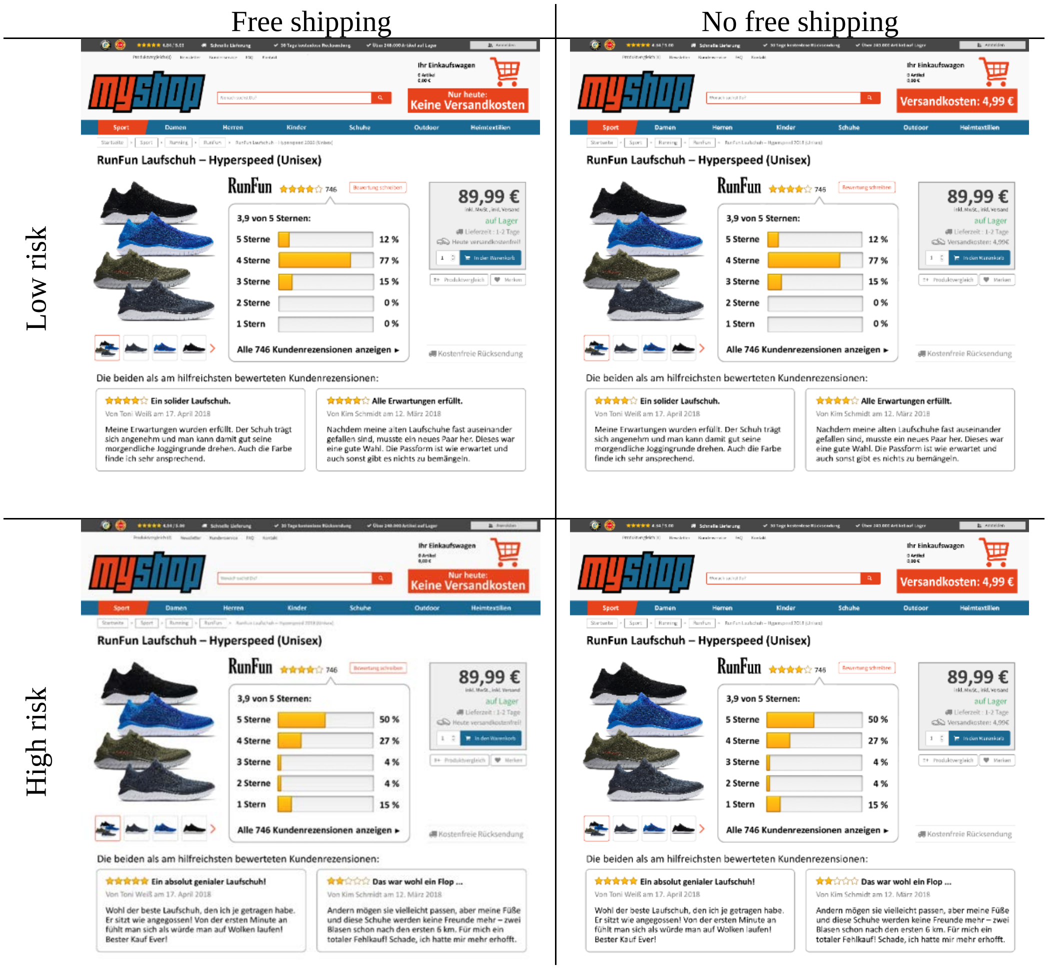

Figure F1.2: Mean risk perception across conditions (Study 4)

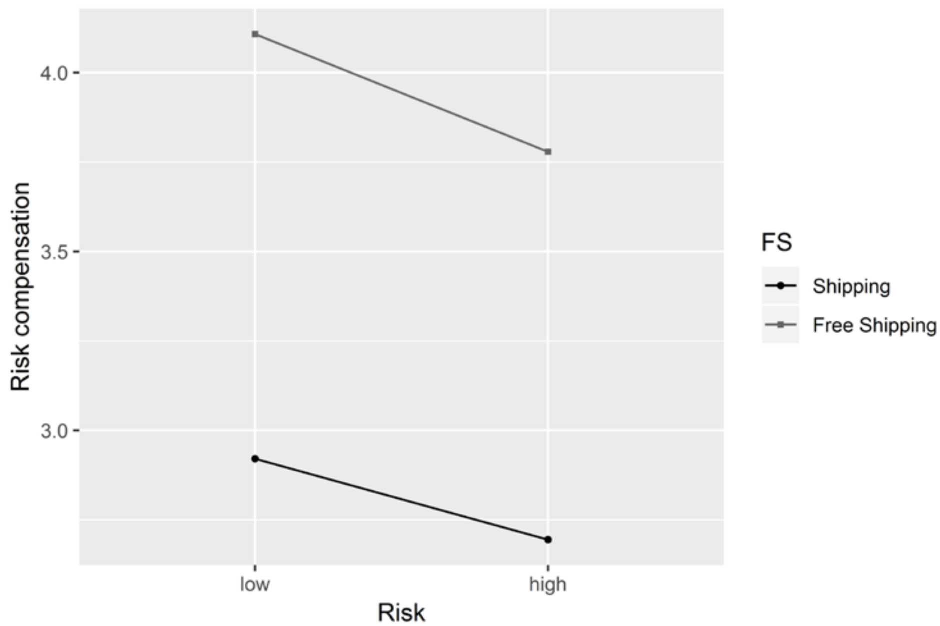

Figure F1.3: Mean affect across conditions (Study 4)

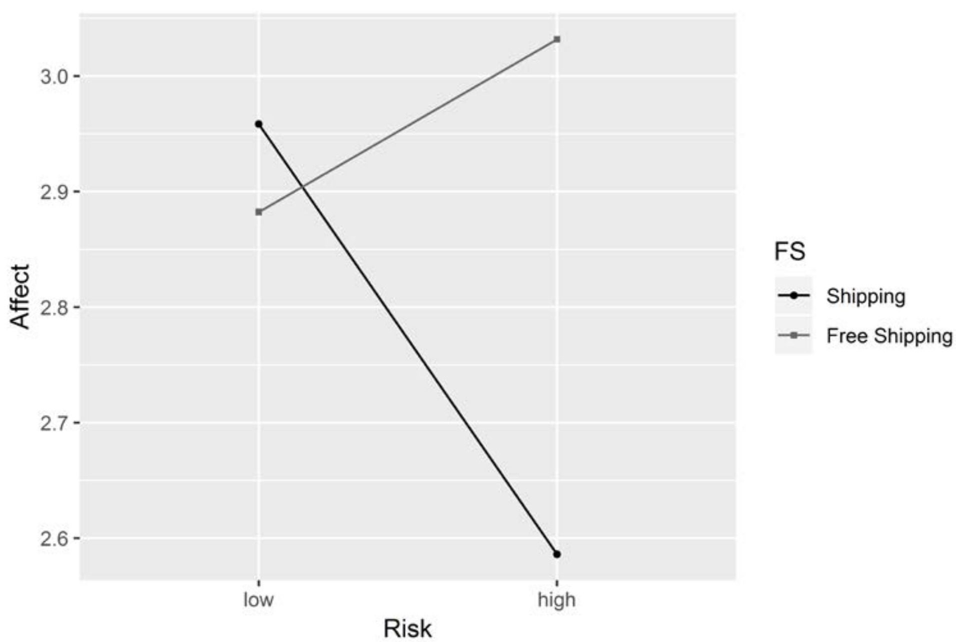

Table F1: Results of mediation analysis of free shipping through affect and risk premium

	Risk premium					Affect					Purchase intent				
	coeff	se	*p*	2.5%	97.5%	coeff	se	*p*	2.5%	97.5%	coeff	se	*p*	2.5%	97.5%
Free shipping	1.137	.192	.000	.759	1.515	.179	.125	.219	-.107	.467	-.203	.107	.061	-.412	.010
Risk premium (RP)											.193	.031	.000	.131	.255
Affect											.747	.042	.000	.657	.829
High Risk (HR)	-.282	.192	.143	-.659	.096	-.092	.145	.527	-.378	.194					
Constant	2.945	.166	.000	2.620	3.272	2.8302	.125	.000	2.539	3.077	.026	.136	.847	-.241	.294
Total indirect effect											.352	.140		.087	.619
FS->RP											.219	.120		.120	.344
FS->Affect											.134	.108		-.083	.344
N	401					401					401				
F (*p*)	18.023 (.000)					1.735 (1.886)					169.98 (.000)				

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