Pricing in Online Retailing: Understanding Drivers of Sales, Revenue, and Profit

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Overview of Contents

1 Introduction 1

2 Looking beyond Sales – Promotion Impact on Profit in Online Retailing 12

3 Crossed Out but Still Relevant? Exploring Online Advertised Reference Prices 45

4 Reach for the Stars – the Interplay of Product Reviews and Price in Online Retailing 87

5 Conclusion 130

6 Appendices 138

7 References 156

Table of Contents

1 Introduction 1

1.1 Research Objectives and Methodology 2

1.2 Structure of the Dissertation 10

2 Looking beyond Sales – Promotion Impact on Profit in Online Retailing 12

2.1 Introduction 13

2.2 Related Literature and Contribution 15

2.2.1 Online Pricing Decisions 15

2.2.2 Profit Impact of Price Reductions 17

2.2.3 Correlates of Promotional Impact 20

2.3 Framework 22

2.4 Empirical Study 24

2.4.1 Data Description 24

2.4.2 Model 25

2.4.3 Demand Model Estimation 26

2.4.4 Results 27

2.4.5 Promotional Impact Calculation 29

2.4.6 Understanding the Impact of Brand-specific Margins 32

2.4.7 Robustness Check 34

2.4.8 Correlates of Sales, Revenue, and Profit Impact 38

2.5 Conclusions, Implications, and Limitations 42

3 Crossed Out but Still Relevant? Exploring Online Advertised Reference Prices 45

3.1 Introduction 46

3.2 Institutional Background and Literature Review 50

3.2.1 Legal Regulations on Advertised Reference Prices 50

3.2.2 Theoretical Fundamentals of Advertised Reference Prices 52

3.2.3 Empirical Research on Advertised Reference Prices..........54
3.2.4 Theoretical Differences Between Online and Offline Shopping..........56
3.2.5 Empirical Research on Online Reference Prices..........57
3.3 Conceptual Framework..........59
3.4 Study 1: Online Experiment..........62
3.4.1 Data Collection and Description..........62
3.4.2 Model..........62
3.4.3 Empirical Results..........63
3.5 Study 2: Field Experiment..........63
3.5.1 Data Collection and Description..........63
3.5.2 Model..........64
3.5.3 Empirical Results..........65
3.5.4 Robustness of Results..........66
3.6 Study 3: Transaction Data..........71
3.6.1 Data Collection and Description..........71
3.6.2 Model..........72
3.6.3 Empirical Results and Functional Form..........74
3.6.4 Robustness of Results..........80
3.6.5 Profit Assessment..........81
3.7 Discussion and Managerial Implications..........84
3.8 Limitations and Future Research..........86
4 Reach for the Stars – the Interplay of Product Reviews and Price in Online Retailing..87
4.1 Introduction..........88
4.2 Contribution and Conceptual Framework..........92
4.2.1 Review Dimension: Valence..........93
4.2.2 Review Dimension: Volume..........94
4.2.3 Review Dimension: Variance..........95

4.2.4 Interactions Between Review Dimensions 95
4.2.5 Price 97
4.3 Empirical Study 100
4.3.1 Product Review Process 100
4.3.2 Data Collection and Description 102
4.3.3 Model 103
4.3.4 Empirical Results 105
4.3.5 Robustness Check 115
4.4 Pricing Decisions and Product Reviews 119
4.5 Discussion and Managerial Implications 123
4.6 Limitations and Future Research 128
5 Conclusion 130
5.1 Main Research Findings and Managerial Implications 131
5.2 Limitations and Future Research 136
6 Appendices 138
6.1 Appendix – Chapter 2 139
6.2 Appendix – Chapter 3 141
6.3 Appendix – Chapter 4 153
7 References 156

List of Figures

Figure 1.1: Structure of the Dissertation....................11
Figure 2.1: Average Brand-specific Profit Margin....................15
Figure 2.2: Framework....................23
Figure 2.3: Histogram of Posterior Means of 160 Promotional Price Indices....................28
Figure 2.4: Histogram of Posterior Means of 160 Cross Price Effects....................28
Figure 2.5: Own Sales Impact per Brand....................31
Figure 2.6: Deviation of Profit Impact with Constant Margin from Profit Impact with Brand-specific Margins....................33
Figure 2.7: Robustness Check – Histograms of Posterior Means of Lagged Coefficients......36
Figure 2.8: Robustness Check – Histogram of Posterior Means of Promotional Price Indices....................37
Figure 2.9: Robustness Check – Histogram of Posterior Means of Cross-Price Indices.........38
Figure 3.1: Conceptual Framework....................61
Figure 3.2: Example of Synthetic Control Group Pre-phase and Manipulation Phase...........70
Figure 3.3: Example of Synthetic Control Group Manipulation Phase and Post-phase..........71
Figure 3.4: Histogram R2R-ratio....................73
Figure 3.5: Sensitivity Analysis R2R-ratio Split....................79
Figure 3.6: Absolute Change in Profit Given R2R-ratio Increase by 0.01 Cumulated per Article....................83
Figure 3.7: Absolute Change in Profit Based on R2R Increase....................83
Figure 4.1: Conceptual Framework....................99
Figure 4.2: Product Information on Overview Website....................100
Figure 4.3: Product Information on Product Detail Website....................101
Figure 4.4: Variance of Product Reviews....................101
Figure 4.5: J-shape of Online Product Reviews (n = 204,904 Unique Reviews)....................103
Figure 4.6: Effects of Valence, Volume, and Variance on Sales....................107
Figure 4.7: Interaction of Volume and Valence at Mean Price and Mean Variance............108
Figure 4.8: Interaction of Variance and Valence at Mean Price and Mean Volume............109
Figure 4.9: Interaction of Valence and Variance at Mean Price by Volume....................110
Figure 4.10: Three-way Interaction of Price, Valence, and Volume at Mean Variance........112
Figure 4.11: Three-way Interaction of Price, Valence, and Variance at Mean Volume........113
Figure 4.12: Three-way Interactions on Price Elasticity....................114

Figure 4.13: Robustness Check – Interaction of Volume and Valence at Mean Price by Variance 118
Figure 4.14: Robustness Check – Three-way Interaction on Price Elasticity 118
Figure 4.15: Price Reduction to Compensate for the Sales Impact of a Decrease in Valence 120
Figure 4.16: Price Reduction to Compensate for the Revenue Impact of a Decrease in Valence 121
Figure 4.17: Price Increase to Compensate for the Profit Impact of a Decrease in Valence . 121
Figure 4.18: Impact of Price Changes on Corporate Objectives 122
Figure 6.1: Heterogeneity Across Margins for Each Country-Category Combination 139
Figure 6.2: Walmart Advertised Reference Prices 141
Figure 6.3: Amazon.com Advertised Reference Prices 142
Figure 6.4: Walmart List Price for Samsung UN50NU7100FXZA in January, 2019 143
Figure 6.5: Amazon.com List Price for Samsung UN50NU7100FXZA in January, 2019 ... 143
Figure 6.6: Samsung.com List Price for Samsung UN50NU7100FXZA in January, 2019 .. 144
Figure 6.7: Historic Prices of Samsung UN50NU7100FXZA on Amazon.com 145
Figure 6.8: Samsung.com List Price for Samsung UN50NU7100FXZA in February, 2019 145
Figure 6.9: Walmart List Price for Samsung UN50NU7100FXZA in February, 2019 146
Figure 6.10: Model a1 147
Figure 6.11: Model b1 148
Figure 6.12: Model c1 149
Figure 6.13: Model a2 150
Figure 6.14: Model b2 151
Figure 6.15: Model c2 152

List of Tables

Table 2.1: Literature Overview on Price Promotions' Profit Impact 19
Table 2.2: Overview of Existing Empirical Findings on Correlates of Revenue and Profit ... 22
Table 2.3: Descriptive Statistics 25
Table 2.4: Posterior Means of Coefficients 27
Table 2.5: Average Unit Sales, Net Revenue, and Profit Impact of 1 Percent Promotional Price Reduction across 160 Brands 30
Table 2.6: Sales, Revenue, and Profit Impact by Brand 32
Table 2.7: Average Profit Impact of 1 Percent Promotional Price Reduction with Brand-Specific Versus Constant Margin 33
Table 2.8: Robustness Check – Posterior Means of Coefficients 35
Table 2.9: Operationalization of Correlates 39
Table 2.10: Posterior Means of Correlates of Promotion Impact 40
Table 2.11: Comparison of Estimation Results with Previous Research 42
Table 3.1: Results Online Experiment 63
Table 3.2: Descriptive Statistics – Field Experiment 64
Table 3.3: Results Difference-in-Difference Estimation 66
Table 3.4: Results Difference-in-Difference with Pre- and Post-Phase Estimation 68
Table 3.5: Results Difference-in-Difference with Week-Specific Intercept Estimation 69
Table 3.6: Descriptive Statistics – Transaction Data 72
Table 3.7: Fixed-Effects Model on Article Level 76
Table 3.8: Results Algorithm by Simonsohn (2018a) 77
Table 3.9: Results Algorithm by Simonsohn (2018a) with Linear Weekly Trend and Subcategory Dummies 78
Table 3.10: Example Estimates for R2R-ratio Split Value of 2 79
Table 3.11: Linear Model Without Fixed Effects 80
Table 3.12: Fixed Effects on Product Landing Page Level 81
Table 3.13: Fixed Effects on Article Level Including Promotion 81
Table 4.1: Overview of Existing Empirical Findings on Product Reviews Including Interactions 92
Table 4.2: Descriptive Statistics – Product Reviews 102
Table 4.3: Results of Fixed-Effects Model 106
Table 4.4: Detailed Impact of Variance on Sales for Valence of Two Stars 110

Table 4.5: Overview of Hypotheses..115
Table 4.6: Robustness Check – Results of Fixed-Effects Model with Lagged Valence, Volume, and Variance 117
Table 5.1: Scope of Individual Chapters..131
Table 6.1: Correlation Table: Demand Model...140
Table 6.2: Correlation Table: Correlates 140
Table 6.3: Scenarios for Visualization of Results..155

1 Introduction

1.1 Research Objectives and Methodology

Marketing research in numerous studies has analyzed a wide variety of instruments designed to steer demand for products. For this substantial amount of research, meta-analyses provide a systematic overview of each field by summarizing the instruments' performance as an elasticity. Elasticities capture the change in the dependent variable, i.e., sales, induced by a change in the marketing instrument by 1 percent. The latest meta-analysis on the relation of price and sales by Bijmolt et al. (2005) reports a price elasticity of -2.62 percent, i.e., reducing the price of a product by 1 percent increases sales by 2.62 percent. Numerous academic studies have assessed the effects of different marketing measures on sales, but we are not aware of any study that has identified a measure of importance higher than price changes. The latest meta-analyses in each field report, e.g., short-term advertising elasticity of 0.12 and long-term advertising elasticity of 0.24 (Sethuraman et al. 2011), shelf-space elasticity of 0.17 (Eisend 2014), and personal selling elasticity of 0.34 (Albers et al. 2010). Thus, these meta-analyses have established the relevance of pricing as a major tool for companies to influence sales. This strong effect of price changes on sales, combined with the fact that managers can adjust prices more quickly than other elements of the marketing mix, such as advertising or product attributes (Shugan 2014), make price the most powerful instrument for companies to stimulate demand.

In practice, pricing decisions differ in complexity along the value chain, in particular, when we compare manufacturers and retailers. Consider the example of a price reduction. For a manufacturer, the price decision about a specific product or brand is typically the result of straightforward calculations: introducing a price reduction increases sales that stem from increased consumption and brand switchers. To make the price reduction economically attractive for the manufacturer, the sales increase must overcompensate for the loss in margin introduced by the price reduction (Srinivasan et al. 2004). Retailers, by contrast, typically find themselves in a more complex situation. The reason for this is that retailers usually offer products from multiple manufacturers, and a price reduction of a single product or brand might cannibalize sales of the remaining alternatives (Srinivasan et al. 2004), which the retailer sells at different prices and profit margins. Interestingly, previous studies have mainly focused on marketing measures for manufacturers, accumulating a substantial amount of research, while guidance for retailers is still sparse (Ailawadi and Gupta 2014). Consequently, the aim of this dissertation is to shed light on the effects of pricing measures for retailers by contributing to relevant research gaps on the impact of price on retailers' corporate objectives. We focus on sales, revenue, and profit as corporate objectives. While some prominent retailers, e.g., Zalando, the largest fashion retailer in Europe, focus on other financial indicators, such as sales or revenue (Schröder 2017), standard economic theory assumes that companies are guided by profit maximization. However, price research for retailers has so far mainly focused on the sales impact of pricing decisions, while the net profit impact of a price change for the retailer is largely unknown (Ailawadi and Gupta 2014). Therefore, this dissertation includes assessments of the profit impact of pricing decisions by retailers.

In recent years, the fundamental premises of retailing have changed, as online shopping has heavily disrupted the retail market. This new environment has the potential to substantially impact the performance of pricing. The most substantial disruption concerns the informational environment: with the emergence of online retailing, transparency across stores and retailers increases to the point that customers have better access to information when making purchase decisions (Granados et al. 2012). This information is of central relevance for pricing, as the retail environment is typically characterized by an information asymmetry that is advantageous to the retailer, since retailers are better informed about their products. Thus, when making purchase decisions, customers perceive risk (Cox and Rich 1964; Murray 1991). More broadly, customers perceive risk in any purchase decision since they cannot foresee if the anticipated value of the acquired product will materialize, since a product might not be able to satisfy the specific customer’s consumption goal. In online settings, this perceived risk of purchases is even higher than for traditional shopping experiences (Lee and Tan 2003). A key reason for this is related to the product itself, that is, “concerns about the quality and suitability of the product” (Forsythe et al. 2006, p. 61). In contrast to traditional shopping, customers may not experience haptic and optic product features first hand, and they are unable to consult in-store sales representatives. In this context for both parties, retailers and customers, risk reduction is advantageous to facilitate purchases (Connelly et al. 2011). In order to reduce the perceived risk, on the one hand, retailers (and manufacturers) provide information about their products (Kirmani and Rao 2000), while, on the other hand, customers actively search for information. The Internet facilitates access to such risk-reducing information for customers, e.g., via price comparison websites, product reviews, or simply by not having to travel to different stores to compare prices. Because of this combination of increased information, easier access, and lower search costs in e-commerce than in traditional settings, the early literature on online pricing anticipated that the online market had the potential for becoming a perfect market (Bakos 1997). In theory, increased transparency and complete availability of price information should result in higher price elasticities, which in turn lead to lower price levels, with prices converging to marginal costs (Ghose and Yao 2011).

At the same time, online shops profit from the cost-efficiency of digital shelf space compared to their offline counterparts, often leading to a much broader assortment online (Grewal et al. 2010). With an increasing number of brands in one category, the similarity of products grows, resulting in customers having to face the agony of choice. Other marketing-mix variables than price, such as advertising messages, are of little help for overwhelmed customers and rarely allow substantial differentiation between brands (van Heerde 1999). Therefore, price is an instrument to differentiate between products. On top of that, the online setting even exacerbates the ease of price adjustments, as no adjustment of physical price tags is required; i.e., menu costs are smaller.

Thus, theory suggests that strong competition and high price transparency characterize e-commerce, which would decrease prices and increase price elasticities.

Extant empirical results do not report evidence of a perfect market online. More interestingly, they do not even offer full support for the theoretical reasoning outlined above, i.e., that the online market is closer to a perfect market than the offline market. As noted above, a shift toward perfect competition would materialize in lower prices, lower price dispersion, and stronger price elasticities. First, following Granados et al. (2012), empirical evidence on whether the actual selling prices are lower online than offline is still mixed. Research by Brynjolfsson and Smith (2000) analyzing books and CDs, by Brown and Goolsbee (2002) for life-insurance products, by Brynjolfsson et al. (2003), again focusing on books, and by Zettelmeyer et al. (2006) for automobile retailing, provide evidence of lower prices online. On the contrary, a recent large-scale study by Cavallo (2017) finds online and offline price levels to be identical 72 percent of the time based on a data set from multichannel retailers. Other, predominantly older, studies find higher prices online: Bailey (1998) reports an online premium for books, software, and CDs, while Lal and Sarvary (1999) offer an analytical model that describes the conditions under which higher prices emerge. Second, while in a perfect market, only one price would exist, i.e., price dispersion would be low, research reports price dispersion to be significant (see Bolton et al. (2006) for an overview of findings). Additionally, the limited research on information search shows that even with low online search costs, customers invest limited time, resulting in low search efforts (Johnson et al. 2004).[1] Finally, empirical evidence on price elasticities in online environments is mixed. On the one hand, Chevalier and Goolsbee (2003) for books, Ellison and Ellison (2009) for memory modules, Ghose and Yao (2011) for transactions of the Federal Supply, and Granados et al. (2012) for airline ticket sales, report strong elasticities online. On the other hand, several authors report less price sensitivity online. Degeratu et al. (2000) find promotion-induced price sensitivity to be lower online than offline. Andrews and Currim (2004) corroborate lower price sensitivity online for groceries. From a household perspective, Chu et al. (2008) and Chu et al. (2010) show that consumers are less price-sensitive online.

Hence, against the background of this stream of previous research, the current state of academic knowledge provides no clear guidance for retailers regarding pricing decisions online. While theoretically the online marketplace should show stronger competition, higher price sensitivities, and lower prices, empirical research provides mixed results. As a consequence, online retailers often operate with existing offline-proven measures in order to influence online sales, while being unsure about the effects. Since retailers "are often operating on razor-thin margins" (Bolton et al. 2006, p. 255), it is worthwhile not only shedding light on the effects of pricing measures on sales and revenue but also assessing their impact on profit in online retailing.

We analyze pricing in online retailing under the overarching theme of a new informational environment. First, the central relation of price and sales, revenue, and profit is in focus. We assess the impact of price changes, in the form of temporary price reductions, against the new informational background of the online environment. Afterwards, we take on two different perspectives to this central relation: on the one hand, we focus on the moderation of this relation by information provided by the retailer, in the form of an offline-proven instrument, namely, advertised reference prices. On the other hand, we analyze the moderation of this relation by online product reviews, which provide information beyond such retailer-provided information and which are a new phenomenon introduced by the Internet.

In practice, for retailers, price reductions commonly materialize in the form of temporary price reductions, i.e., price promotions, and these price reductions will be the focus of this research. Many studies have analyzed the effect of price changes and price promotions on brand sales

[1] Johnson et al. (2004, p. 299) find that "[o]n average, households visit only 1.2 book sites, 1.3 CD sites, and 1.8 travel sites during a typical active month in each category."

for manufacturers. Much less, however, is known about the impact of price changes and price promotions on retailer's sales, revenues, and profits, while, to the best of our knowledge, no study to date has addressed the profit implications of online promotions for online retailers, although facilitated information access online might influence the performance of these price reductions. By considering the profit impact of price reductions for online retailers this dissertation follows a recent research priority by The Marketing Science Institute[2] (2018) that calls for a channel-specific assessment of the performance of online price reductions. We address this research gap through three steps: first, we estimate a demand model including heterogenous brand-specific elasticities. In a second step, we utilize these brand-specifically estimated elasticities to derive the net quantity impact of a price reduction and multiply the quantity impact by brand-specific and week-specific prices and profit margins to obtain the revenue and profit impact of a price reduction. In the last step, we relate the change in the retailer's sales, revenue, and profit to characteristics of the brand on promotion with a focus on profit. Thus, our analysis, which is joint work with Dominik Papies, addresses the following research questions:

(1.1) What are the brand-specific effects of price promotions on online retailers' sales, revenue, and profit?

(1.2) Which brand- and promotion-specific factors affect the sales, revenue, and profit impact of price promotions?

After the assessment of this central relation of pricing in online retailing, we focus on the moderation of this relation by information provided by the retailer. When customers can quickly search for information themselves, the informational value of price cues provided by the retailer on the specific website might diminish. We focus on advertised reference prices to analyze whether information provided by the retailer is still capable of influencing customers' purchase decisions online. Advertised reference prices are prices that retailers display in combination with a lower actual selling price to make the offer appear more attractive by influencing the reference point against which customers evaluate it (Compeau and Grewal 1998; Mazumdar et al. 2005). Offline, existing research found advertised reference prices to

[2] The Marketing Science Institute (MSI) is a non-profit organization with a strong network of leading marketing academics and practitioners and aims to align marketing science and practice. In a biennial process, the MSI gathers information from its network to set priorities that are supposed to advance marketing research. According to these priorities, the MSI finances academic research that attempts to positively impact marketing practice (Marketing Science Institute 2019).

be a powerful measure to increase purchase intentions (Mazumdar et al. 2005). Online, advertised reference prices are characterized by strong prevalence, continuous display, and rising public media coverage due to their potentially deceptive usage (Streitfeld 2016a, 2016b; Bartz 2017; Wisoff 2017). Based on a literature review, we identify four aspects, which we address with our analyses to advance existing knowledge on advertised reference prices.

First, while advertised reference prices are generally supposed to impact purchases positively, if they appear with high frequency, or if they are constantly displayed, their impact might diminish (Compeau and Grewal 1998; Ailawadi et al. 2006). We aim to address this contradiction by analyzing the effects of advertised reference prices in an online shop which continuously displays advertised reference prices. Additionally, to clearly differentiate between the effects of advertised reference prices and temporary price reductions we concentrate on manufacturer-suggested retail prices, since displaying a manufacturer-suggested retail price is not temporarily restricted.

Second, while the majority of the existing literature focuses on offline settings, the theory suggests that online the premises for advertised reference prices have changed as a result of facilitated information access. The facilitated information access of the online environment might influence the performance of advertised reference prices since customers can check competitive prices online with just one click. Hence, the information conveyed by advertised reference prices might be substituted. As existing research on advertised reference prices online is scarce and the findings are mixed (Jensen et al. 2003; Lii and Lee 2005), we aim to add to the knowledge on advertised reference prices in online settings by analyzing advertised reference prices in an online shop.

Since both, the first and the second aspect outlined above, might induce a diminishing impact of advertised reference prices on sales, they lead to the following research question:

(2.1) Do manufacturer-suggested retail prices have an impact on sales-related variables online?

The third aspect focuses on the credibility of advertised reference prices online. Offline research finds that even implausible and inflated advertised reference prices impact purchase decisions positively (Urbany et al. 1988; Biswas and Blair 1991; Compeau and Grewal 1998). Online, improved information access, in combination with increasing awareness of potentially deceptive prices, could affect the impact of the credibility of advertised reference prices on sales. Hence, we assess this relation by asking the following exploratory research question:

(2.2) *How does the credibility of a manufacturer-suggested retail price impact sales online?*

Fourth, if with lower credibility the effect of the advertised reference price on sales decreases, since it is not perceived as a credible signal, the actual selling price might gain importance (or vice versa). To the best of our knowledge, existing research has not yet assessed the moderation of price elasticities by the credibility of advertised reference prices, although this might mirror the main impact of credibility on sales explored in research question *2.2*. Thus, in order to gain insights into the interplay of the actual selling price and the credibility of the advertised reference price, we explore the moderation of the actual selling price by the credibility of the advertised reference price.

(2.3) *Does the credibility of a manufacturer-suggested retail price moderate the impact of the actual selling price on sales online?*

Following the research priority published by the Marketing Science Institute (2018, p. 4) to assess "how customers' increasing reliance on price can be attenuated in order to improve margins," we show the revenue and profit impact for different degrees of credibility of advertised reference prices.

Finally, we change the perspective and analyze whether information that is not fully under the control of the retailer, namely, online product reviews, can change the impact of price on sales. Customers use online product reviews heavily to reduce their perceived risk. According to a recent survey, 93 percent of respondents[3] consider reviews to have an impact on their purchase decisions (Podium 2017). This might substantially impact the role of price. For example, for products with many and positive reviews, the perceived risk of the investment could decrease, to the point that price is a less relevant factor for this product and thereby decreasing the impact of price changes on sales. Therefore, we assess whether this information changes the impact of price on sales and, hence, whether retailers should include such information in their pricing strategies.

Product reviews convey information via three dimensions (Chintagunta et al. 2010). First, they convey it via the average rating referred to as *valence*, which displays the level of satisfaction other customers derive from the product (Chevalier and Mayzlin 2006; Duan et al. 2008; Kostyra et al. 2016). Second, they provide information via volume, which is the number of

[3] A total of 2,005 respondents took part in the survey in 2017 (Podium 2017).

reviews other customers have provided for the specific product (Chevalier and Mayzlin 2006; Duan et al. 2008; Kostyra et al. 2016). Third, variance conveys information on the spread in average reviews (Godes and Mayzlin 2004; Sun 2012). These review dimensions are signals of the products' quality and therefore have the potential to change the perception of risk involved in the purchase for the customer (Erdem et al. 2002; Kostyra et al. 2016), which in turn might moderate the impact of price on sales.

A considerable amount of research has already analyzed online product reviews; however, the findings are still mixed, and the role of prices has mostly been neglected. To address these issues, we propose to comprehensively integrate existing research on product reviews and pricing research. To the best of our knowledge, we are the first to interact all three review dimensions with price and ask the following research questions:

(3.1) Do valence, volume, and variance moderate the impact of price on sales?

(3.2) Do valence, volume, and variance – individually and comprehensively – have an impact on sales?

Again this dissertation follows the research priority by the Marketing Science Institute (2018) by assessing profit impact and identifying pricing strategies for a retailer to counteract the impact of a change in valence, not only on sales and revenue but also on profit.

To address our research questions, we collect data from a large European online retailer with more than five million active customers and more than one billion euros in revenue in 2017. The retailer offers a large variety of products including, for example, groceries, electronics, and accessories across multiple countries in Europe. The full data set comprises five years and seven countries with different informational attributes. The data provides both a product perspective and a customer perspective. Based on the most recent meta-analysis on price elasticities, we focus on demand models. Following Bijmolt et al. (2005, p. 151), "price elasticities are largely independent of whether consumer heterogeneity is modeled" while they differ across product categories. In addition to the above-described transaction data, we include data from a laboratory online experiment. Finally, we follow Gneezy (2017) in her call for field experiments and conduct a field experiment with the same online retailer.

Based on the seven research questions described above, this dissertation attempts to contribute to current research gaps in online retail pricing and to add to the understanding and implications of pricing decisions for practitioners by assessing whether and how to account for the online environment in pricing decisions. The following section provides an outline of the dissertation.

1.2 Structure of the Dissertation

This dissertation sets out to answer the research questions described above structured along four chapters. We depict the connection between these chapters in Figure 1.1.

Subsequent to this introduction, Chapter 2, which is joint work with Dominik Papies, focuses on research questions *1.1* and *1.2* by analyzing the impact of price reductions on sales, revenue, and foremost profit. The chapter follows three steps. Initially, we estimate a demand model using a Bayesian multi-level approach. The resulting parameters then serve as a basis to generate the unit impact of a price reduction, i.e., the monetary impact of a price reduction in euros. Finally, we offer correlates to explain the differences in monetary impact. The results are discussed considering both existing offline research and managerial implications.

Chapter 3 follows an exploratory approach to answer research questions *2.1*, *2.2*, and *2.3* and sheds light on advertised reference prices as a marketing measure for online retailers. We approach the research questions with a unique combination of three empirical studies based on an online experiment, a field experiment, and a large transaction data set. We analyze data with Bayesian and frequentist models and add a sales and profit impact calculation to assess the profitability of changes in the advertised reference price. We summarize the exploratory findings from all three studies, juxtaposing and discussing their impact for researchers and practitioners.

Chapter 4 asks whether online product reviews moderate the impact of prices on sales by merging research on product reviews and pricing. We test seven hypotheses to answer research questions *3.1* and *3.2* on the moderating effect of product review dimensions on price, as well as on the main effects of these dimensions on sales. The study further provides scenarios, in which we assess whether retailers can counteract the sales impact of changes in product reviews with a pricing strategy. After empirical testing of the seven hypotheses we discuss our findings and consider the implications for research and practice.

Chapter 5 concludes this dissertation, with a discussion of the overarching findings, as well as limitations and suggestions for future research.

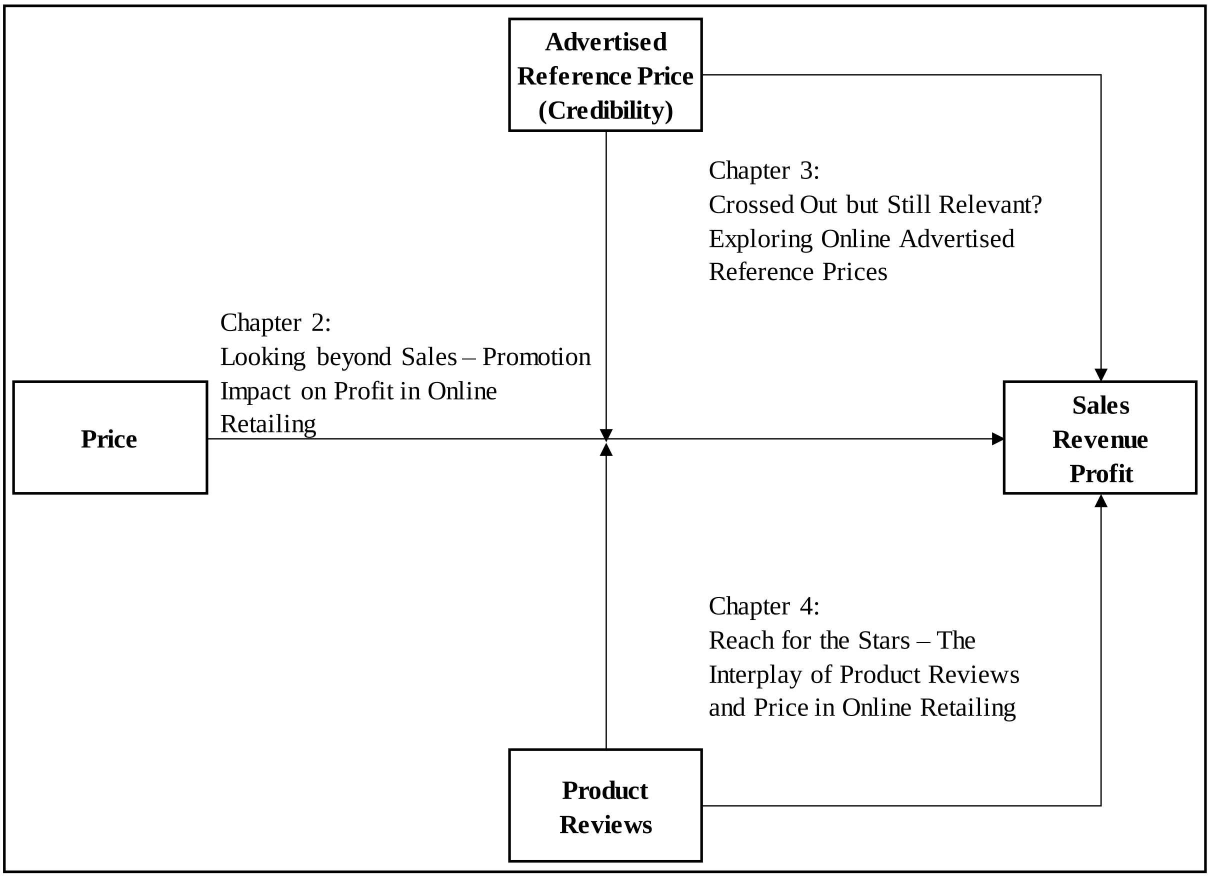


Figure 1.1: Structure of the Dissertation

2 Looking beyond Sales – Promotion Impact on Profit in Online Retailing

Joint work with Dominik Papies. Dominik Papies contributed to the analyses, gave feedback, and revised the draft of the working paper.

2.1 Introduction

More and more retail dollars are spent online and the sales volume in e-commerce is steadily increasing (Miller and Washington 2017). While some popular examples such as Amazon suggest that this also leads to a similar surge in profits, many online retailers in fact generate poor or even negative profits. One prominent example is the German online retailer Zalando, which is struggling to grow its profits despite strong growth in sales and revenue (McGee 2017; Buck 2018). In such an environment, the pricing decisions of retailers are likely to be of critical importance for at least two reasons. First, pricing decisions directly affect the margin at which products are sold. Second, it is well established that price changes have a strong and immediate effect on brand *sales* (e.g., Bijmolt et al. 2005), and the strong impact of price promotions on sales has been studied in great detail (e.g., van Heerde et al. 2003). One key finding from this research is that price and promotion elasticities with respect to *sales* are much larger than, e.g., advertising elasticities. Much less, however, is known about the impact of price changes and price promotions on *profits*. This observation in particular holds true for retailers, where the effects of price promotions are largely unclear (Ailawadi and Gupta 2014). This dearth of research and knowledge concerning retailing and profit is surprising because strategic pricing decisions are more complicated for retailers than for manufacturers. The reason for this is that retailers usually carry a large number of products that compete against one another (Levy et al. 2004; Grewal et al. 2010), which implies that a price promotion on one product may lead to a sales increase at the retailer for this product that comes entirely from other brands in the same store, leading to a net effect of zero. What’s more, for most firms, profit, and not sales, is the ultimate long-term goal that ensures survival. In support of these considerations, Ailawadi et al. (2009, p. 50) state that the “few recent studies that have considered the profit impact of promotions show that it can be quite different from sales impact, so more research is needed in this area.”

This dearth of research is due to the fact that, so far, only a few studies have analyzed the impact of price promotions on retailer profits, and we see two important voids in this literature stream. First, to the best of our knowledge, no research on the profit impact of promotions uses recent data or considers the online context, which is at odds with the fact that consumers are spending more and more retail dollars online. Second, the few studies that analyze the profit impact of price promotions either make the assumption that all brands in a category – be they large or small, high- or low-priced – have equal contribution margins for the retailer (Ailawadi et al. 2006), or they assume that different brands do not differ in manufacturer allowances

(Srinivasan et al. 2004). We argue that it is important to use brand-specific contribution margins for profit calculations. Let us consider the case of a promotion on a high-margin brand. If this promotion draws sales primarily from competing low-margin brands, the profit impact for the retailer is more beneficial compared to a situation in which it draws sales from high-margin competing brands. As Figure 2.1 shows, the data we use in this study exhibits substantial heterogeneity in retailer margins across brands, which highlights the relevance of accounting for this heterogeneity. Hence, the profit impact of a price promotion might differ substantially from its sales impact. We therefore contribute to the literature by addressing these voids and by shedding light on the question of the impact of price promotions on (online) retailer's profit and how this assessment depends on the consideration of brand-specific contribution margins and allowances. More specifically, we will address the following research questions:

(1.1) What are the brand-specific effects of price promotions on online retailers' sales, revenue, and profit?

(1.2) Which brand- and promotion-specific factors affect the sales, revenue, and profit impact of price promotions?

To answer these questions, we obtain a unique data set with weekly brand-level sales of the top ten brands in four categories across four countries during a five-year period until September 2017 from a large European online retailer with more than five million active customers and more than one billion euros in revenue in 2017. Relying on a Bayesian multi-level model, we analyze within-category own and cross effects of promotions, accounting for brand-specific contribution margins and brand-specific manufacturer allowances. The results suggest that price promotions are, on average, unprofitable for the retailer that we analyze, and this unprofitability arises primarily as a result of the reduction in margins, and to a lesser degree because of brand-switching.

In the next section, we outline our contribution to the literature. In Chapter 2.3, we describe the framework, before describing the data and the empirical analysis in Chapter 2.4. We provide a discussion in Chapter 2.5.

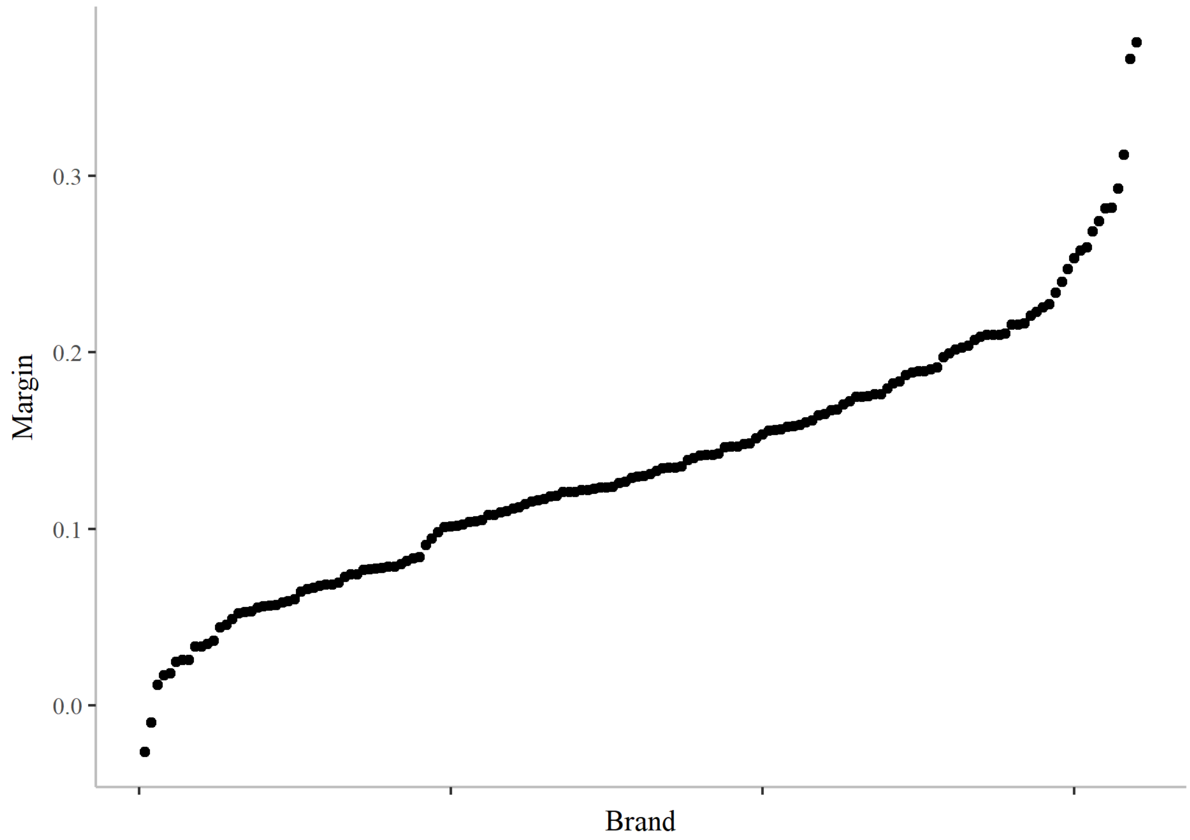


Figure 2.1: Average Brand-specific Profit Margin

2.2 Related Literature and Contribution

2.2.1 Online Pricing Decisions

For bricks-and-mortar settings it is well established that a price reduction leads to a substantial sales increase of the price-reduced, focal brand. The most recent meta-analysis in this field reports an average own-price elasticity of -2.62[4] (Bijmolt et al. 2005). This strong effect, combined with the fact that managers can adjust prices more quickly than other elements of the marketing mix, such as advertising or product attributes (Shugan 2014), make prices and price promotions a go-to marketing instrument to stimulate demand.

It is probable that the online channel emphasizes these characteristics of price as a marketing instrument because, e.g., menu costs are smaller (e.g., no adjustment of price tags). In addition to the ease of price adjustments, online shops profit from the cost-efficiency of digital shelf space compared to offline shelf space, leading to a broader and deeper assortment being available online (Grewal et al. 2010). On top of that, online retailers typically operate without

[4] For groceries with a high stockpiling propensity, elasticities are closer to zero (Bijmolt et al. 2005).

regional restrictions and draw their customers from the entire market because travel costs are eliminated, which is likely to increase competition in the online domain. Combined with the fact that online shoppers face much lower search costs than shoppers in bricks-and-mortar setting, the early literature on online pricing saw the potential in the Internet for a perfect market (Bakos 1997). In theory, increased transparency and complete availability of price information should result in higher price elasticities, which in turn leads to lower price levels, and prices in such a perfect market should converge to marginal costs (Ghose and Yao 2011).

Thus, theory suggests that the online market place is characterized by higher competition and higher price transparency, which would drive prices down and price sensitivity up. If this is the case, it is likely that online retailers operate at lower margins, which in turn makes it more likely that price promotions in the online domain will be unprofitable.

So far, empirical evidence on the question of whether the *price level*[5] online is different from that offline is mixed. Brown and Goolsbee (2002) find lower prices in the life-insurance industry resulting from online price comparisons that reduce search costs. The authors base their findings on an extensive data set covering 1992 to 1997. In contrast, Cavallo (2017) finds online and offline price levels to be identical 72 percent of the time based on a large-scale data set of multi-channel retailers covering December 2014 to March 2016. Regarding search costs, based on individual-level panel data, Johnson et al. (2004) show that the search effort is rather limited, with customers visiting only 1.2 to 1.8 sites during a one-month period.

Empirical evidence on *price elasticities* in online environments is also mixed. Chevalier and Goolsbee (2003), Ellison and Ellison (2009), Ghose and Yao (2011), and Granados et al. (2012) report strong elasticities online. Chevalier and Goolsbee (2003) find online price elasticities ranging from -3.5 to -0.45 for books. Ellison and Ellison (2009) estimate price elasticities for memory modules, for which price search engines are influential in the sales process. They find that some products are extremely price-sensitive with price elasticities of up to -33.1. Ghose and Yao (2011) estimate online and offline price elasticities for transactions of the Federal Supply Services in the U.S. in 2000. The online elasticity of -1.47 is stronger than the offline market's elasticity of -0.84. Granados et al. (2012) compare the price elasticities of online and offline airline ticket sales based on data from September 2003 until August 2004. Online demand is more elastic than offline demand. However, they find online price elasticities to

[5] Empirical evidence on the price level is mixed, while empirical evidence on price expectations online points in the direction of lower expectations than offline.

depend on the channel and customer group ranging between -0.89 and -2.28, while offline elasticities are in the range of -0.34 and -1.33. More price-sensitive customers self-select in the online channels, accounting for 22 percent of the elasticity difference between online and offline. In contrast, several authors report less price sensitivity online. Based on grocery data from 1995 to 1997, Degeratu et al. (2000) find promotion-induced price sensitivity to be lower online than offline. Andrews and Currim (2004) support this notion that online consumers are less price sensitive than offline consumers of groceries using panel data from 1995 to 1997. From a household perspective, Chu et al. (2008) show that the same household has lower price sensitivity when shopping online for groceries than offline. Chu et al. (2010) underline the findings that consumers are less price sensitive online. The authors base their analyses in both studies on data from the early 2000s.

Against the background of this stream of previous research, we conclude that the online marketplace should in theory show stronger competition, higher price sensitivities, and lower prices. Empirical evidence in support of this theory, however, is not unambiguous. These characteristics of the online marketplace suggest that it is important to consider how the profitability of price promotions fares in the online market place.

2.2.2 Profit Impact of Price Reductions

Within the wide field of studies considering the impact of price reductions, we focus on those studies that analyze profit (see Table 2.1). All five studies are based on offline data from the U.S. The most recent data set used in these studies is 16 years old (Ailawadi et al. 2006), while the others are based on data from the 1980s and 1990s. Two out of five studies (Srinivasan et al. 2004; Dawes 2012) rely on the data set of Dominick's Finer Foods, which is a former U.S. grocery chain based in the Chicago area. The profit calculations based on this data set, as well as the data set used by Mulhern and Leone (1991), include brand-specific wholesale prices but no manufacturer funding. Ailawadi et al. (2006) and Walters and MacKenzie (1988) do not include brand-specific margins for cross effects but assume an average margin for the competing brands. Most studies focus on a small subset of brands, e.g., assessing the profit impact of private-label brands (Dawes 2012).

Walters and MacKenzie (1988) start this stream of research by applying a structural equation model to analyze the store profitability of two grocery supermarkets using weekly data, including specific margin information from the years 1983 to 1985. They focus on the impact of three different promotional schemes (loss leader, in-store price specials, and double couponing) on profit, sales, and traffic. The results indicate that, depending on the promotional scheme, profit is affected in diverse ways. For loss leaders, profit is impacted through traffic rather than sales, and for couponing the opposite is true, while in-store price specials have no impact. As a result, they highlight the importance of building store traffic. Brand-specific analyses are not part of their study, as they take on a category perspective.

Mulhern and Leone (1991) focus on the impact of cross-category relations on profit with a demand model in log sales. Two complementary categories with four brands each from a grocery chain are analyzed. For each category, a system of seemingly unrelated regressions on brand level is estimated. The analysis reveals both substitution effects within category, as well as complementary effects across categories. The authors use cost data on wholesale prices without promotional allowances. Importantly, they do not consider a second-stage regression to obtain factors that drive profitability.

Srinivasan et al. (2004) take a more holistic view by quantifying and explaining the impact of price promotions on both manufacturer and retailer revenue, as well as retailer traffic and profits, using a vector autoregressive model. Their data source is the database of Dominick’s Finer Foods (DFF). The authors include weekly scanner data from 1989 to 1994 in 21 categories. The focus is on the three best-selling brands per category. In line with literature, a positive impact of promotions on retailer and manufacturer *sales* is found. Regarding revenue, promotions are more attractive to manufacturers than to retailers as a result of a strong post-promotion dip for retailers. The vector autoregressive models on retailer category *margin* reveal a negative impact for most brands. In a second stage, the authors explain those effects using brand and category characteristics. For retailer margins, market share, promotional frequency, and promotional depth, they identify a negative association with profit. The authors consider wholesale prices but no promotional allowances, which are now a major component in the promotional relationships between manufacturers and retailers. According to the authors, promotional support by manufacturers started in 1994; therefore, they restrict their data to the period ending in 1994.

Ailawadi et al. (2006) take on a decompositional approach on promotion level using scanner data from CVS, a major US drug retailer, from the year 2003. The promotional sales increase is decomposed into its components, i.e., consumption from other periods, other stores, and other brands, as well as a cross-category effect (halo effect). For the CVS data, the authors find that 45 percent of the gross lift comes from brand switching within the store, which is not considered as being incremental. For those brand-switching movements, the authors use an average category margin, i.e., not considering margin differences per brand. Another 10 percent comes from future periods, and the remaining 45 percent is considered to be incremental lift coming from other stores, new users, or increased consumption. Additionally, a positive cross-category impact is found. Most of the promotions are not profitable for the retailer. Furthermore, the decomposition restricts brand switching to substitution. Potential complementary or category expansion effects are found in the halo effect. The profit impact of the halo effect is calculated using the average store margin. For profit, cross-brand impact is substantial (Ailawadi et al. 2006). In a second-step regression Ailawadi et al. (2006) analyze a high number of correlates, for which they find opposing effects for sales versus profit. "Deep, featured promotions on high 'consumer-pull' brands generate high net unit impact, but they are also the ones for which the retailer's promotional margin is substantially lower than regular margin, resulting in lower net profit impact" (Ailawadi et al. 2006, p. 520). In line with Srinivasan et al. (2004), net profit impact, discount depth, and share have a negative effect on profit, although Ailawadi et al. (2006) include promotional funding by manufacturers.

Dawes (2012) focuses on promotional impact on a more granular level, with a demand model. The authors analyze cannibalization between different sizes of the same brand based on the same data and time period as Srinivasan et al. (2004). Regarding profit, the focus is on the private-label brands of the retailer alone. The authors report a negative impact of promotions on private-label profits.

Study	**Observation Period**	**Number of Brands**	**Online**	**Brand-specific Margin Incl. Allowances**	**Brand-specific Margin for Cross Effects**	**Data Origin**	**Profit Drivers**
Walters and MacKenzie (1988)	1983–5	Not specified	-	Yes	-	USA, Midwest	-
Mulhern and Leone (1991)	1986–8	8	-	-	-	Regional data	-
Srinivasan et al. (2004)	1989–94	63	-	-	Yes	USA, Midwest	Yes
Ailawadi et al. (2006)	2003	177 categories	-	Yes	-	USA	Yes
Dawes (2012)	1989–94	16	-	-	Yes	USA, Midwest	-
This study	2012–17	160	Yes	Yes	Yes	4 European countries	Yes

Table 2.1: Literature Overview on Price Promotions' Profit Impact

Given the substantial changes in retailing in recent decades (e.g., online retailing, the surge in private labels, the increasing relevance of manufacturer allowances), we add to the existing literature by including the growing importance of temporary price reductions and considering correlates of the monetary impact of such price promotions. On top of that, we seek to overcome existing limitations in the literature and base profit calculations on brand-specific margins for cross effects, including manufacturer allowances.

2.2.3 Correlates of Promotional Impact

A number of existing studies link price elasticities to market, brand, or category characteristics (see an overview in Fok et al. 2006, p. 445). However, only two studies discuss the correlates of revenue and profit: Ailawadi et al. (2006) analyze the correlates of net unit impact and Srinivasan et al. (2004) examine the correlates of elasticities. We select correlates based on these two existing studies, as well as data properties. As a result of its novel online setting, our analysis remains exploratory.

Brand Size

The size of a brand, i.e., the share of units sold of a given brand in the respective category, has been found to have an impact on both own and cross effects. Larger brands are commonly more heavily advertised, increasing the probability of customers switching from other brands and other stores (Krishna 1992). For own price elasticities, Bolton (1989) finds high-share brands to be more price-inelastic, based on store-level scanner data. Bemmaor and Mouchoux (1991) underpin this finding with experimental data, and Vilcassim and Jain (1991) with household panel data. For cross-price elasticities, asymmetric relations regarding brand share are documented. The asymmetry concerns the impact on each other, i.e., that price reductions on high-share brands reduce sales of smaller brands, while reductions on smaller brands affect sales of high-share brands to a lesser degree (see, for example, Sethuraman (1995, p. 284) in the context of national and private-label brands). Sethuraman and Srinivasan (2002) show that the relation reverses when considering absolute impact compared to the elasticity approach. However, in their study category expansion is excluded from consideration (Sethuraman and Srinivasan 2002). Regarding profit impact, Ailawadi et al. (2006) and Srinivasan et al. (2004) report that a higher market share of a brand leads to a lower impact on category profit. This finding is in line with the notion that large brands exert stronger market power, thereby offering less manufacturer funding for the retailer.

We add *line length* as a further attribute of brand size, which has not yet been studied in the context of correlates. The number of products sold under one brand name represents the line length. We positively associate line length with brand size, expecting analogous results.

Price Level

The effects of brands in different segments or tiers on one another have been generalized in a meta-analysis by Sethuraman et al. (1999). The asymmetric price effect describes that price reductions of higher-priced brands have a larger impact on the market share of lower-priced brands than vice versa. A stronger effect holding for both elasticities and units is the neighborhood effect, i.e., “brands that are closer to each other in price have larger cross-price effects than brands that are priced farther apart” (Sethuraman et al. 1999, p. 23). Regarding profit, only Ailawadi et al. (2006) include a brand’s relative price, reporting a positive impact, i.e., price reductions on high-priced brands drive category profit.

Private Label

One of the reasons for retailers to sell private-label products is to skip the manufacturers in the value chain and thereby generate higher profits. Ailawadi et al. (2006) report a strong positive impact of store brands on profits, while Srinivasan et al. (2004) find no significant effect.

Price Range

Raju (1992) shows that deeper discounts increase elasticity on category level, and Fok et al. (2006) report the same effect on brand and category level. For a retailer, a higher price reduction leads to a smaller profit margin given no increase in manufacturer financing. Srinivasan et al. (2004) find that promotional depth has a negative impact on the total promotional elasticity on both retailer revenue and margins, and this finding is corroborated by Ailawadi et al. (2006). The price range of a brand captures all price changes within the brand thereby it also illustrates the promotional depth.

Frequency of Promotions

The theory and the empirical findings deliver contradictory results on the impact of the frequency of price reductions. On the one hand, a high frequency of promotions leads to price-conscious customers, who buy more items on sale (Mela et al. 1997). On the other hand, reference prices might be reduced over time, leading to less effective discounts (Kalyanaram and Winer 1995). For sales, Fok et al. (2006) find a significant impact on brand level, meaning that high frequency causes smaller elasticities, and no effect on category level. Nijs et al. (2001) report a contrary effect on category level. These mixed findings are reflected in profit research. Ailawadi et al. (2006) find a positive impact, while Srinivasan et al. (2004) report a negative impact.

Intensity of Promotions

With respect to promotions, we additionally include the intensity of promotions of a brand, i.e., the share of items of a brand that is on promotion compared to the promotion share within the associated category. Ailawadi et al. (2006) report that promotions on a greater share of items in a category increase the net sales impact, while they decrease the net profit impact. Srinivasan et al. (2004) do not include this correlate. Table 2.2 summarizes the empirical findings on the correlates of revenue and profit.

	Ailawadi et al. (2006)		**Srinivasan et al. (2004)**		**Consistent Profit Impact Across Studies**
	Sales	Profit	Revenue	Profit	
Brand Size	+	-	+ (n.s.)	-	Yes
Price Level	-	+	Not incl.	Not incl.	Unclear
Private Label	-	+	- (n.s.)	+	Yes
Price Range	+	-	-	-	Yes
Promotion Frequency	-	+	+	-	No
Promotion Intensity	+	-	Not incl.	Not incl.	Unclear

Table 2.2: Overview of Existing Empirical Findings on Correlates of Revenue and Profit

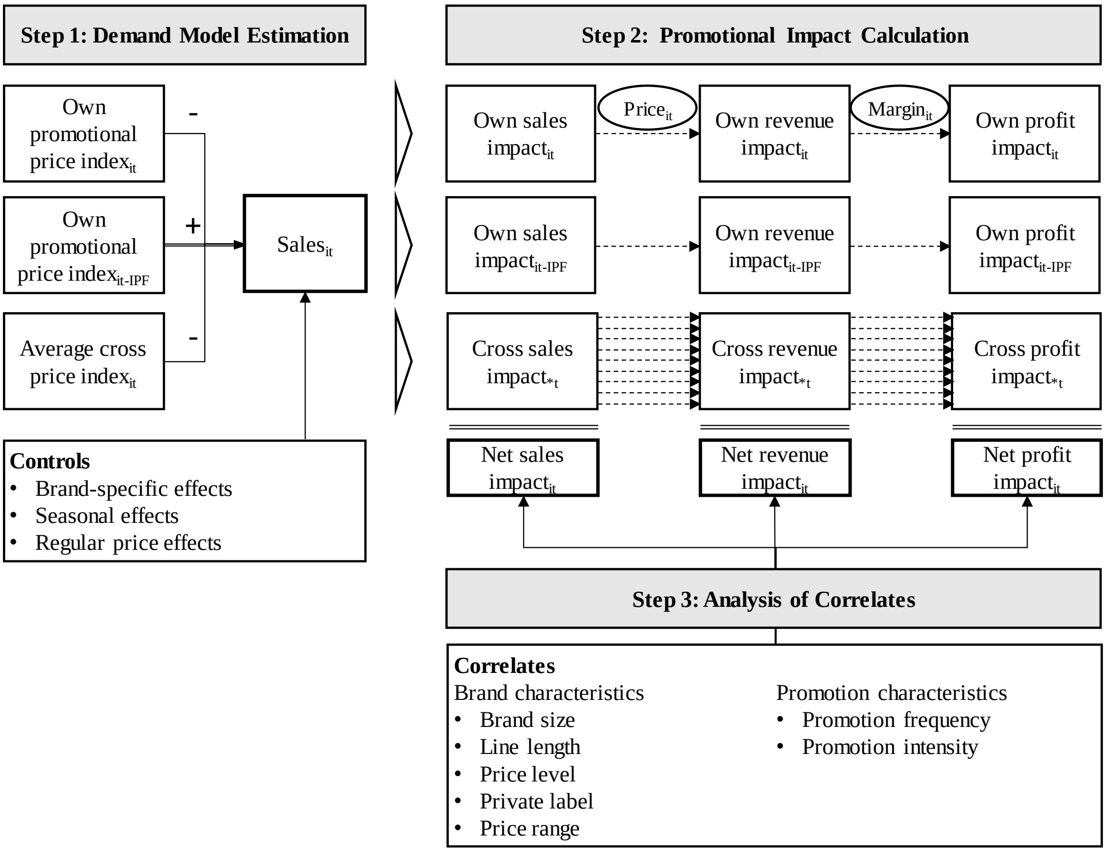
We add to the limited and mixed knowledge on the correlates of promotional performance, as we rely on existing studies concerning variable selection and aim to deepen our understanding of correlates. Based on the correlates we offer guidelines for promotion setting. On top of that, to the best of our knowledge, we are the first to analyze the correlates of sales, revenue, and profit in an online context.

2.3 Framework

Our framework, which we show in Figure 2.2, consists of three main parts. In the first step, we estimate response elasticities. To this end, we estimate a demand model with a focus on the brands' own price effect, the cross-price effects, and potential carry-over effects that may arise as a result of, e.g., stockpiling. A core theme of the empirical approach is that we allow all brands in our data set to have heterogeneous own-price elasticities and heterogeneous cross-price elasticities, i.e., we allow all elasticities to vary across brands. The result of step 1 is a set of elasticities, which we then utilize in step 2.

In step 2 we utilize the previously estimated elasticities to calculate the net effect of a change in promotional price by 1 percent on unit sales for the *retailer*. This net effect includes the contemporaneous demand reaction for the focal brand, potential dynamic effects (e.g., stockpiling), and cross-effects from other brands. By multiplying the unit sales by prices that vary over time and brands, we obtain the revenue effect. By multiplying the revenue effect with the margin, which again varies over brands and time, we obtain the profit impact for the retailer if a brand is on promotion.

In the third and last step, we relate the change in the retailer's sales, revenue, and profit, respectively, to characteristics of the brand on promotion. Here, we cover potential factors that have been used in previous research on promotion profitability.



Note: The cross impact of brand i is the sum of the changes in sales, revenue, or profit of all other brands within the same category induced by a change in the actual price of brand i.[6]

Figure 2.2: Framework

[6] IPF = inter-purchase frequency. The subscript it-IPF indicates that the variable is lagged by the brand-specific inter-purchase frequency (IPF).

2.4 Empirical Study

2.4.1 Data Description

Our data set comprises weekly sales and price data from an online retailer without any physical stores, and the data set includes data from four European markets. The transactional data covers the five-year period from September 2012 until September 2017. We select the four categories that show the highest turnover rate at this online retailer. The products are groceries with high stockpiling propensity. In each category and each country, out of those brands selling at least one item in each week of the five-year period, we include the top ten brands in terms of sales. The top ten brands account, on average, for 88 percent of sales per category. In sum, we cover a total of 160 country–category–brand combinations.

For each brand, we aggregate the actual prices of items to the brand level using constant sales-based weights before taking the log (Srinivasan et al. 2004). We calculate the sales-based weight for a specific item of a brand by cumulating the sales of this specific item over the entire five-year period and dividing these cumulated sales by the total sales that the respective brand cumulates over the same period. We account for different package sizes using price per kg sold. As we are interested in brand-level elasticities to derive the brand-specific correlates of price promotion impact, the aggregation to brand level does not limit our results.

The original data set contains only the actual price. To differentiate between promotional and regular prices, we make use of a nominal variable included in the data set flagging the promotion status of an item. We determine a brand’s regular price based on the brand’s share of items flagged as being on promotion in each week, so that the regular price is the actual price of the surrounding five weeks with the minimal promotion share. To measure promotional price elasticities, we use a price index, i.e., the actual divided by the determined regular price. Using a price index allows for cross-category comparison while measuring the size of the promotion (Fok et al. 2006). To control for cross-price effects, we include the respective average cross-price indices across all competing brands. The products that the retailer sells are measured in weight (kg), and we aggregate across items per brand in a category. Hence, our dependent variable is the logarithm of the total weekly unit sales (in kg) of each brand in each category (see Table 2.3 for descriptive statistics). In Table 6.1 in the Appendix, we provide a correlation table that shows the bivariate correlations between all variables that we use in the first step of our analysis.

Country	Cate-gories	Brands	Actual Price in € per kg				Sales in kg				Promotion Share			
			Mean	sd	Min.	Max.	Mean	sd	Min.	Max.	Mean	sd	Min.	Max.
A	4	40	5.40	2.50	1.79	15.05	2,622	4,890	3	46,889	0.09	0.10	0.00	0.77
B	4	40	3.77	1.76	1.55	12.76	4,251	3,914	61	23,389	0.14	0.11	0.00	0.60
C	4	40	3.94	1.69	1.26	10.65	1,636	2,172	1	17,595	0.16	0.13	0.00	1.00
D	4	40	3.71	1.63	1.41	11.19	1,806	2,609	2	25,282	0.13	0.13	0.00	0.88
Total	16	160	4.20	2.05	1.26	15.05	2,579	3,709	1	46,889	0.13	0.12	0.00	1.00

Table 2.3: Descriptive Statistics

2.4.2 Model

We use a multi-level demand model in logs to analyze the own and cross effects of temporary promotional price changes on sales at brand level within one category and one country. This is the first step of our analysis. We include promotional, regular, and cross-price variables as explanatory variables, i.e., the current and lagged[7] promotional price index of brand *i*, the current regular price of brand *i* as well as the average of the price-indices of the competing nine brands in each category:

$$\log(\text{Quantity})_{it} = \alpha_{\text{Brand}_i} + \alpha_{\text{Quarter}_q} + \beta_{1i} * \log(\text{Promotional Price Index})_{it} \tag{2.1}$$

$$+ \beta_{2i} * \log(\text{Promotional Price Index})_{it\text{-IPF}} + \beta_{3j} * \log(\text{Cross Price Index})_{it}$$

$$+ \beta_4 * \log(\text{Regular Price})_t + \beta_5 * \log(\text{Category Quantity})_t + \varepsilon_{it}$$

$\alpha_{Brand} \sim \text{normal}(\mu_{Brand}, \sigma_{Brand})$	$\beta_{1i} \sim \text{normal}(\mu_1, \sigma_1)$	$\beta_{2i} \sim \text{normal}(\mu_2, \sigma_2)$	$\beta_{3j} \sim \text{normal}(\mu_3, \sigma_3)$
$\mu_{Brand} \sim \text{normal}(0, 1)$	$\mu_1 \sim \text{normal}(-1, 3)$	$\mu_2 \sim \text{normal}(1, 3)$	$\mu_3 \sim \text{normal}(0.3, 3)$
$\sigma_{Brand} \sim \text{normal}(0, 1)$	$\sigma_1 \sim \text{normal}(0, 1)$	$\sigma_2 \sim \text{normal}(0, 1)$	$\sigma_3 \sim \text{normal}(0, 1)$
$\alpha_{Quarter} \sim \text{normal}(\mu_{Quarter}, \sigma_{Quarter})$	$\beta_4 \sim \text{normal}(\mu_4, \sigma_4)$		
$\mu_{Quarter} \sim \text{normal}(0, 1)$	$\beta_5 \sim \text{normal}(\mu_5, \sigma_5)$		
$\sigma_{Quarter} \sim \text{normal}(0, 1)$			

We utilize the hierarchical model structure and account for brand heterogeneity in the following ways. First, we include random brand-specific intercepts. Second, to account for heterogeneous customer responses to changes in price, we estimate brand-specific own-price elasticities. In the case of *I* different brands, this leads to *I* different price elasticities. Furthermore, we control for seasonal variation in sales. To account for possible seasonality, we include random

[7] We include a lagged promotional price index based on the brand-specific inter-purchase frequency (IPF). Price index = log (Price/regular Price).

intercepts, each covering 12 consecutive weeks. We choose the period of 12 consecutive weeks to generate the best model convergence. Unit root tests show that sales series are stationary.[8]

The second step of our analysis concerns calculation of the promotional impact on sales, revenue, and profit. For this analysis, we use the estimated coefficients from the first step to predict the change in unit sales for brand *i* that occurs after a 1 percent decrease in the actual price of brand *i* in t, and in t-IPF.[9] We denote these changes in unit sales as the *own-sales impact* (in t, t-IPF). We derive the cross effects in the same manner, i.e., given a price reduction of brand *i*, we sum up the difference in units sold of all other brands in the category except for brand *i*. This amount is the *cross-sales impact* of brand *i* in the respective category. Importantly, for revenue and profit, we multiply sales with brand- and time-specific prices and contribution margins. To obtain the *category net impact* for each brand, we add the own and cross impact of the price reduction. This gives us the full category net impact of a 1 percent price reduction after considering all cross effects and the reduced margin of the price-changing brand. We repeat this across all weeks of our observation period and use this predicted impact on unit sales, revenue, and profit as the dependent variable in a second regression to assess how brand characteristics affect the impact of price reductions.

2.4.3 Demand Model Estimation

We estimate the demand model using Bayesian estimation with No-U-Turn sampling (Stan Development Team 2017). We set generic, weakly informative hyperpriors and priors normally distributed at location 0 and spread 1 for the intercepts. Based on extensive existing research on price elasticities, we set negative hyperpriors for the promotional price index, and positive hyperpriors for the lagged promotional price index and the cross-price index. We estimate 16 chains and base the posterior results on a total of 64,000 draws, of which we use the first 32,000 for warm-up. All chains are well converged and mixed with a potential scale reduction factor ($\hat{R}$) of close to 1 (see last column in Table 2.4) (Gelman et al. 2013).

---

[8] We test stationarity with the Phillips-Perron test. The null hypothesis of the Phillips-Perron test, that x has a unit root, i.e., that it is non-stationary, is rejected at 0.01.

[9] IPF = inter-purchase frequency. For each customer we calculate a brand-specific purchase frequency. We derive the number of weeks between the first and the last order of each customer and divide this by the number of orders of this specific brand by this specific customer. The average of all customer-specific purchase frequencies for one brand gives us the brand-specific inter-purchase frequency, which we use to lag the promotional price index. We exclude all orders conducted by customers who only bought once from the calculation of the inter-purchase frequency.

2.4.4 Results

Table 2.4 shows the results of the demand model estimation. The second column of Table 2.4 reports the posterior means; the mean promotional price elasticity (-2.30) is the mu of the 160 estimated brand-specific posterior price elasticity means. Figure 2.3 shows the heterogeneity of promotional price index coefficients. As expected, posterior means of the promotional price index coefficients are below zero and elastic, such that a promotional price decrease induces a sales increase. One brand constitutes an exception with a positive own-price elasticity; however, this coefficient is not significant. Furthermore, we do not find a stockpiling effect based on the brand-specific inter-purchase frequency, as the coefficient is small and exhibits low significance levels indicated by the 0.5 and 99.5 percentiles of the posterior interval in parentheses in column 2 of Table 2.4. This interval clearly includes zero for the lagged promotional price index.

Coefficient	**μ**	**Number of Coefficients**	$\hat{R}$
Promotional Price Index	-2.30 (-2.63; -1.96)	160	1.00
Promotional Price Index t-IPF	-0.01 (-0.26; 0.23)	160	1.00
Cross Price Index	0.54 (-0.06; 1.15)	160	1.00
Regular Price	-2.80 (-2.88; -2.73)	1	1.00
Category Sales	0.75 (0.73; 0.77)	1	1.00
Intercept Brand	1.57 (-0.11; 3.45)	20	1.11
Intercept Quarter	1.87 (0.00; 3.53)	160	1.11

Note: Posterior mean followed by 0.5 and 99.5 percentiles of posterior interval in parentheses.

Table 2.4: Posterior Means of Coefficients

The cross-price elasticities of the average cross-price index within category are relatively strong, with a mu of 0.54. While a recent meta-analysis shows an average cross-price elasticity of 0.26 (Auer and Papies forthcoming), we find stronger substitutional relations in this online data set. Cross-price coefficients display a more diverse picture, including substitutive and complementary brand relations within category (Figure 2.4), meaning that a price reduction might increase or decrease sales of competitive brands.

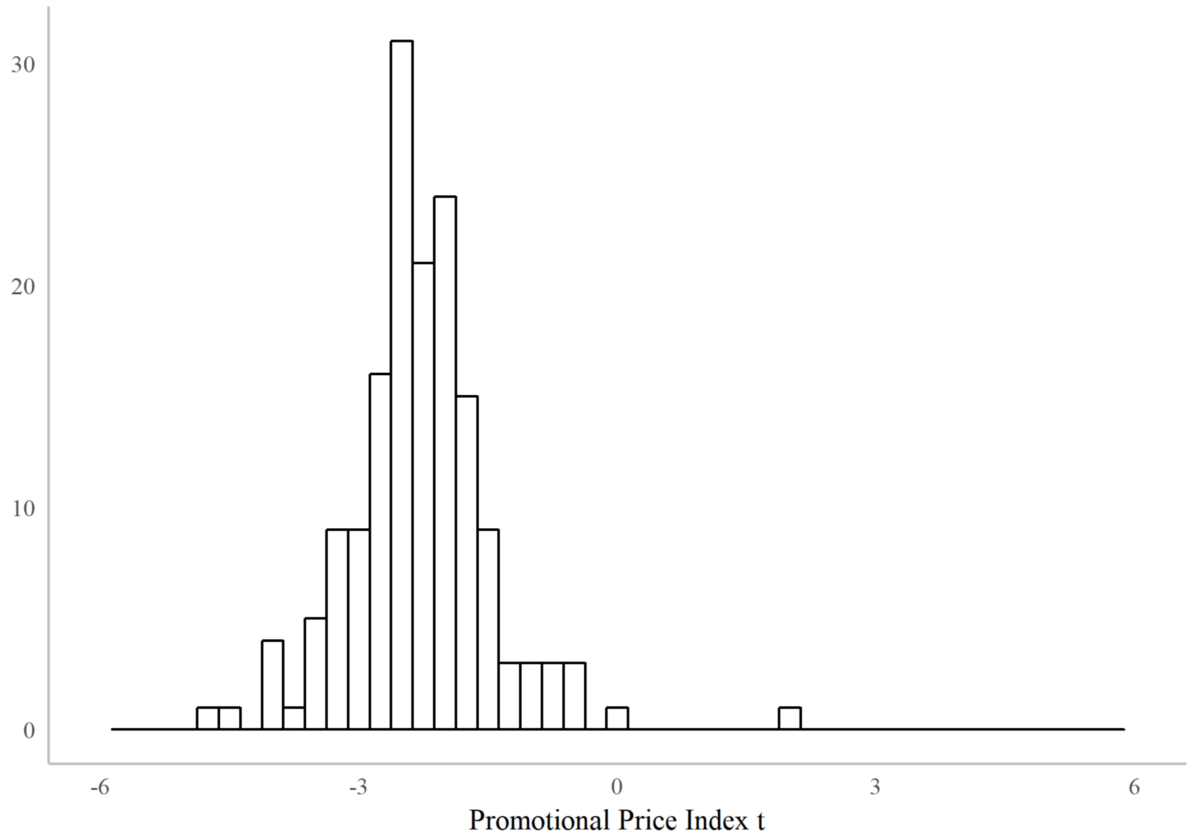


Figure 2.3: Histogram of Posterior Means of 160 Promotional Price Indices

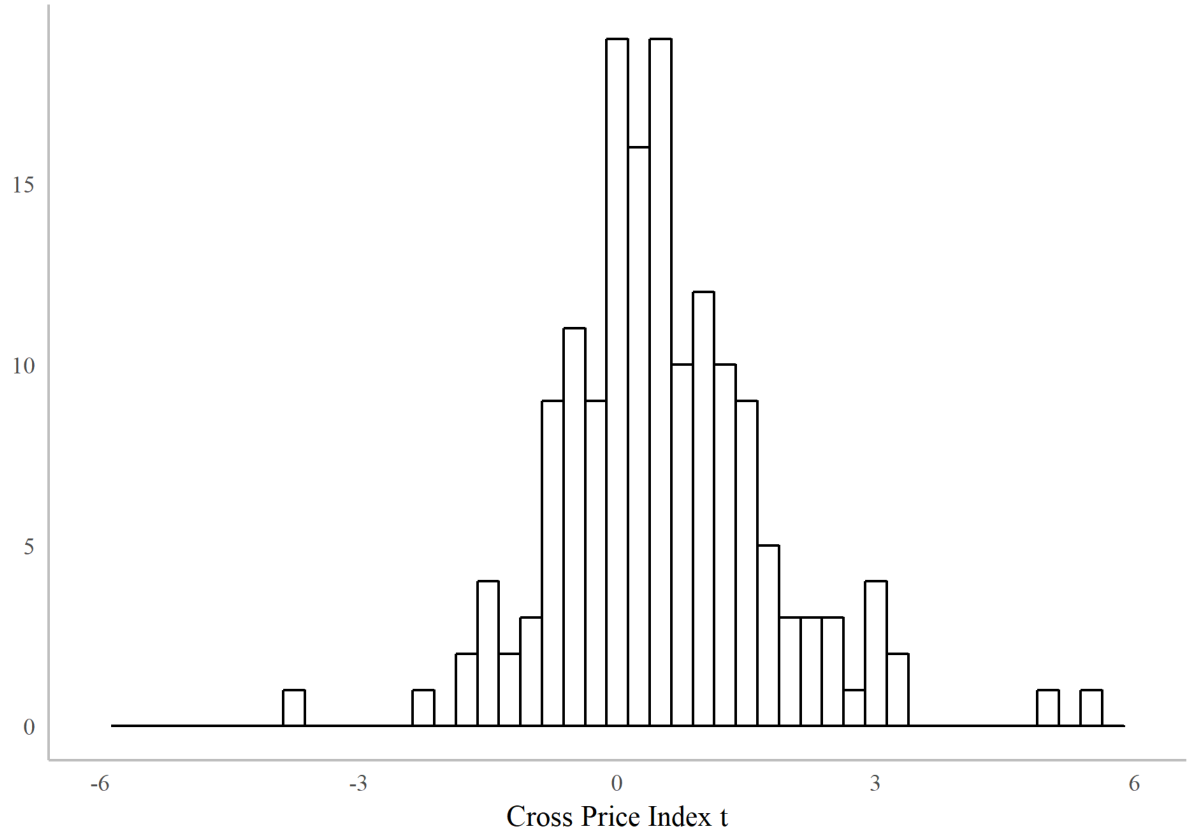


Figure 2.4: Histogram of Posterior Means of 160 Cross Price Effects

We estimate the regular price elasticity as homogenous across brands, and we obtain a posterior mean of -2.80. The magnitude of this coefficient, relative to the promotional price elasticity, is unexpected, being stronger than the mu of the hierarchically estimated posterior mean of the promotional price elasticity. Existing research offers mixed findings on regular price elasticities. Fok et al. (2006) find strong dispersion in regular price elasticities, including both positive and negative regular price elasticities. Jedidi et al. (1999) show that, in the case of long-term promotions, consumers are more sensitive to changes in regular price and less sensitive to promotional price discounts.

Further results include substantial brand-specific dispersion. Hence, the introduction of a brand-specific varying intercept accounts for the brand-specific heterogeneity.

2.4.5 Promotional Impact Calculation

We use the estimated posterior means of coefficients to derive the impact of a 1 percent promotional price reduction on quantity, revenue, and profit of a category.

First, we separately reduce the actual price as part of the promotional price index of brand i in t and in t-IPF by 1 percent to compute changes in the quantity sold of brand i induced by the price of brand i (see Table 2.5, rows one and two). We calculate the net revenue and profit from those units by multiplying each brand's quantity with the respective week- and brand-specific prices and profit margins. We repeat this process for every week and every brand in our data set.

We capture within-category cross effects using the estimated cross-price elasticity of the average cross price index per category. To this end, we compute the quantity change of each of the competing nine brands when the price of the focal brand in the average cross price is reduced (Table 2.5, row 3 displays the sum of the quantity impact of the nine competing brands within category). For revenue and profit we again multiply each brand's quantity with the respective week- and brand-specific prices and margins. Hence, the cross impact of the focal brand i is the sum of the quantity changes of the nine competing brands within the same category and country induced by a 1 percent price reduction of the price of brand i. We derive "impact" as the difference between the sales (revenue/ profit) predicted from actual prices and the sales (revenue/ profit) predicted after a 1 percent price reduction.

The results of this calculation, averaged across weeks and brands, are shown in Table 2.5. The columns show the effect of a 1 percent price promotion on sales, revenue, and profit, respectively. The rows represent the own impact, the lagged impact, the cross impact, and the total across these three effects. In column one and row one, we see the own impact of a 1 percent price promotion, measured in units. This suggests that, on average, sales increase as a result of the negative own-price elasticity when a brand is on promotion. This positive effect is barely affected by stockpiling, and somewhat reduced because of cannibalization effects, i.e., the price promotion for the focal brand also draws demand from competing brands. The net category impact is also positive, which is evidence of a primary demand increase due to the price promotion, i.e., total demand at the retailer increases as a result of the price promotion.

A similar picture emerges for the case of revenue. We again find a positive impact due to the own-price effect, and negative effects due to substitution effects across brands. The net effect, however, is still positive.

For the case of profit, the results are different. The own impact is negative, i.e., decreasing prices reduces profit, even before we consider substitution effects across brands. The total effect on profit is also negative, and substantial. Table 2.5 displays the means across all weeks, brands, categories, and countries.

	Sales		**Net Revenue**		**Profit**	
Own impact in t	62.53	(-0.14; 357.36)	118.01	(-54.11; 728.88)	-60.44	(-294.78; 0.23)
Own impact in t-1	1.33	(-58.15; 68.42)	2.67	(-188.28; 198.67)	0.66	(-24.64; 29.48)
Cross impact	-12.41	(-97.23; 31.16)	-43.51	(-307.57; 100.9)	-5.17	(-41.32; 14.68)
Net category impact	51.46	(-50.86; 365.56)	77.17	(-267.17; 752.19)	-64.96	(-309.14; 7.06)

Note: 2.5 and 97.5 percentiles of impact based on 250 random draws in parentheses.

Table 2.5: Average Unit Sales, Net Revenue, and Profit Impact of 1 Percent Promotional Price Reduction across 160 Brands

While, on average, the impact of sales and revenue is positive and the profit impact of a price reduction is negative, there is considerable variation resulting from the estimation over brands and weeks. To show the heterogeneity resulting from the estimation, we simulate the sales, revenue, and profit impact of 250 randomly selected draws, i.e., we repeat the brand- and week-specific calculation of the unit impact 250 times with 250 randomly drawn coefficients. The 2.5 and 97.5 percentiles of the sales, revenue, and profit impact of these 250 randomly selected draws are displayed in parentheses in Table 2.5. For example, in row 1, column 1 of Table 2.5 we present the average unit increase of 62.53 kg across all brands and weeks due to a 1 percent price reduction, followed by the information about the distribution in parentheses. 2.5 percent of the simulated brand- and week-specific unit impacts are smaller than -0.14 kg, while 97.5

percent of these are smaller than 357.36 kg. Figure 2.5 highlights this distribution of unit impact for row 1, column 1 of Table 2.5.

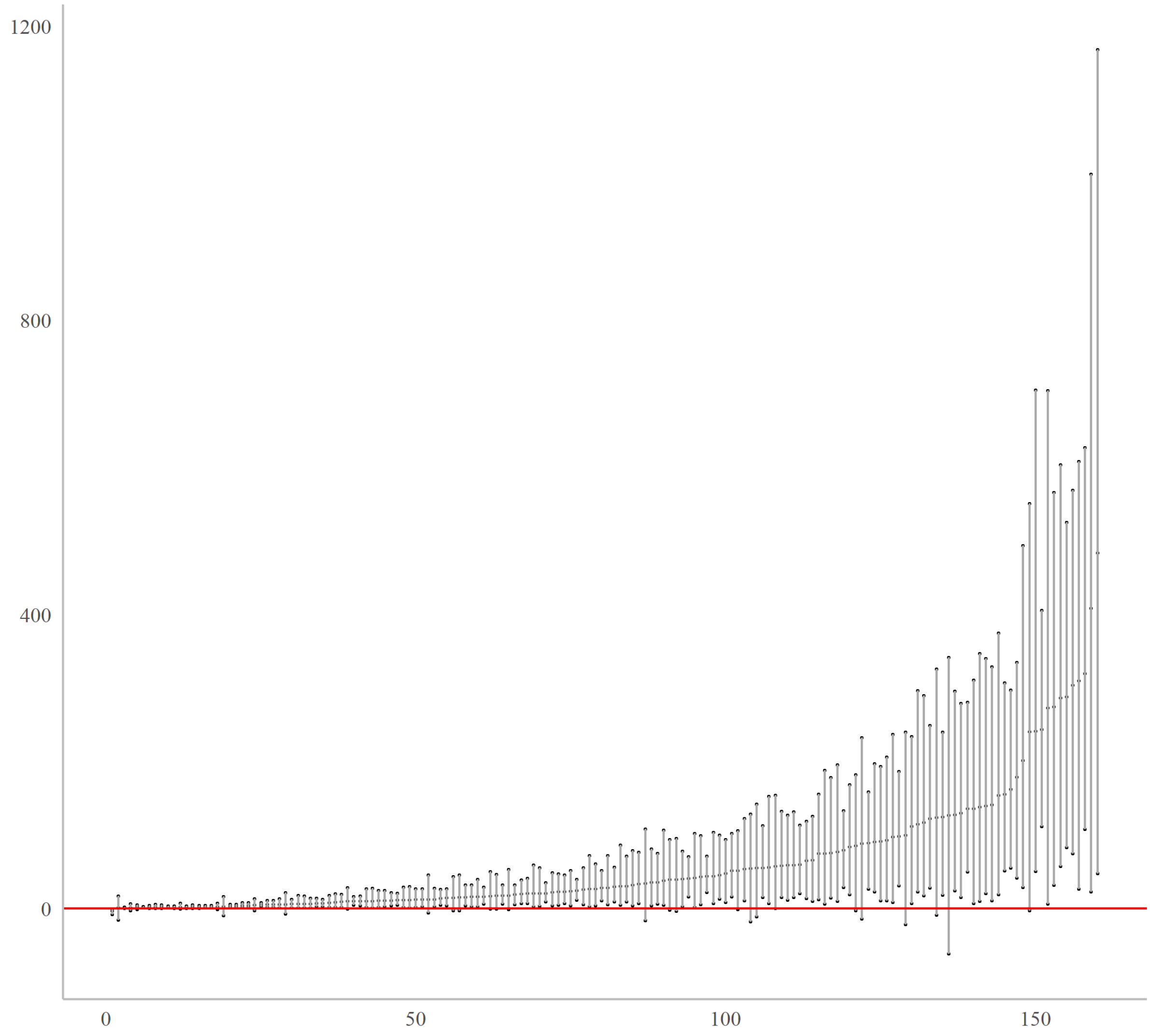


Figure 2.5: Own Sales Impact per Brand

The x-axis of Figure 2.5 shows the 160 brands sorted by size of the mean unit impact. For each brand, the mean unit impact is vertically surrounded by the 2.5 percent quantile below the mean and the 97.5 percent quantile above the mean. The red horizontal line highlights the unit impact of zero. Figure 2.5 underlines that the impact of a price reduction on the brand's own sales is mostly positive, while only few of the 2.5 quantiles drop below the zero line.

Table 2.6 shows these graphs for each of the cells of Table 2.5, with each graph sorted by size of the mean impact of the specific cell. Table 2.6 highlights that, while the simulation corroborates the directions of own, cross, and net effects, it exhibits substantial dispersion for the insignificant stockpiling effect.

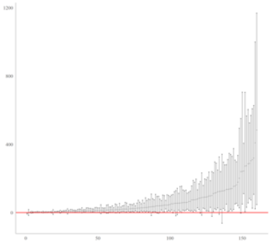
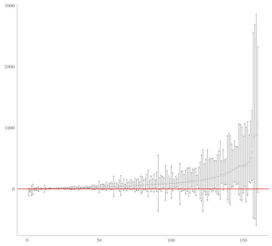
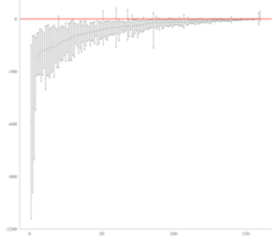
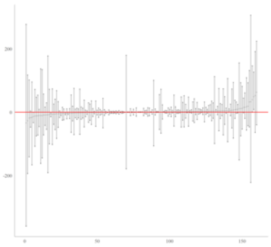
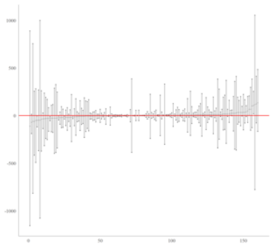
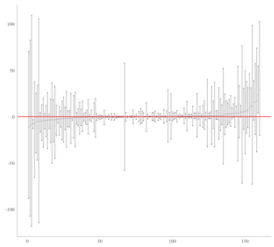
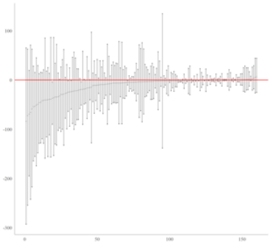
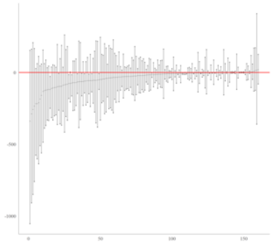
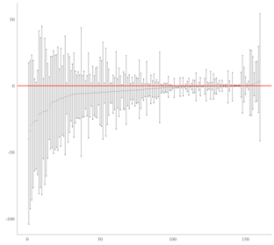
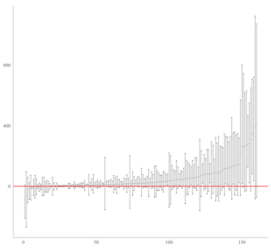
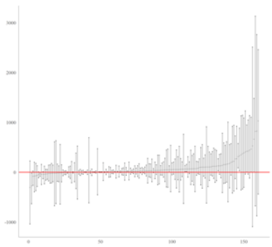
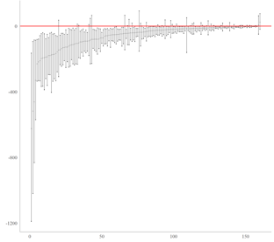
	Sales	**Net Revenue**	**Profit**
Own impact in t			
Own impact in t-IPF			
Cross impact			
Net impact			

Table 2.6: Sales, Revenue, and Profit Impact by Brand

2.4.6 Understanding the Impact of Brand-specific Margins

An important contribution of this paper lies in our ability to consider brand-specific margins. To explore the value of brand-specific margins, in both the own effects and the cross effects, we assess whether the results change if we apply a constant margin as the average across all contribution margins that we observe in a given category. Table 2.7 shows the results of this assessment and displays the differences in profit impact. Using a category margin leads to a slight overestimation of the negative cross impact, an underestimation of the negative own impact, and an underestimation of the total impact.

	Profit	
	Brand-specific Margin	Constant Category Margin
Own impact in t	-60.44	-56.00
Own impact in t-1	0.66	0.44
Cross impact	-5.17	-6.03
Net category impact	-64.96	-61.58

Table 2.7: Average Profit Impact of 1 Percent Promotional Price Reduction with Brand-Specific Versus Constant Margin

Importantly, however, the results differ greatly across brands. Figure 2.6 shows the relative deviation of the net profit impact calculated with a constant margin, compared to the net profit impact calculated with brand- and time-specific margin by brand.[10]

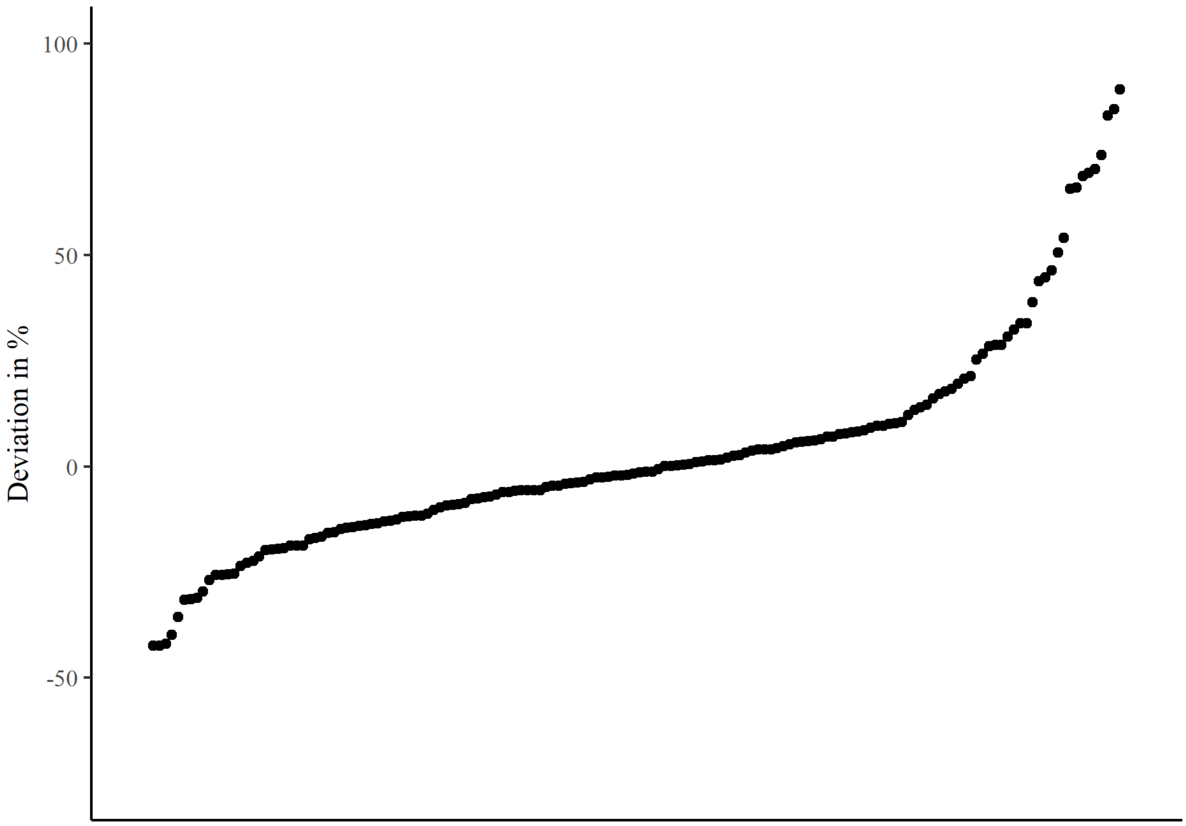


Figure 2.6: Deviation of Profit Impact with Constant Margin from Profit Impact with Brand-specific Margins

[10] Four brands with very strong deviations are removed for visual presentation.

The graph indicates that for roughly one-third of the brands, the net profit impact for the retailer is similar when constant margins are used, compared to brand-specific margins. For one-third, we observe an overestimation of the profit impact of up to 100 percent, and for another third, we observe an underestimation of up to 50 percent. This analysis highlights that brand-specific margins are extremely important if a retailer seeks to analyze for which brands promotions enhance or hurt a retailer's profit.

2.4.7 Robustness Check

One unexpected finding from the above analysis concerns the insignificance of stockpiling effects, meaning that price reductions in the past do not influence current sales significantly. Of the 160 lagged price elasticities estimated in the main model, for only four brands the effects are positive and do not include zero in the posterior interval, and for two brands the effects are negative without including zero in the posterior interval. To assess whether this finding is idiosyncratic to the specific model specification chosen, we conduct a robustness check. In this chapter we re-estimate the model with a different constellation of lagged promotional price index variables. While the main model includes the promotional price index lagged by the brand-specific inter-purchase frequency, including only this specific week as a lagged variable, we now estimate a wider range of weeks to capture the stockpiling effect. We use the average inter-purchase frequency across all brands after excluding one-time customers, which is 13.5 weeks. To capture more information on potential stockpiling effects the robustness check includes lags from week t-1 up to week t-14. To limit the number of parameters to be estimated, we average neighboring weeks. For example, instead of including the promotional price index lagged by one week and lagged by two weeks separately, we calculate the average of the two and include this average as variable in the model indicated by the subscript t-1.5. Hence, this robustness check includes seven lags of the promotional price index, covering 14 weeks. With the exception of this adjustment, the model equation and the priors and hyperpriors remain similar to Equation 2.1. We estimate the stockpiling effect with heterogeneous, brand-specific coefficients, i.e., for each of the seven lags we estimate 160 brand-specific coefficients.

$$\log(\text{Quantity})_{it} = \alpha_{\text{Brand}_i} + \alpha_{\text{Quarter}_q} + \beta_{1i} * \log(\text{Promotional Price Index})_{it} \tag{2.2}$$
$$+ \beta_{2i} * \log(\text{Promotional Price Index})_{it-1.5} + \beta_{3i} * \log(\text{Promotional Price Index})_{it-3.5}$$
$$+ \beta_{4i} * \log(\text{Promotional Price Index})_{it-5.5} + \beta_{5i} * \log(\text{Promotional Price Index})_{it-7.5}$$
$$+ \beta_{6i} * \log(\text{Promotional Price Index})_{it-9.5} + \beta_{7i} * \log(\text{Promotional Price Index})_{it-11.5}$$
$$+ \beta_{8i} * \log(\text{Promotional Price Index})_{it-13.5} + \beta_{9j} * \log(\text{Cross Price Index})_{it}$$
$$+ \beta_{10} * \log(\text{Regular Price})_t + \beta_{11} * \log(\text{Category Quantity})_t + \varepsilon_{it}$$

$\alpha_{Brand} \sim \text{normal}(\mu_{Brand}, \sigma_{Brand})$ $\quad\beta_{1i} \sim \text{normal}(\mu_1, \sigma_1)$ $\quad\beta_{2i-8i} \sim \text{normal}(\mu_{2\text{-}8}, \sigma_{2\text{-}8})$

$\mu_{Brand} \sim \text{normal}(0, 1)$ $\quad\mu_1 \sim \text{normal}(-1, 3)$ $\quad\mu_{2\text{-}8} \sim \text{normal}(1, 3)$

$\sigma_{Brand} \sim \text{normal}(0, 1)$ $\quad\sigma_1 \sim \text{normal}(0, 1)$ $\quad\sigma_{2\text{-}8} \sim \text{normal}(0, 1)$

$\alpha_{Quarter} \sim \text{normal}(\mu_{Quarter}, \sigma_{Quarter})$ $\quad\beta_{9i} \sim \text{normal}(\mu_9, \sigma_9)$ $\quad\beta_{10} \sim \text{normal}(\mu_{10}, \sigma_{10})$

$\mu_{Quarter} \sim \text{normal}(0, 1)$ $\quad\mu_9 \sim \text{normal}(0.3, 3)$ $\quad\beta_{11} \sim \text{normal}(\mu_{11}, \sigma_{11})$

$\sigma_{Quarter} \sim \text{normal}(0, 1)$ $\quad\sigma_9 \sim \text{normal}(0, 1)$

Table 2.8 shows the results of this robustness check. The second column reports the posterior means followed by the 0.5 and 99.5 percentiles of the posterior interval.

Coefficient	**μ**	**Number of Coefficients**	$\hat{R}$
Promotional Price Index	-2.28 (-2.59; -1.97)	160	1.00
Promotional Price Index t-1.5	-0.14 (-0.58; 0.30)	160	1.00
Promotional Price Index t-3.5	-0.10 (-0.53; 0.32)	160	1.00
Promotional Price Index t-5.5	-0.09 (-0.52; 0.33)	160	1.00
Promotional Price Index t-7.5	-0.04 (-0.45; 0.38)	160	1.00
Promotional Price Index t-9.5	-0.07 (-0.52; 0.39)	160	1.00
Promotional Price Index t-11.5	0.08 (-0.43; 0.59)	160	1.00
Promotional Price Index t-13.5	0.15 (-0.36; 0.66)	160	1.00
Cross Price Index	0.53 (-0.04; 1.12)	160	1.00
Regular Price	-2.71 (-2.78; -2.63)	1	1.00
Category Sales	0.75 (0.74; 0.77)	1	1.00
Intercept Brand	1.65 (-0.27; 3.47)	160	1.14
Intercept Quarter	1.68 (-0.15; 3.62)	20	1.14

Note: Posterior mean followed by 0.5 and 99.5 percentiles of posterior interval in parentheses.

Table 2.8: Robustness Check – Posterior Means of Coefficients

We initially focus on the lagged promotional price indices. A significant positive parameter for the promotional price index variable lagged by t-n indicates stockpiling, meaning that a price reduction in t-n decreases sales in t. Thus, if stockpiling takes place, customers buy more of the price-reduced brand in t-n, not to increase immediate consumption of the brand, but to stock it and consume it over time. The robustness check reveals that the posterior means of lags 1.5 to 9.5 are negative, while the lags closest to the inter-purchase frequency, namely, lags 11.5 and 13.5, are positive. However, the posterior interval displayed in parentheses in Table 2.8 includes zero for all lags. Since for lags 1.5 to 9.5 slightly more of the posterior density is below zero, we can tentatively conclude that a negative effect is more likely than a positive effect. In contrast, for lags 11.5 and 13.5 more of the posterior density is above zero, such that a positive effect is slightly more likely than a negative effect. Hence, at very low levels of probability, there is some spillover after the price reduction, meaning that people buy more one week after the price reduction and slightly stockpile in the weeks closer to the inter-purchase frequency. Furthermore, the size of the posterior means is larger than the coefficient of 0.01 in the main model. We illustrate all 160 coefficients for each of the lagged variables, in total 1,120 coefficients, in Figure 2.7.

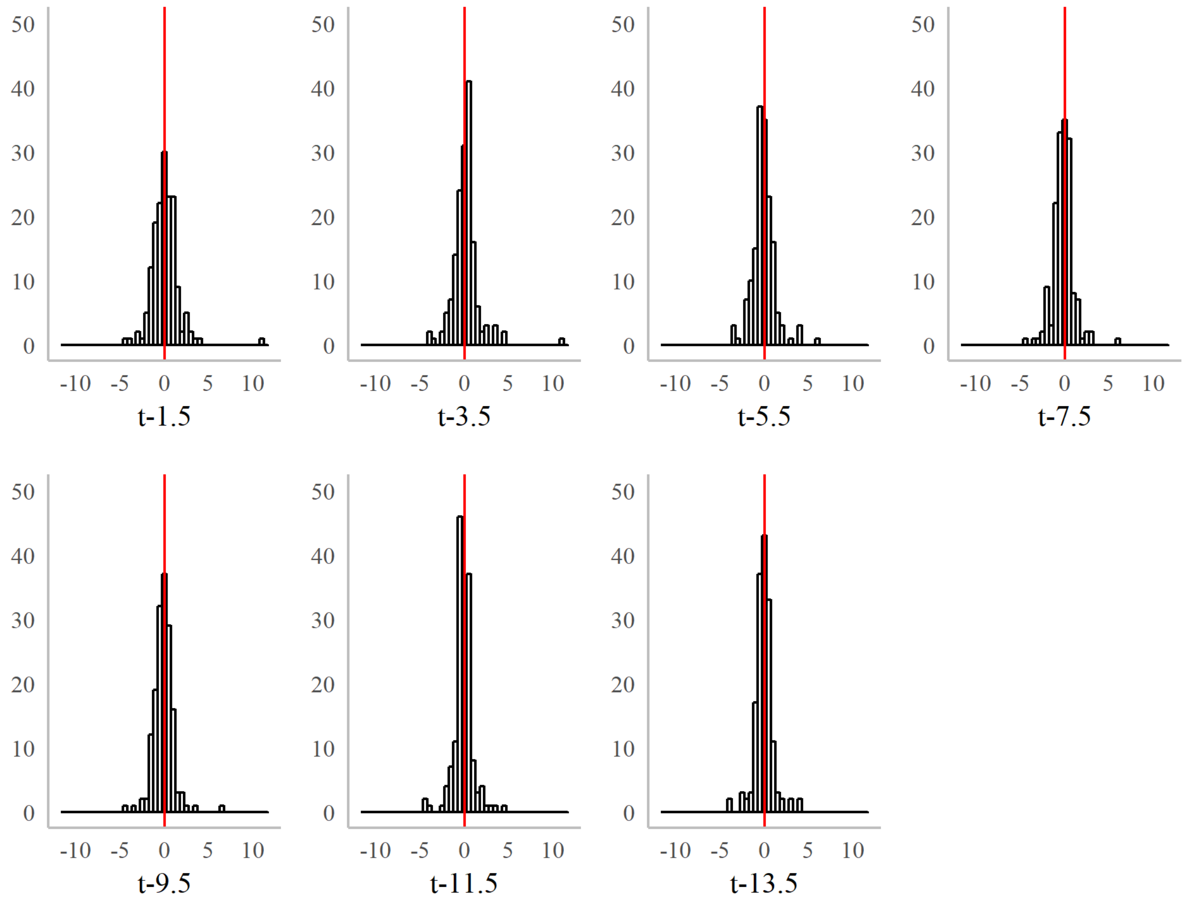


Figure 2.7: Robustness Check – Histograms of Posterior Means of Lagged Coefficients

The red vertical line in Figure 2.7 is set at zero, splitting the graph into negative and positive coefficients. The histograms reveal some outliers with strongly positive as well as negative elasticities and show the slight shift to more positive values with increasing lags.

The remaining variables are robust to the new operationalization to capture stockpiling. The mean promotional price elasticity is -2.28, which is very similar to the elasticity of -2.30 in the main model. Figure 2.8 shows the heterogeneity of promotional price index coefficients. Again, the distribution closely resembles the main model (Figure 2.3). Furthermore, corroborating our previous findings, the new posterior mean of the cross-price elasticities differs by only 0.01 from the previous model, with a similar distribution displayed in Figure 2.9. Finally, the regular price elasticity is again stronger than the promotional price index.

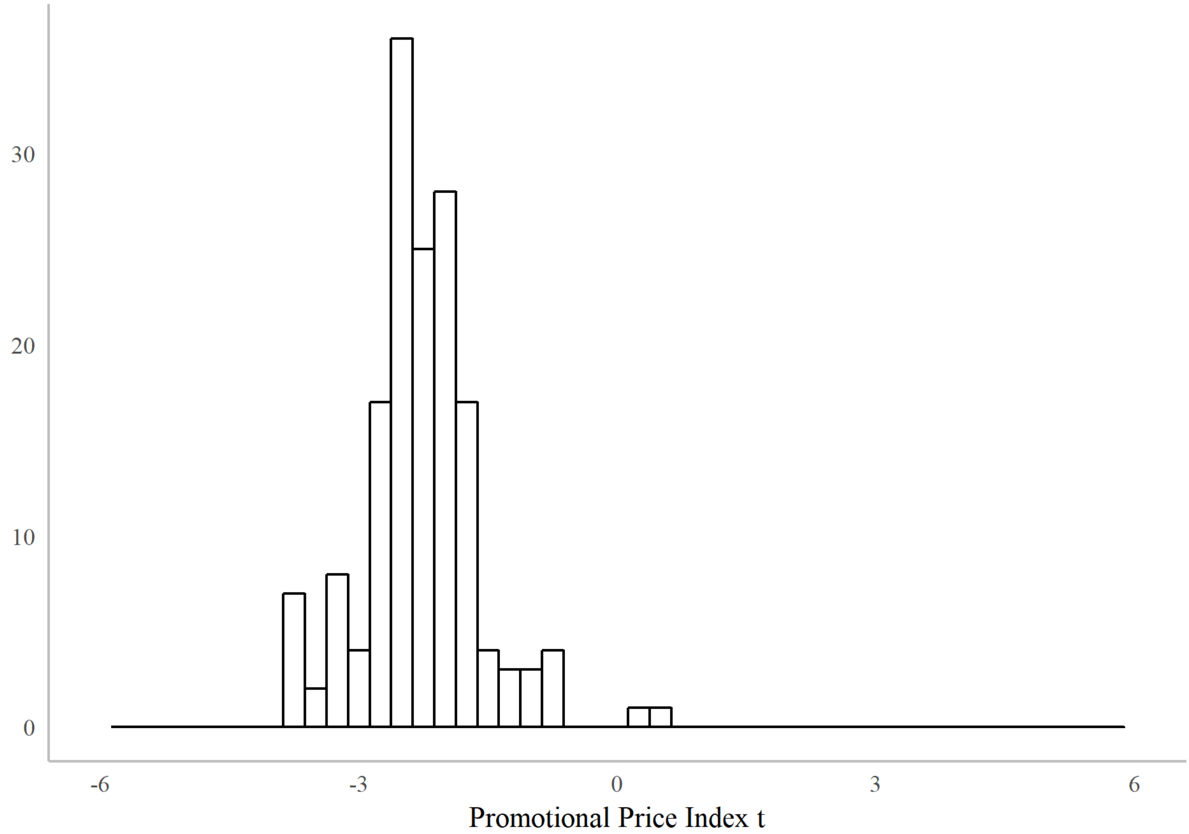


Figure 2.8: Robustness Check – Histogram of Posterior Means of Promotional Price Indices

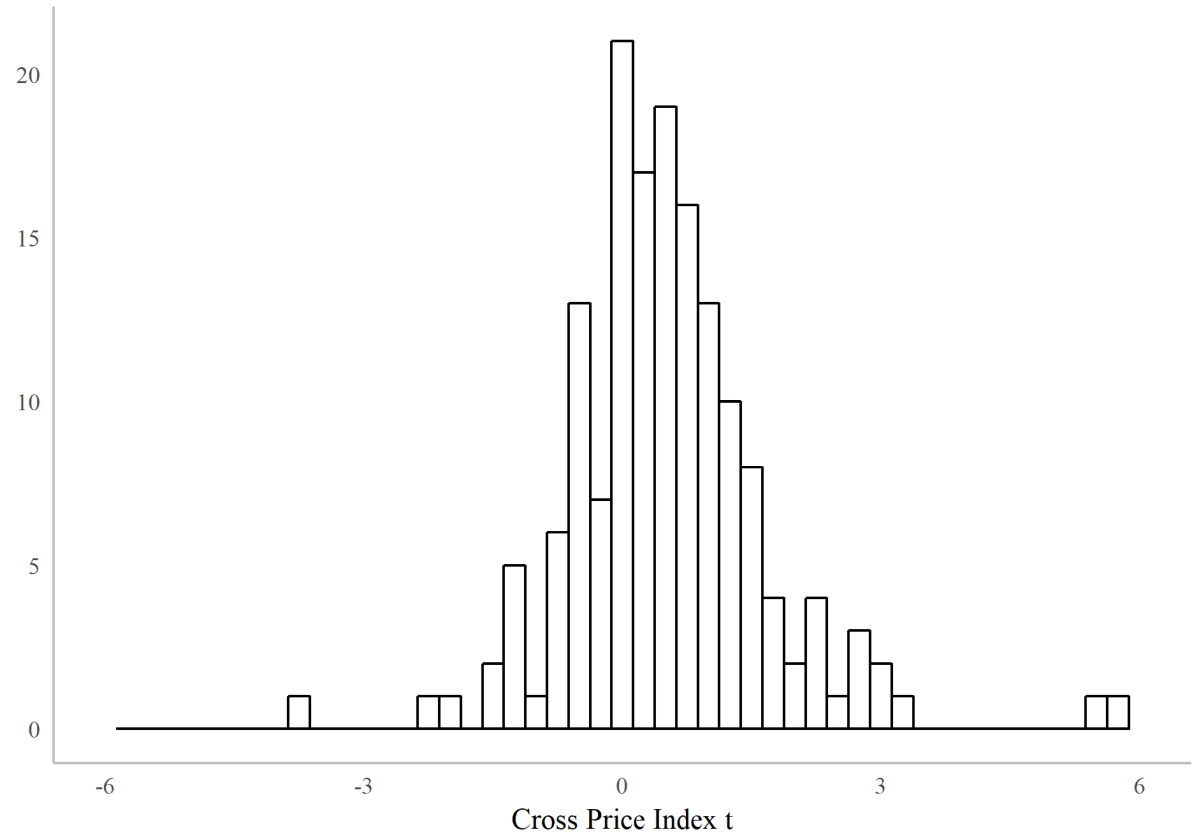


Figure 2.9: Robustness Check – Histogram of Posterior Means of Cross-Price Indices

In sum, the robustness check adds to our understanding of stockpiling, as we find signals for decreasing sales as the price reduction approaches the inter-purchase frequency. However, the evidence is not strong, since for 1,042 out of 1,120 estimated coefficients the posterior interval includes zero. At the same time, the adjusted model specification corroborates the findings of the main model regarding the remaining parameters.

2.4.8 Correlates of Sales, Revenue, and Profit Impact

The results from the first two steps that we report above suggest that online promotions are, on average, financially disadvantageous to the online retailer. However, the results also show that there is substantial heterogeneity across brands, i.e., for some brands, we see strong negative effects, while for other brands, the effects are less negative. We hypothesize that the brand-specific outcomes will vary predictably along brand and promotion characteristics. Based on the existing literature, we analyze a broad set of correlates of net sales, revenue, and profit impact, i.e., we consider five brand characteristics (brand size, line length, price level, private label, price range) and two characteristics that are related to the brands' promotional activities (promotion frequency, promotion intensity). Table 2.9 provides an overview of the variables that we use in this regression. Table 6.2 in the Appendix, provides a correlation tables that shows the bivariate correlation between all variables that we use in this regression.

Brand Characteristic	**Operationalization**	**Mean (SD)**	**Min.**	**Max.**
Brand Size	$\frac{\text{Ø weekly brand sales}}{\text{Ø weekly category sales}}$	0.10 (0.09)	0.01	0.59
Line Length	Number of items sold per brand	52.53 (43.92)	1.00	370.00
Price Level	$\frac{\text{Ø brand price}}{\text{Ø category price}} - 1$	0.00 (0.37)	-0.58	1.13
Private Label	Private label = 1	0.12 (0.32)	0.00	1.00
Price Range	$\frac{\text{max. brand price – min. brand price}}{\text{Ø brand price}}$	0.33 (0.21)	0.07	1.16
Promotion Frequency	$\frac{\text{Number of weeks - no-promo weeks}}{\text{Number of weeks}}$	0.72 (0.27)	0.00	1.00
Promotion Intensity	$\frac{\text{Share of items per brand on promo}}{\text{Ø share of items in category on promo}}$	1.00 (0.98)	0.00	10.00

Table 2.9: Operationalization of Correlates

We measure *brand size* as the quotient of brand-specific weekly sales and total weekly category sales. The number of products sold under one brand name represents the *line length*. The *price level* of a brand is the weekly brand price divided by the weekly mean category price. A dichotomous variable indicates whether a brand is a *private-label* brand. We compare the spread between the maximum and minimum price of a brand across all weeks with its mean price to generate *price range* as an indicator for the depth of price reductions. We include the share of weeks with items on promotion to indicate *promotion frequency*. Additionally, the ratio of the weekly share of items of a brand on promotion compared to the weekly promotion share within the category captures *promotion intensity*.

The data set contains the estimated weekly net sales, net revenue, and net profit impact per brand. We analyze the impact of 160 brands and each week so that the data set comprises 38,887 data points for sales, revenue, and profit each.

To understand the relation between these variables and the brand- and week-specific sales (revenue/ profit) impact of a price promotion, we estimate a model in which the sales (revenue/ profit) impact of a promotion serves as the dependent variable, and the factors summarized in

Table 2.9 are the regressors. We again use random intercepts per brand *i*, include country dummies *c* and category dummies *j*, and select the correlates that we described in Chapter 2.2.3.[11]

$$\text{Impact}_{it} = \alpha_{\text{Brand}_i} + \beta_1 \text{*Country}_c + \beta_2 \text{*Category}_j + \beta_3 \text{* Brand Size}_{cij} + \beta_4 \text{* Line Length}_{cijt} \quad (2.3)$$
$$+ \beta_5 \text{* Price Range}_{cij} + \beta_6 \text{* Price Level}_{cij} + \beta_7 \text{* Private Label}_i$$
$$+ \beta_8 \text{* Promotion Frequency}_{cij} + \beta_9 \text{* Promotion Intensity}_{cijt} + \epsilon_{it}$$

We again use a Bayesian approach (Stan Development Team 2017) and set generic, weakly informative priors normally distributed at location 0 and spread 1. We estimate 16 chains with 2,500 iterations each, so that we base the posterior results on a total of 40,000 draws, of which we use the first 20,000 as warm-up. Again, all chains are well converged and mixed with a potential scale reduction factor ($\hat{R}$) of (close to) 1. We summarize the main results in Table 2.10.

	Sales	**Net Revenue**	**Profit**
Brand Size	**0.412** (0.402; 0.422)	**0.398** (0.388; 0.409)	**-0.385** (-0.396; -0.374)
Line Length	**0.271** (0.259; 0.282)	**0.320** (0.308; 0.332)	**-0.311** (-0.323; -0.299)
Price Level	**-0.088** (-0.104; -0.072)	**0.021** (0.005; 0.038)	**-0.068** (-0.084; -0.051)
Private Label	-0.017 (-0.145; 0.110)	-0.033 (-0.158; 0.091)	-0.026 (-0.159; 0.108)
Price Range	**0.053** (0.044; 0.061)	**0.123** (0.115; 0.133)	**-0.073** (-0.083; -0.064)
Promotion Frequency	**-0.026** (-0.036; -0.016)	**0.048** (0.038; 0.058)	-0.003 (-0.014; 0.007)
Promotion Intensity	0.004 (-0.003; 0.011)	0.003 (-0.004; 0.011)	-0.001 (-0.008; 0.007)

Note: All variables are standardized. Posterior mean followed by 2.5 and 97.5 quantiles of posterior interval in parentheses. We print the mean in bold if the 95-posterior interval excludes zero.

Table 2.10: Posterior Means of Correlates of Promotion Impact

We find that *brand size* is positively associated with the impact of a price promotion on sales and revenue, i.e., the larger the brand, the larger the gain in terms of category volume and revenue. For profit, however, we observe the opposite, i.e., the larger the brand, the more detrimental the impact with regard to profit. This finding is in line with previous research (Srinivasan et al. 2004; Ailawadi et al. 2006), and it underscores an important dilemma that retailers face when deciding on price promotions: depending on their goals, it may help or hurt them to promote large brands. It helps top-line results such as sales and revenue, but it hurts profits. Hence, we support existing empirical research in that large brands have the power to

[11] We estimate using standardized variables.

draw sales to a brand, while the reduction in profit margin due to the price reduction removes the positive effect.

A similar picture emerges for *line length*. Running promotions on brands that feature a long product line helps sales and revenue, but it also hurts profits. This variable has not been considered in previous research, and therefore we cannot compare the findings with previous research.

Concerning the *price level* of a brand, Ailawadi et al. (2006) report a negative sales and a positive profit impact, while we find a negative impact on both sales and profit, i.e., for high-priced brands, the impact on sales and profit is more negative than for low-priced brands, while revenue is positively affected. One potential explanation for this finding is that a high price level for a given brand does not necessarily translate into high margins for the retailer. It is possible that the relative margin for high-priced brands is lower than that for low-priced brands.

For *private labels*, our results suggest that the impact of a price promotion on category volume and revenue is smaller compared to national brands, and this finding is in line with previous research. We note, however, that these effects should be treated with caution, as the posterior interval includes zero. For profit, our findings deviate from previous research because we cannot replicate the positive effect that Ailawadi et al. (2006) and Srinivasan et al. (2004) find. The mean of the posterior distribution is negative, but the interval clearly includes zero, so we view this result as inconclusive.

We further support previous findings on the positive sales impact of *price range*. We compare price range to the promotional depth variable used by Ailawadi et al. (2006) and Srinivasan et al. (2004). We find that, the wider the price range, the higher the sales and revenue impact. In contrast to Srinivasan et al. (2004), our results show a positive impact for revenue as well, while the negative relation with profit is in line with previous studies.

We assess two characteristics that are related to the brands' promotional activities. *Promotion frequency* indicates that the more weeks that a brand includes items on promotion, the lower the sales, while revenue is positively affected. For profit the results are inconclusive. Within a given week, *promotion intensity* indicates the share of items of a brand on promotion, compared to the category average. However, the effects of *promotional intensity* remain inconclusive with respect to sales, revenue, and profit.

	Sales		Revenue		Profit	
	Previous Research	This Study	Previous Research	This Study	Previous Research	This Study
Brand Size	+	+	(+)	+	-/-	-
Line Length		+		+		-
Price Level	-	-		+	+	-
Private Label	-	(-)	(-)	(-)	+/+	(-)
Price Range	+	+	-	+	-/-	-
Promotion Frequency	-	-	+	+	+/-	(-)
Promotion Intensity	+	(+)		(+)	-	(-)

Note: Previous research lists results from Ailawadi et al. (2006) and/or Srinivasan et al. (2004). Entries in parentheses indicate insignificant results.

Table 2.11: Comparison of Estimation Results with Previous Research

2.5 Conclusions, Implications, and Limitations

In this study we assess the profitability of price reductions in online retailing, considering brand-specific contribution margins and manufacturer allowances. We analyze a unique transactional data set that spans five years from a large online retailer across four countries, four categories, and 160 brands in total. We find significant promotional price index elasticities in a range close to offline elasticities. Hence, as in offline studies, price reductions lead to sales increases of the focal brand. From a managerial perspective, despite the ubiquity of information online, price reductions are still capable of steering demand. Managers can therefore use price reductions, for example, to attract demand to grow a specific brand or to empty inventories if perishable goods approach the expiry date. At the same time, strong cross-price elasticities with high dispersion and the posterior mean twice as strong as the most recent meta-analysis shows (Auer and Papies forthcoming), suggest strong competition between brands within category. Managers of retailers can use this information on cross relations, for example, in the case of delivery difficulties. Faced with delivery difficulties, retailers can try to shift demand to other brands in the category in order to prevent harm from customers being disappointed with long delivery times. In such a case, managers can use the opportunity to steer demand to other brands in the category through price increases of the brand that is currently not available and/or price reductions of substitutive brands in the same category.

In contrast to offline studies, we do not find strong stockpiling effects, although the products in the data set can be stockpiled. We conduct a robustness check, and the results of this test are suggestive of stockpiling effects; however, these effects are largely insignificant. For retailers, this is a very positive effect, since they do not sacrifice future sales at regular profit margins for increasing current sales at reduced margins. A reason for this effect might be higher purchase frequency at lower basket size, since there is no effort of travelling and carrying involved in online shopping. Increasing purchase frequency with lower basket size, however, would be less beneficial for the retailer, since handling and shipping costs lower the profit margin. From a managerial perspective, the insights on stockpiling can change promotional planning by retailers. Usually, manufacturers and retailers set up a promotion plan for a specific period of time, which details the promotions. If there are fewer stockpiling effects, retailers have more freedom in compiling the promotion plans of different manufacturers within a category.

Furthermore, we find a relatively stronger impact of regular price changes, as opposed to promotional price changes. In environments with a high frequency of promotions, the regular price might therefore serve as a stronger signal. For retailers, this could be a shift from today's strong focus on highlighting temporary price changes of the actual price to managing the regular price as a powerful measure, since customers seem to be aware of the long-term price level at the retailer. Managing this price level can be an additional tool for managers steering demand.

Based on the unit calculations, we further find that price reductions positively affect retailer sales. The combination of strong own-price elasticities, strong cross-price elasticities, and low stockpiling lead to a net increase in the category. Hence, the price reduction can attract new demand that neither stems from stockpiling nor completely arises from the other brands in the category. Hence, we find that the promotional sales increase online has two main sources – brand switching within category and store switching.[12]

Temporary price reductions, however, on average reduce the retailer's profits. The main reason for this unprofitability of promotions is that the increase in demand for brands is not strong enough to offset the lower margins. We find cross effects, which are a source of unprofitability, as they account for approximately 20 percent of the quantity increase, and further lower profits as a result of lost sales at regular margins. For retail managers, this information is crucial when managing for profit. The combination of heterogeneity across margins and strong cross-price elasticities reveals opportunities to understand and steer the profit impact of a price reduction.

[12] In theory, increased consumption is an additional source, which is, however, not likely for these product types.

We hypothesize, based on the existing literature, that brand and promotion characteristics drive sales, revenue, and profit impact. With an analysis of correlates, we find that decisions about promotions are strategic decisions for retailers. Online retailers cannot increase sales, revenue, and profit with the same managerial action. If firms are interested in driving sales and revenue, they should focus their promotions on high-share brands with a large price range. In line with previous findings, a stronger promotion frequency diminishes the sales impact but increases revenue. If profit is the central corporate objective, the opposite is true: promotions on low-share brands with low price ranges are advisable. Interestingly, we do not find a significant impact of promotional features, namely, promotional frequency and promotional intensity, on profit, whereas brand characteristics are relevant in guiding managers' actions with respect to promotion profitability.

We note the following limitations of this study: it would be desirable to include information on additional marketing-mix variables (e.g., email newsletters). Furthermore, to keep the number of estimated coefficients and model complexity at a reasonable level, we have to restrict the analysis to the top ten brands per category. Similar to previous research, this implies that our findings may hold primarily for larger brands.

Our research reports the diminishing importance of stockpiling online. This raises fruitful questions for future research, for example, whether online shopping, requiring less effort (travelling, carrying), makes customers shop more often, or buy less, and whether customers rely on high promotion frequencies online.

Our data set includes goods sold by one retailer in four categories. Following Bijmolt et al. (2005, p. 151), who state that "price elasticities are largely independent of whether consumer heterogeneity is modeled" while they differ across product categories, we account for product heterogeneity. However, we do not dive into category differences. Hence, future research could extend our findings by category moderation.

Moreover, data is collected from one pure online retailer, which raises questions about the generalizability of our findings to other retailers. Therefore, to strengthen confidence in the validity of our findings, future research could enhance the generalizability by combining data from several retailers.

3 Crossed Out but Still Relevant? Exploring Online Advertised Reference Prices

3.1 Introduction

In the search for a 50-inch television on Amazon.com and Waltmart.com, four of the first five products listed show a crossed-out list price next to the actual selling price (see Figure 6.2 and Figure 6.3 in the Appendix).[13] As indicated by the example, retailers often display the actual selling price in combination with a higher advertised reference price, for example, a manufacturer-suggested retail price or a competitor's price (Compeau and Grewal 1998; Mazumdar et al. 2005). The rationale behind this for the retailer is to make the offer appear more attractive by influencing the reference point against which customers evaluate it. Prior research underlines that advertised reference prices are a powerful measure to increase purchase intentions (Mazumdar et al. 2005). Furthermore, empirical studies highlight that even inflated advertised reference prices have a positive impact on purchase evaluations (Urbany et al. 1988; Biswas and Blair 1991). Returning to the Amazon–Walmart example, one of the top five products is identical across retailers and is offered at $447.99 by both. However, the two retailers compare the actual selling price of the identical product against different list prices. On Amazon.com the list price is $599.99, whereas on Walmart.com a list price of $749.99 is referenced (see Figure 6.4 and Figure 6.5 in the Appendix). Hence, on Wallmart.com the customer might get the impression of saving $300, while the savings appear to be $150 on Amazon.com. The manufacturer also advertises a list price of $599.99 on its own website, while selling the product for $449.99 (Figure 6.6 in the Appendix). This example is not unusual: A price comparison website reveals that on Amazon.com, over the course of the past seven months, the product has never been offered for the list price (see Figure 6.7 in the Appendix). On the manufacturer's website and Walmart.com, the reduction in comparison to the list price is also in place for longer than a month (see Figure 6.8 and Figure 6.9 in the Appendix).

This example highlights the main aspects of this study: first, the disruption of the retail market by e-commerce, with both the option to compare prices easily and ubiquitous reference prices constantly displayed by retailers; and, second, the role of the credibility of advertised reference

[13] We choose televisions as example, since televisions are part of the product category of computers and personal electronics, which attracts the largest amount of consumer spending online ($76 billion in 2015 with 15 percent growth). We further choose Amazon.com and Walmart.com because together they account for 28 percent of traffic in the U.S. (Miller and Washington 2017).

prices, i.e., the distance of the advertised reference price from the regular selling price, in purchase situations.

First, the disruption of the retail market by e-commerce[14] has introduced easy price comparisons for customers. In theory, the Internet lowers the cost of information search by facilitating access to information (Bakos 1997). With the cost of searching for information online being lower, customers might rely less on price information provided by the retailer in the form of advertised reference prices and instead search for information by comparing prices across stores. For example, price search engines provide the price of a specific product at different retailers or at different points in time (for example, Figure 6.7 in the Appendix). Where customers can compare actual selling prices across retailers with just one click, the informational value of the advertised reference price might be challenged. Furthermore, advertised reference prices are ubiquitous online; both major retailers and the manufacturer in the example provide advertised reference prices, and they provide them over a long period of time. Existing research provides contradictory findings for a long-term display of advertised reference prices. On the one hand, research in the field of reference prices supports the positive impact of advertised reference prices on purchases (Urbany et al. 1988; Compeau and Grewal 1998). On the other hand, research on price promotions reports that the impact of promotions on sales decreases once promotions become too frequent (Jedidi et al. 1999; Ailawadi et al. 2006). We consider the display of an advertised reference price in combination with an actual selling price to be a promotional framing. Hence, when the advertised reference price is displayed constantly its impact on sales might be reduced.

Second, the credibility of advertised reference prices might influence purchase decisions. Research on advertised reference prices offline shows that even inflated advertised reference prices have a positive impact on customers' evaluations of the offer (Urbany et al. 1988; Biswas and Blair 1991). However, as outlined above, online customers can easily check whether advertised reference prices are credible and thus they can detect inflated advertised reference prices. The credibility of advertised reference prices might impact purchasing following two avenues: first, the credibility of advertised reference prices might directly impact sales; and, second, the credibility of the advertised reference price might have an effect on the impact of

[14] Although online purchases currently represent a relatively small share of retail sales (7.3 percent in 2015 in the U.S.) e-commerce realizes strong growth (15 percent growth in 2015 in the U.S.) (Miller and Washington 2017).

the actual selling price on sales, i.e., the moderation of the price elasticity by the credibility of the advertised reference price.

The example further highlights the special role of list prices, i.e., manufacturer-suggested retail prices, with respect to credibility. In the example, the advertised reference price is a manufacturer-suggested retail price, which is not charged by any party, including the manufacturer itself. In general, to prevent inflated advertised reference prices, they are subject to substantial legal regulations, in Germany the “Gesetz gegen den unlauteren Wettbewerb” (UWG). If the retailer decides to use its own historic price as the advertised reference price, the legislation requires the retailer to regularly sell the advertised product for the higher advertised reference price and only to discount it temporarily (§5 UWG). In order to display a competitor’s price, the retailer needs to ensure that the comparison is fair (§6 UWG). For manufacturer-suggested retail prices, however, the actual selling price at the retailer never has to match the manufacturer-suggested retail price, which might make this type of advertised reference price less credible. Adding to credibility concerns, in recent years legal and public interest in deceptive pricing has increased. High-profile cases concerning the display of deceptive reference prices in the U.S., including companies such as Overstock.com and Walgreen’s, have attracted strong public interest in the topic. As a consequence, deceptive pricing litigation has experienced a resurgence (Streitfeld 2016a, 2016b; Bartz 2017; Wisoff 2017). In June 2016 the customer advocacy organization truthinadvertising.org was tracking 61 federal U.S. class-action lawsuits on this topic (Salls 2016). Furthermore, substantial settlements of such cases generated additional attention. For example, the popular fashion label Michael Kors was confronted with a class action lawsuit for printing fictitious manufacturer-suggested retail prices on items produced only for their outlet stores. The Michael Kors Holdings Ltd agreed to a $4.88 million payment to settle the lawsuit (Stempel 2015). Hence, the credibility of manufacturer-suggested retail prices might also have suffered from major publicity about deceptive pricing lawsuits and settlements.

It is notable that, despite the strong prevalence of advertised reference prices online, despite strong growth in e-commerce, and despite developments questioning the credibility of advertised reference prices, empirical research has so far dedicated limited attention to the role of advertised reference prices online. The aim of this chapter is therefore to shed light on the role of advertised reference prices, in the form of manufacturer-suggested retail prices, in e-commerce. Hence, the first objective of this study is to explore whether displaying advertised reference prices, compared to not displaying them, impacts online purchases.

(2.1) *Do manufacturer-suggested retail prices have an impact on sales-related variables online?*

Given the facilitated information access online and the increasing awareness for potentially deceptive advertised reference prices, we further analyze whether the credibility of the advertised reference price has an impact on sales online. We operationalize credibility as the ratio of manufacturer-suggested retail price and regular price, i.e., the larger the distance between the manufacturer-suggested retail price and the price that is regularly paid by the customer, the lower the credibility. Therefore, we ask the following exploratory research question:

(2.2) *How does the credibility of a manufacturer-suggested retail price impact sales online?*

Finally, we explore whether this credibility moderates the effect of the actual selling price on sales, since with the decreasing credibility of the advertised reference price the actual selling price might gain relevance. Hence, we set out to answer the following exploratory questions:

(2.3) *Does the credibility of a manufacturer-suggested retail price moderate the impact of the actual selling price on sales online?*

Following this analysis, we conduct a sales and profit impact calculation. From a retailer's perspective, we calculate the profit impact of a reduction in the actual selling price against the background of different distances between the manufacturer-suggested retail price and the regular price.

In sum, this study sets out to shed light on advertised reference prices in online settings. We aim to add to limited and mixed existing findings on the impact of advertised reference prices on sales and to address the related research gaps. To the best of our knowledge, we are the first to analyze the interplay of the credibility of advertised reference prices and actual selling prices and to assess the profitability of changes in the distance to the manufacturer-suggested retail price.

We approach these exploratory research questions using a unique combination of three empirical studies. In study one, we administer an online experiment to assess the impact on purchase intentions of displaying versus not displaying an advertised reference price within an online shopping experience. The online experiment imitates the process of an online purchase and offers high internal validity on the impact of the advertised reference price on purchase intentions. To corroborate the findings from the laboratory study, to the best of our knowledge we are the first to administer a field experiment in cooperation with a large online shop on advertised reference prices. The experiment in study two mirrors the online survey and adds the idea of infinite promotion frequency, as the online shop constantly displays the manufacturer-suggested retail price for the products under investigation. We analyze whether the elimination and consecutive re-introduction of the advertised reference price have an impact on the online purchase process. With the combination of online and field experiments, our aim is to paint a precise picture of the impact of displaying an advertised reference price on purchase-related dependent variables. With the third empirical study, we address whether the credibility of reference prices impacts sales. In a large transaction data set, we assess the impact on sales of the ratio of manufacturer-suggested retail price and regular price and analyze whether this ratio moderates the impact of the actual selling price on sales. In sum, we address our research questions through an online experiment, a field experiment, and analysis of a large and recent set of transaction data.

We structure the remainder of the chapter as follows. We initially provide the basic legal regulations and a literature review on comparative pricing in Chapter 3.2. Subsequent to an overview of the relevant legal regulations in Germany on advertised reference prices in Chapter 3.2.1, we underline the relevant theoretical fundamentals of advertised reference prices in Chapter 3.2.2 and summarize the existing empirical research in Chapter 3.2.3. Since most studies in the field of advertised reference prices deal with traditional offline shopping, we point out the theoretical differences between online and offline shopping and the potential impact on advertised reference prices in Chapter 3.2.4. Afterwards Chapter 3.2.5 outlines the limited empirical research on advertised reference prices in e-commerce. Based on the literature review, we identify gaps and outline our contributions to the field of advertised reference prices in Chapter 3.3. We provide these contributions through three empirical studies and report the results in Chapters 3.4, 3.5, and 3.6. Finally, we discuss our findings in Chapter 3.7 and offer managerial implications and avenues for future research in Chapter 3.8.

3.2 Institutional Background and Literature Review

3.2.1 Legal Regulations on Advertised Reference Prices

Advertised references prices are subject to substantial legal regulations. To understand and analyze the use of advertised reference prices in retailing, we first outline the relevant legal regulations. As we conduct our three empirical studies in Germany, we focus on German law. In Germany the “Gesetz gegen den unlauteren Wettbewerb” (UWG) regulates comparative pricing. We differentiate comparative prices according to three types: *retailers' own historic prices*, *competitors' prices*, and indirect prices, that is *manufacturer-suggested retail prices*.

§5 UWG is the legal basis for comparisons with *retailers' own historic prices* to prevent deceptive advertising. To use their own past prices as advertised reference prices, retailers need to verify that they usually sell the product for the advertised reference price and only temporarily for the reduced price. The past price may not be inflated merely to pretend there is price reduction. The advertised products need to be in stock for at least two days and prices may not be used to deceive customers in any other dimension (Eschweiler 2006).

§6 UWG regulates *competitors' prices* as advertised reference prices. Comparative advertising directly or indirectly refers to competitors, their products, or services. Comparative advertising is permitted if it is not unfair, as described in §6 (2) UWG. Among others, the advertising company acts unfairly if the comparison does not refer to products or services with the same purpose, if it does not refer to substantial, relevant, objective, verifiable, and typical attributes of the product or the price of the product, if the company does not differentiate itself clearly from its competitors, if the advertising company influences or exploits the competitor's reputation unfairly, or if it advertises a copy of the competitor's offer. Furthermore, the competitor needs to be clearly identifiable. Retailers have to declare a price reduction with a competitor's price as advertised reference price as temporary and the price comparison has to be based on full costs (Eschweiler 2006).

Manufacturer-suggested retail prices are the last and focal group of advertised reference prices in this study. The manufacturer-suggested retail price is a price suggestion provided by the manufacturer of the product. For this type of price, German jurisdiction assumes that the customer understands that this price is a suggestion and that, in contrast to its own price comparisons, the retailer does not need to sell the product for the advertised price. However, the retailer must still adhere to the fundamentals of fair competition, as regulated in the UWG. The manufacturer-suggested retail price must be a valid current suggested price provided by the manufacturer and must refer to the specific product offered. The manufacturer-suggested retail price has to be a common market price; therefore, it may not be inflated, and must be based on a solid calculation (BGH, November 27, 2003 – Az. I ZR 94/01). The manufacturer-suggested retail price must be valid at the time of the advertisement. If the manufacturer no longer provides a manufacturer-suggested retail price in its current price list, the retailer may no longer use this price as the manufacturer-suggested retail price given a short transition phase

(BGH, January 29, 2004 – Az. I ZR 132/01). In such cases, the retailer must point out that it is a former manufacturer suggested retail price. Jurisdiction also enforces fair competition with manufacturer suggested retail prices online, for example, Amazon has been sentenced for displaying an inflated manufacturer-suggested retail price (LG Cologne, October 2, 2014 – 81 O 74/14).

With respect to all three types of advertised reference prices, the retailer is responsible for informing the customer about the type of reference price, whether it is a historic own price, the price of a competitor, or the manufacturer-suggested retail price. However, the manufacturer-suggested retail price is the only advertised reference price that the retailer may display constantly without verifying that the product is sold anywhere at this price.

For the remainder of this paper we focus on advertised reference prices in the form of manufacturer-suggested retail prices.

3.2.2 Theoretical Fundamentals of Advertised Reference Prices

A large body of literature has investigated the impact of reference prices on price evaluation, search intentions, and purchase decisions. With respect to the problem under investigation we outline the relevant theoretical fundamentals of reference prices.

Adaptation-level theory provides the theoretical basis (Helson 1964). Buyers evaluate the actual price of an offer in relation to an adaptation level, that is, the internal reference price (Monroe 1973). Contextual stimuli, as well as memory of past purchases, form this internal reference price (Krishnamurthi et al. 1992; Mayhew and Winer 1992; Mazumdar et al. 2005). Hence, customers evaluate the price of an offer against their internal reference price to determine whether or not the offer is attractive (Monroe 1973). Numerous empirical studies support this theory, to the point that it is a common empirical generalization that internal reference prices influence purchase decisions (for an overview of empirical evidence see Kalyanaram and Winer (1995) and Mazumdar et al. (2005)).

Assimilation-contrast theory reflected on price research adds dynamic aspect to reference prices, that is, the impact of new price stimuli on customers' current internal reference price (Sherif and Hovland 1961). Customers perceive a range of prices to be acceptable, in other words, the internal reference price is a price surrounded by an acceptable price region.[15]

[15] See, for example, Kalyanaram and Little (1994) for empirical evidence of a range of price insensitivity around a reference price.

Depending on the distance between the new price stimulus and the internal reference price, customers update their internal reference price. New price stimuli are, for example, a new price for the same item or price information from the environment. These new price stimuli are referred to as external reference prices.[16] If the external reference price falls within the acceptable price region very close to the internal reference price, the customer integrates the new external reference price which does not change the internal reference price. An external reference price that falls within the acceptable region, but further away from the internal reference price, moves the internal reference price toward the external reference price, in other words, it updates the internal reference price. External reference prices outside the acceptable region are not credible and do not move the internal reference price. Customers contrast these external reference prices, such that they perceive them as being even further away from the internal reference price (Compeau and Grewal 1998).

In summary, external reference prices and the actual selling price influence the internal reference price in its respective direction. An external reference price above the internal reference price, above the actual selling price, and within the acceptable region, increases the internal reference price. The comparison between external reference price, actual selling price, and internal reference price forms the perceived value of the individual offer. The higher the actual selling price compared to the internal reference price, the lower the perceived value, while a higher internal reference price increases the perceived value (Grewal et al. 1998). Perceived value, in turn, has a positive impact on purchase and a negative impact on search intentions: the more valuable the offer, the lower the intention to search for more information on competitive offers and the higher the probability of buying (Grewal et al. 1998). This relationship incentivizes the retailer to set external reference prices in the direct environment of the actual selling price to positively influence customers' internal reference price region and consequently to decrease their intentions to search and increase their willingness to buy. Such external reference prices provided by the retailer at the point of purchase in a product-specific manner are known as advertised reference prices (Mazumdar et al. 2005). Within reference price research, our focus is on advertised reference prices.

[16] Mayhew and Winer (1992) add empirical evidence that internal and external reference prices are distinct constructs.

3.2.3 Empirical Research on Advertised Reference Prices

An extensive stream of existing empirical literature deals with advertised reference prices, i.e., prices provided by the seller at the point of purchase as a point of comparison for the actual selling price (Mazumdar et al. 2005). In addition, the literature on price promotions discusses advertised reference prices as part of a promotional framing. We consult the promotion literature with respect to the impact of constantly displaying advertised reference prices. In the following, we lay out the key empirical findings in the area of advertised reference prices.

Based on the theories that we outlined above, advertised reference prices serve as an instrument for retailers to increase the internal reference price, in order that the customer perceives the offer as a gain. Existing research from the field of reference prices agrees upon the positive impact of advertised reference prices on internal reference prices. The perceived value of the offer increases, such that the customer's willingness to continue searching decreases (Della Bitta et al. 1981; Urbany et al. 1988) and willingness to buy increases (Urbany et al. 1988; Compeau and Grewal 1998). Multiple laboratory studies show this positive impact of an advertised reference price on the internal reference price and consequently the price and purchase evaluation (e.g., Biswas and Blair 1991; Compeau and Grewal 1998; Grewal et al. 1998). Compeau and Grewal (1998) offer an integrative meta-analysis of 38 empirical studies on comparative price advertising. The authors find that advertised reference prices have a positive impact on internal reference price and value perception, and a negative impact on search intentions.

Resulting from this strong positive impact of advertised reference prices, research on deceptive advertised reference prices gained interest. Exaggerated advertised reference prices give the customer the impression of saving money, while the actual savings depend on whether or not the advertised reference price is valid (Compeau and Grewal 1998). Research suggests that even exaggerated advertised reference prices facilitate purchase (Urbany et al. 1988; Biswas and Blair 1991). The meta-analysis by Compeau and Grewal (1998, p. 263) concludes that even exaggerated advertised reference prices strongly influence consumers, meaning that they have a high "potential for deception". Research on the sticker-shock effect concentrates on the distance between reference price and actual selling price and focuses on brand choice as dependent variable. The sticker-shock effect was introduced by Winer (1986) and captures the difference between reference price and actual selling price and expects a positive impact on utility of a positive difference and a negative impact on utility of a negative difference between reference price (both internal and external) and actual selling price (Mazumdar et al. 2005).

Mazumdar et al. (2005) provide an overview on research on the sticker shock effect and conclude that the symmetric sticker shock effect on brand choice is empirically generalizable.

In sum, reference price research agrees on the positive impact of advertised reference prices, with even exaggerated advertised reference prices having a positive impact on consumers' purchase evaluations.

However, customers update their internal reference price using temporal and situational stimuli, including advertised reference prices, current selling price, prior prices, and other stimuli in the shopping environment. Hence, the informational value of the advertised reference price might change over time. Several empirical studies using longitudinal data investigate the long-term impact on customers' shopping behavior. Kalwani and Yim (1992) report that promotional frequency and depth negatively affect customers' price estimates. Customers form promotion expectations, such that they buy frequently promoted brands only when promoted, i.e., if the expected promotions are not in place, this will have adverse effects (Kalwani and Yim 1992). Alba et al.'s (1994) experiment on promotional depth and frequency shows that subjects assign a lower basket price to stores with frequent, shallow discounts compared to stores with high but infrequent discounts. Alba et al. (1999) support the notion that different promotional strategies regarding the depth and frequency of discounts results in diverging price evaluations. In sum, following Compeau and Grewal (1998) for items repeatedly being on sale, customers get used to the lower actual selling price compared to the higher advertised reference price which drives the internal reference price toward the lower selling price, thereby decreasing the impact of the advertised reference price on the purchase decision. Thus, in this context there is empirical evidence supporting the notion that frequent price reductions lead to reduced internal reference prices, which in turn results in less beneficial evaluations of the actual selling price. Furthermore, if customers get used to the lower actual selling price, while the importance of the advertised reference price decreases, this might hint at a moderation of the actual selling price by the advertised reference price.

In sum, on the one hand, research suggests a positive impact of advertised reference prices on purchase. On the other hand, highly frequent promotions lose their impact on purchase. Thus, based on empirical findings, advertised reference prices are expected to raise internal reference prices and thereby positively influence purchase decisions, even if the advertised reference prices are inflated. Repeatedly or continuously displaying advertised reference prices, however, might decrease the credibility of advertised reference prices and, thereby, diminish their impact on internal reference prices and consequently on purchase. Moreover, vice versa, the role of the actual selling price might be strengthened, if the advertised reference price loses relevance due to lower credibility. To the best of our knowledge, this relation has not yet been analyzed empirically.

3.2.4 Theoretical Differences Between Online and Offline Shopping

In the following, we outline theoretical work on the differences between online and offline shopping with respect to prices.

Early theoretical studies on the development of electronic marketplaces anticipated drastically reduced search costs for customers, to the point that markets are (nearly) perfect, which again would lead to lower prices (Bakos 1997). In theory, lower search costs increase price competition because consumers have higher incentive to search for lower prices (Johnson et al. 2004). In perfect markets the role of advertised reference prices would diminish as customers would have full information. In practice, no perfect market has yet emerged online. However, the Internet facilitates search since comparison shopping websites provide price information for a specific product across stores at a click. In traditional offline settings, consumers can only acquire comparable price knowledge by travelling from one store to another, which is costly. Hence, the information conveyed by advertised reference prices might be substituted, e.g., by price search engines.

Thaler (1985) offers another theoretical perspective for why price expectations and purchase behavior might differ online when compared to traditional offline settings. Following Thaler (1985), consumers evaluate prices depending on the context. In his experiment, customers were willing to pay more for the same product when they purchased it in a fancy hotel rather than in a small grocery store. Transferring this idea, the different environment online allows different price evaluations. Adding to this notion, consumers might link online retailing to lower costs (e.g., lower overhead costs, underestimated shipping and handling costs) and larger supply (because of the number of potential retailers online). This may further lead consumers to believe that prices online should be lower (Hardesty and Suter 2005). This easier information access and lower price expectations may affect the performance of advertised reference prices via two avenues. First, the ease of access to prices other than the advertised reference price might reduce its impact. Second, for the same advertised reference price displayed online and offline, for example, a manufacturer-suggested retail price, the distance between the advertised reference price and the internal reference price differs between online and offline if internal reference prices, namely, price expectations, are lower online than offline. Following assimilation-contrast theory, customers contrast external reference prices outside the acceptable price range such that they perceive them as being even further away from the internal reference price and eventually do not move the internal reference price. Hence, the further away the advertised reference price from the internal reference price, the higher the probability of contrast which diminishes the impact of the advertised reference price (Hardesty and Suter 2005). In sum, these theoretical considerations suggest that customer might perceive advertised reference prices online differently than offline, which would be reflected in the performance of advertised reference prices.

3.2.5 Empirical Research on Online Reference Prices

Based on the theoretical considerations that we describe above, internal reference prices, meaning price expectations (not necessarily actual prices), and the importance of advertised reference prices might be lower online. We first report existing empirical research on online price expectations. Afterwards, we summarize empirical findings on online advertised reference prices.

Several studies provide empirical support for lower price expectations online.[17] However, here we focus on price expectations rather than actual selling prices. Hardesty and Suter (2005) administered a controlled experiment. They report that customers have lower price expectations (internal reference price) online than offline. Johnson et al. (2004) focus on the relationship between information access and search effort. The authors analyze whether reduced search costs online increase information search. Despite lower search costs, customers exert limited search effort. Nevertheless, the review of online pricing by Ratchford (2009) concludes that although no perfect competition emerged, improved access to information characterizes the online environment. Hence, the empirical evidence suggests lower price expectations online and an improved access to information, which is not necessarily leveraged by consumers.

[17] We focus on price expectations, which are different from actual selling prices. With respect to actual selling prices, following Granados et al. (2012) empirical evidence on whether the actual selling prices are lower online than offline is mixed. Research by Brynjolfsson and Smith (2000) analyzing books and CDs, by Brown and Goolsbee (2002) for life insurance products, by Brynjolfsson et al. (2003) focusing again on books, and by Zettelmeyer et al. (2006) for automobile retailing provide evidence for lower prices online. Other predominantly older studies find higher prices online: Bailey (1998) for books, software, and CDs and Lal and Sarvary (1999) offer an analytical model which describes conditions under which higher prices emerge.

So far, lower price expectations and improved access to information theoretically suggest a diminished role of advertised reference prices online. However, dedicated empirical studies are scarce. To the best of our knowledge, only two existing studies explicitly address the role of advertised reference prices in online settings. Jensen et al. (2003) focus on the impact on price perceptions and search intentions of the inclusion of an advertised reference price online versus offline.[18] They conducted three empirical studies: a classroom survey (sample of 137 students), an Internet survey (sample of 344 subjects), and a mail panel survey (household research sample of 243 subjects). Across the studies, price expectations were lower online than offline. Additionally, all three studies surprisingly revealed lower price search intentions online than offline. The three studies led to partly diverging results regarding the impact of advertised reference prices by channel. In the classroom survey, the effect of the advertised reference price in the Internet ad on price perceptions was positive but less positive than in offline settings. In the Internet survey with a larger sample size, this interaction effect was replicated, while the main effect of the advertised reference price was insignificant. In the mail panel survey, the impact of the advertised reference price was not significantly moderated by channel, but the main effect was significant.

Lii and Lee (2005) compare the performance of plausible and implausible advertised reference prices online and offline with respect to internal reference price, price-search intention, and perceived value.[19] They conducted a laboratory experiment with 142 students. Subjects had a lower latitude of acceptable price limits (lower prices) and a smaller width of this acceptable price range in the online channel than in offline retail channels. In contrast to Jensen et al. (2003), the authors show that customers have a higher internal reference price when exposed to an advertised reference price in the online channel than when exposed to an advertised reference price offline. They also show that consumers have lower price-search intention and report higher perceived value of the offer when exposed to an advertised reference price in the online channel than when exposed to an advertised reference price offline. Hence, Lii and Lee (2005) report that in the online channel, advertised reference prices lead to higher internal reference prices, lower search intentions and higher perceived value than offline. Further, implausible advertised reference prices increase internal reference prices, decrease price-search

[18] The authors do not include purchase intention in their studies.

[19] The authors do not include purchase intention in their study.

intentions, and increase perceived value compared to a plausible advertised reference price in both channels.

While these studies agree upon lower price expectations online, they offer diverging insights into advertised reference prices. Jensen et al. (2003) conclude that the role of advertised reference prices is stronger offline than online, while Lii and Lee (2005) provide evidence for the opposite.

Hence, the existing research offers evidence for lower price expectations online, while evidence on the role of advertised reference prices is scarce and mixed. Existing findings are limited to the extent that both empirical studies rely on laboratory experiments or surveys with limited sample size.

3.3 Conceptual Framework

The review of the literature reveals five avenues along which we aim to enhance the academic discourse on advertised reference prices.

First, the literature review exhibits contradictory findings in different research streams, which are relevant in terms of the impact of advertised reference prices on sales. While research on reference prices supports the positive impact of displaying an advertised reference price on purchase evaluation, research on promotions suggests that with increasing frequency of price reductions their impact on sales diminishes (Compeau and Grewal 1998; Ailawadi et al. 2006). This study aims to address this contradiction by analyzing the continuous display of the manufacturer-suggested retail price next to the actual selling price on sales, i.e., the situation of a constant promotional framing.

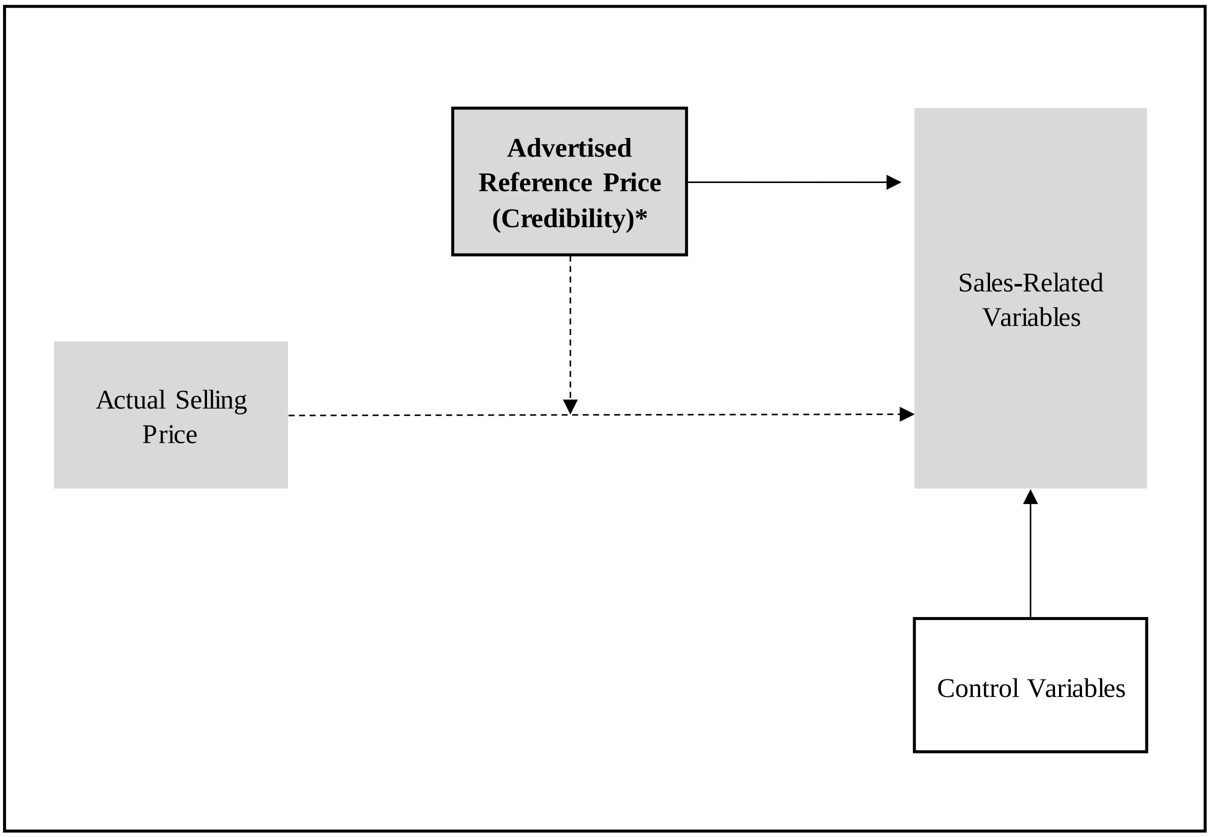
Second, naturally, the existing literature has analyzed the performance of advertised reference prices against the specific background of that time, namely, in offline settings. At the same time, theory suggests that online the premises for advertised reference prices have changed as a result of facilitated information access. To the best of our knowledge, to date only two studies have tried to capture the performance of advertised reference prices online based on laboratory experiments and surveys, and they offer mixed findings (Jensen et al. 2003; Lii and Lee 2005). Thus, this study aims to add to the limited research and it focuses on advertised reference prices in online settings by analyzing data from a field experiment and transaction data from real purchases online.

Third, existing research reports a positive impact on the purchase intentions of inflated and implausible advertised reference prices, meaning that in offline settings even inflated advertised reference prices impact customers' purchase decisions positively (Urbany et al. 1988; Biswas and Blair 1991; Compeau and Grewal 1998). The online environment, however, enables customers to access information and compare prices more easily to detect whether an advertised reference price is credible. This improved access to information, in combination with public media increasing skepticism about advertised reference prices, could potentially influence the impact of the credibility of advertised reference prices on sales online. Consequently, we explore whether the credibility of advertised reference prices, operationalized as the quotient of manufacturer-suggested retail price and regular price, has an impact on sales and which functional form the relation might follow. In this context, the functional form is substantial. A positive linear relation would imply that with increasing distance between manufacturer-suggested retail prices and regular prices, the positive impact on sales increases, meaning that even manufacturer-suggested retail prices with potentially low credibility increase sales. In contrast, a quadratic relation could imply that with increasing distance between manufacturer-suggested retail prices and regular prices the impact on sales is positive only up to a certain point, and afterwards decreasing credibility further has a negative impact on sales (inverted u-shape). Existing research on the credibility of online advertised reference prices is based on one laboratory study, which finds that implausible advertised reference prices increase perceived value (Lii and Lee 2005). Thus, in order to gain more insights into the impact of credibility on sales online, we focus on the functional form of this relation based on a large transactional data set.

Fourth, to the best of our knowledge, existing research has not yet assessed the moderation of price elasticities by the credibility of advertised reference prices, although this might mirror the impact of credibility, as outlined above. If with decreasing credibility the relevance of the advertised reference price diminishes, the actual selling price might gain importance, since the advertised reference price is no longer perceived as a credible signal. Thus, in order to shed light on the interplay between the actual selling price and the credibility of the advertised reference price, we explore whether the credibility of the advertised reference price moderates the actual selling price.

Finally, in order to assess the relevance of credible advertised reference prices for corporate objectives, we assess the profit impact of price changes in different scenarios. To the best of our knowledge, these questions concerning profit have not yet been in focus of existing research.

In sum, this study aims to shed light on the impact of advertised reference prices in purchase situations online by following the four avenues outlined above. Figure 3.1 depicts the focal relations. We initially address the first and second avenue by analyzing the main effect of displaying an advertised reference price on sales in an online setting based on two experimental studies. We further follow the third avenue and explore the role of the credibility of such advertised reference prices with regards to sales based on a fixed-effects model and transactional data. Finally, with the same model, we assess the fourth avenue, i.e., whether customers rely more strongly on the actual selling price if the credibility of the manufacturer-suggested retail price is low, i.e., whether the advertised reference price moderates the price elasticity (dashed lines in Figure 3.1), and we assess the profit impact of credibility for the retailer.



*Note: Study three focuses on the credibility of advertised reference prices operationalized as the quotient of manufacturer-suggested retail price and regular price.

Figure 3.1: Conceptual Framework

3.4 Study 1: Online Experiment

3.4.1 Data Collection and Description

We administer a 2 x 2 between-subjects factorial design in an online experiment. The structure of the experiment closely resembles an online purchase process. Subjects initially read a short, neutral newsletter article about online shopping to set the scene. They are randomly assigned either to a fictitious online shop or to a well-known retailer, in order to rule out familiarity with the store as a confounding variable. The respondents see a typical representation of a product with product features and price and then evaluate their purchase intention. This is repeated for a second product type. Randomly, either both or none of the products shows an advertised reference price. The advertised reference price does not include any further information regarding its type, namely, whether it is a past price, competitor's price, or manufacturer-suggested retail price. Finally, we measure purchase intention on a seven-point Likert scale following Sweeney et al. (1999). We sent the online invitation to take part in this survey via e-mail to university members in June 2017.[20] Within one week 346 respondents took part in the online experiment of which 276 passed the manipulation checks.[21] As each respondent evaluates two products, we generate 552 observations. Overall, 81 percent of respondents are female at mean age of 27 years. Typical of a university sample, a high share of respondents has a higher education with 44 percent of respondents having a university degree and being on relatively low income; 75 percent of the respondents report a net income below € 2,000.

3.4.2 Model

We analyze the effects of displaying an advertised reference price on the purchase intention of respondent i using a linear regression as displayed in equation 1. *ARP* is a dichotomous variable indicating whether an advertised reference price was in place (= 1). *Shop* indicates whether the subject is shopping at a fictitious (= 1) or a real online retailer. *Product* differentiates between a high-priced (printer cartridge = 1) and a relatively low-priced (washing detergent) product type, both of which each respondent evaluates. We estimate the model using a Bayesian approach and rely on a Hamiltonian Monte Carlo sampler implemented in Stan (Stan Development Team 2017).

[20] The full survey generated 628 responses. For this research, we exclude data from 282 subjects: a manipulation of the credibility of online prices based on a newspaper article is excluded, such that only those respondents in a credible setting are used for this study.

[21] Manipulation checks tested whether the respondent could remember if an advertised reference price was displayed or not.

$$\text{Purchase Intention}_i = \alpha + \beta_1 * \text{ARP}_i + \beta_2 * \text{Shop}_i + \beta_3 * \text{Product} + \epsilon_i \quad (3.1)$$

3.4.3 Empirical Results

We set generic, weakly informative priors normally distributed at location zero and scale ten. We analyze the model using Bayesian estimation with No-U-Turn sampling (Stan Development Team, 2017). We estimate four chains and base the posterior results on a total of 32,000 draws, of which we use the first 16,000 for warm-up. All chains are well converged and mixed with a potential scale reduction factor ($\hat{R}$) of 1.00 (Gelman et al. 2013).

Coefficient	Posterior Mean	
Intercept	**2.73**	(2.38; 2.88)
ARP	**0.40**	(0.14; 0.65)
Shop	-0.14	(-0.39; 0.12)
Product	**1.03**	(0.78; 1.28)

n=552
Note: Posterior mean followed by average 2.5 and 97.5 percentiles of posterior interval in parentheses. For posterior means printed in bold, zero is not included on the 95-posterior interval

Table 3.1: Results Online Experiment

The results indicate a positive impact of displaying an advertised reference price on purchase intention (see Table 3.1). Purchase intention varies by product type with a higher purchase intention for the more expensive product. The framing of the shop, whether or not respondents are familiar with it did not significantly impact their purchase intention.

In this laboratory setting, when evaluating their purchase intention, we did not actively provide any additional information on, for example, competitive prices. The displayed advertised reference price functions as the only stimulus to influence the customer-specific internal reference price, while the respondent still has the chance to search for more information online. Study one supports previous research in that advertised reference prices have a positive impact on purchase intentions, at least in these laboratory settings.

3.5 Study 2: Field Experiment

3.5.1 Data Collection and Description

We administer a field experiment at an online retailer without any physical stores in a major European market. The total observation period covers 30 weeks from October 2017 to April 2018. We select six brands from six categories with two products each. Within each brand one of the products serves as the control product, while the other product is manipulated (experimental product). The default setting for these products is the display of a manufacturer-suggested retail price next to the actual sales prices. Thus, the online shop usually presents all 12 products in conjunction with an advertised reference price. The treatment in the experimental group is therefore the elimination and later re-introduction of the manufacturer-suggested retail price. Consequently, we split the observation period into three phases: a pre-phase, the manipulation phase, and a post-phase. The pre-phase represents no change to usual behavior, in other words, for a period of 11 weeks we monitor sales with advertised reference prices being displayed for both experimental and control products. In the subsequent manipulation period, we remove the advertised reference prices from the experimental products for 12 weeks. Finally, we re-introduce the advertised reference price for the experimental products for the subsequent seven weeks. In the observation period, these products totaled 165,000 visits and 10,000 orders (see Table 3.2 for descriptive statistics). We assess the data with respect to three dependent variables: weekly product visits, cart additions and sales in six categories for which Table 3.2 shows rather high variation. The products are groceries and accessories with high stockpiling propensity. We include five branded and one private label (PL) brand.

Brand i	**Type**	**Product j**	**Average Weekly Price**		**Average Weekly Visits**		**Average Weekly Cart Additions**		**Average Weekly Orders**	
			mean	sd	mean	sd	mean	sd	mean	sd
1	Groceries	Control	5.29	0.96	255	50	96	18	76	15
		Experimental	5.29	0.96	305	70	115	19	82	14
2	Groceries	Control	10.99	0.00	266	44	103	27	21	5
		Experimental	10.99	0.00	236	41	78	27	17	4
3	Accessories	Control	20.28	0.90	111	32	9	3	2	1
		Experimental	25.06	0.37	338	92	56	19	13	4
4	Groceries	Control	30.39	1.04	187	29	35	9	13	5
		Experimental	27.29	1.21	286	65	56	16	23	9
5	Groceries	Control	14.99	0.00	47	11	11	5	8	4
		Experimental	9.59	0.00	39	12	14	6	13	5
PL	Accessories	Control	53.61	3.53	2706	795	323	113	87	38
		Experimental	75.77	8.26	853	325	62	31	16	9

Table 3.2: Descriptive Statistics – Field Experiment

3.5.2 Model

We use a difference-in-difference approach to analyze the effects of a temporary advertised reference price elimination on visits, cart additions, and sales. We estimate the data on all available six brands within one model as displayed in equation 3.2. To control for brand-specific variation, products in both the experimental and the control groups belong to the same brand in the same category. *Treatment* is a dummy variable indicating whether product j belongs to the experimental (= 1) or the control group within one brand. *Time* indicates whether week t is in the manipulation period (= 1). The interaction of treatment and time equals 1 for an experimental product in the manipulation phase, zero otherwise. We include the logarithm of the actual selling price of product j in week t to control for price differences across products and *price* as price per weight unit to control for different package sizes.

$$\log(Y_{jt}) = \alpha_i + \beta_1 * \text{treatment}_j + \beta_2 * \text{time}_t + \beta_{3i} * \text{treatment} * \text{time}_{jt} + \beta_4 * \log(\text{price})_{jt} + \epsilon_{jt} \quad (3.2)$$

We utilize the model structure and account for brand heterogeneity in the following ways: First, we include random brand-specific intercepts α_i. Second, to account for heterogeneous customer responses across brands to the elimination of the advertised reference price, we estimate the interaction of treatment and time in a brand-specific manner. The coefficient β_{3i} is a vector with i brand-specific coefficients.

3.5.3 Empirical Results

We set generic, weakly informative priors normally distributed at mean zero and scale ten.[22] Hierarchical estimation requires hyperpriors, which are priors on priors (Stan Development Team 2018). The hyperpriors for α_i and β_{3i} for scale follow a half-cauchy distribution, with the prior mean fixed at zero.[23] We analyze the model using Bayesian estimation with No-U-Turn sampling (Stan Development Team, 2017). We estimate four chains and base the posterior results on a total of 32,000 draws, of which we use the first 16,000 for warm-up. All chains are well converged and mixed with a potential scale reduction factor ($\hat{R}$) of 1.00 (Gelman et al. 2013).

Table 3.3 displays the results of the Bayesian difference-in-difference estimation. Negative coefficients for the interaction of time and treatment indicate that not displaying an advertised reference price decreases visits, cart additions, and quantity sold. Within brands and across dependent variables, the direction of impact is consistent. Thus, if the elimination of advertised reference price for brand i decreases (increases) visits, this will translate to a decrease (increase) in cart additions as well as in quantity sold (with one exception, i.e., brand 5). However, the analysis does not reveal a consistent significant impact of the elimination of advertised

[22] $\beta_1 \sim \text{normal}(0, 10)$, $\beta_2 \sim \text{normal}(0, 10)$, $\beta_4 \sim \text{normal}(0, 10)$

[23] $\alpha_i \sim \text{normal}(0, \text{Scale})$, $\beta_{3i} \sim \text{normal}(0, \text{Scale})$, $\text{Scale} \sim \text{cauchy}(0, 5)$; with “Scale” bounded at 0

reference prices across brands. For two out of six brands, the coefficients are significant in the posterior interval with opposing signs. For the remaining brands, posterior intervals include zero. We find structural differences between the type of category, i.e., grocery and accessories. For the grocery categories, posterior means are mostly negative (insignificant), while they are rather positive for accessories (again brand 5 with small number of sales is an exception). We do not find structural differences between the branded categories and the private label products.

	log(Visits)	**log(Cart Additions)**	**log (Quantity sold)**
Coefficient	Posterior mean	Posterior mean	Posterior mean
Treat.*Time Brand 1	-0.12 (-0.32; 0.09)	-0.14 (-0.46; 0.18)	-0.08 (-0.43; 0.27)
Treat.*Time Brand 2	-0.18 (-0.39; 0.02)	**-0.44** (-0.79; -0.11)	**-0.38** (-0.76; -0.03)
Treat.*Time Brand 3	**0.39** (0.17; 0.61)	**0.61** (0.25; 0.97)	**0.52** (0.14; 0.92)
Treat.*Time Brand 4	-0.01 (-0.22; 0.2)	-0.14 (-0.47; 0.18)	-0.22 (-0.59; 0.13)
Treat.*Time Brand 5	-0.06 (-0.27; 0.15)	0.06 (-0.27; 0.39)	0.16 (-0.18; 0.52)
Treat.*Time PL	**0.46** (0.21; 0.71)	0.18 (-0.18; 0.55)	0.24 (-0.15; 0.64)
Time	-0.03 (-0.12; 0.06)	0.04 (-0.11; 0.18)	-0.06 (-0.21; 0.09)
Treatment	**0.26** (0.17; 0.35)	**0.46** (0.32; 0.6)	**0.47** (0.32; 0.62)
log Price per Unit	**-2.09** (-2.35; -1.83)	**-2.66** (-3.06; -2.26)	**-3.37** (-3.81; -2.94)
Intercept Brand 1	**8.02** (7.71; 8.33)	**7.61** (7.12; 8.1)	**8.92** (8.39; 9.45)
Intercept Brand 2	**4.91** (4.79; 5.03)	**3.64** (3.44; 3.84)	**4.65** (4.43; 4.87)
Intercept Brand 3	**10.31** (9.68; 10.95)	**9.42** (8.43; 10.41)	**10.59** (9.5; 11.66)
Intercept Brand 4	**6.64** (6.46; 6.82)	**5.23** (4.94; 5.51)	**7.52** (7.21; 7.83)
Intercept Brand 5	**5.93** (5.65; 6.21)	**5.06** (4.61; 5.5)	**7.22** (6.73; 7.7)
Intercept PL	**13.15** (12.44; 13.87)	**12.36** (11.23; 13.48)	**14.30** (13.07; 15.52)

Note: Posterior mean followed by average 2.5 and 97.5 percentiles of posterior interval in parentheses. For posterior means printed in bold zero is not included on the 95-posterior interval

Table 3.3: Results Difference-in-Difference Estimation

All brand intercepts are significant controlling for heterogeneity across brands. The inclusion of the log price per weight unit reveals that a price reduction increases visits, cart additions and quantity sold. The posterior mean of -3.27 for the price elasticity with log quantity sold as dependent variable is strong but still in line with expected price elasticities in retailing (Bijmolt et al. 2005).

3.5.4 Robustness of Results

Equation 3.2 does not differentiate between the pre- and post-phase, as in both periods we show the advertised reference prices. However, in an environment with constantly displayed advertised reference price, re-introduction in the third phase might differ from the first phase.

Hence, in a second model we differentiate between the three experimental phases to obtain insights into the re-introduction of the advertised reference price. We again estimate all six categories within one model. The *treatment* variable captures whether product j belongs to the experimental group (= 1). We then split time into two separate variables: *time elimination* is an indicator variable with value 1 if week t is in the manipulation period, that is, the period in which we eliminate the advertised reference price. The second time variable, *time re-introduction*, is an indicator variable assigning 1 to the last phase, namely, the re-introduction of the advertised reference price. We interact the treatment variable separately with these two time variables, namely, time elimination respectively time re-introduction. To account for heterogeneous customer responses across brands to advertised reference price elimination and re-introduction, we estimate the interaction in a brand-specific manner, such that the coefficients β_{3i} and β_{5i} are vectors of length i. Again, we include the actual selling price of product j in week t as well as random brand-specific intercepts α_i.

$$\log(Y_{jt}) = \alpha_i + \beta_1 * \text{treatment}_j + \beta_2 * \text{time elimination}_t + \beta_{3i} * \text{ treatment } * \text{ time elimination}_{jt} \\ + \beta_4 * \text{time reintroduction}_t + \beta_{5i} * \text{ treatment } * \text{ time reintroduction}_{jt} + \beta_5 * \log(\text{price})_{jt} + \epsilon_{jt} \tag{3.3}$$

We estimate the model using a Bayesian approach and rely on a Hamiltonian Monte Carlo sampler implemented in Stan (Stan Development Team 2017). We set generic, weakly informative priors normally distributed at location zero and scale ten. The results are reported in Table 3.4. Chains are well converged and mixed with a potential scale reduction factor ($\hat{R}$) of 1.00 (Gelman et al. 2013). Including a time structure of elimination and subsequent re-introduction of advertised reference price does not reveal a consistent impact on visits, cart additions, or quantity sold.

Coefficient	log(Visits) Posterior mean	log(Cart Additions) Posterior mean	log (Quantity sold) Posterior mean
Treat.*Time elim. brand 1	-0.12 (-0.31; 0.06)	-0.14 (-0.46;0.19)	-0.13 (-0.49;0.21)
Treat.*Time elim. brand 2	**-0.23** (-0.41; -0.05)	**-0.50** (-0.83;-0.17)	**-0.52** (-0.89;-0.15)
Treat.*Time elim. brand 3	**0.44** (0.25; 0.64)	**0.76** (0.42;1.12)	**0.55** (0.18;0.92)
Treat.*Time elim. brand 4	0.02 (-0.16; 0.21)	-0.10 (-0.43;0.22)	-0.27 (-0.64;0.08)
Treat.*Time elim. brand 5	-0.12 (-0.31;0.06)	0.11 (-0.22;0.44)	0.05 (-0.29;0.4)
Treat.*Time elim. brand PL	0.20 (-0.02;0.43)	-0.12 (-0.5;0.27)	-0.19 (-0.62;0.23)
Treat.*Time re-intro. brand 1	0.03 (-0.19; 0.26)	-0.05 (-0.45;0.35)	-0.21 (-0.67;0.25)
Treat.*Time re-intro. brand 2	**-0.29** (-0.52; -0.06)	-0.37 (-0.78;0.03)	**-0.66** (-1.13;-0.2)
Treat.*Time re-intro. brand 3	0.19 (-0.04; 0.42)	**0.53** (0.11;0.95)	0.03 (-0.45;0.48)
Treat.*Time re-intro. brand 4	0.18 (-0.05; 0.41)	0.14 (-0.28;0.54)	-0.22 (-0.69;0.24)
Treat.*Time re-intro. brand 5	-0.13 (-0.36; 0.1)	**0.60** (0.2; 1)	-0.20 (-0.66; 0.25)
Treat.*Time re-intro. brand PL	**-0.72** (-0.99; -0.46)	**-0.98** (-1.43; -0.53)	**-1.45** (-1.99; -0.9)
Time elimination	**-0.14** (-0.22; -0.05)	-0.01 (-0.16; 0.14)	0.02 (-0.14; 0.19)
Time re-introduction	**-0.27** (-0.37; -0.17)	-0.13 (-0.3; 0.05)	**0.29** (0.08; 0.5)
Treatment	**0.27** (0.19; 0.36)	**0.43** (0.27; 0.58)	**0.56** (0.39; 0.74)
log Price per Unit	**-1.78** (-2.02; -1.54)	**-2.29** (-2.72; -1.86)	**-2.92** (-3.39; -2.45)
Intercept Brand 1	**7.75** (7.46; 8.05)	**7.23** (6.71; 7.75)	**8.26** (7.68; 8.85)
Intercept Brand 2	**5.13** (5.01; 5.24)	**3.85** (3.64; 4.06)	**4.72** (4.49; 4.95)
Intercept Brand 3	**9.59** (8.99; 10.2)	**8.45** (7.36; 9.53)	**9.30** (8.11; 10.48)
Intercept Brand 4	**6.52** (6.34; 6.7)	**5.03** (4.71; 5.34)	**7.12** (6.76; 7.47)
Intercept Brand 5	**5.72** (5.45; 5.98)	**4.63** (4.15; 5.1)	**6.61** (6.08; 7.14)
Intercept PL	**12.49** (11.83; 13.16)	**11.51** (10.34; 12.69)	**13.08** (11.78; 14.38)

Note: Posterior mean followed by average 2.5 and 97.5 percentiles of posterior interval in parentheses. For posterior means printed in bold zero is not included on the 95-posterior interval

Table 3.4: Results Difference-in-Difference with Pre- and Post-Phase Estimation

We further test whether the inclusion of a random intercept per week (α_{2t}) changes the results (equation 3.4). We estimate the model as before using a Bayesian approach and rely on a Hamiltonian Monte Carlo sampler implemented in Stan (Stan Development Team 2017). All chains are well converged with a potential scale reduction factor ($\hat{R}$) of (close to) 1.00. Table 3.5 shows that the coefficients of the interactions do not diverge from results displayed in Table 3.3, while price elasticity gets slightly stronger. The inclusion of a weekly intercept does not reveal any structural changes in the impact of advertised reference prices on visits, cart additions, or quantity sold when compared to previous results displayed in in Table 3.3.

$$\log\left(Y_{jt}\right) = \alpha_{1i} + \alpha_{2t} + \beta_1 * \text{treatment}_j + \beta_2 * \text{time}_t + \beta_{3i} * \text{treatment} * \text{time}_{jt} + \beta_4 * \log(\text{price})_{jt} + \epsilon_{jt} \tag{3.4}$$

Coefficient	**log(Visits)** Posterior mean	**log(Cart Additions)** Posterior mean	**log (Quantity sold)** Posterior mean
Treat.*Time Brand 1	-0.13 (-0.31; 0.05)	-0.14 (-0.45; 0.16)	-0.07 (-0.41; 0.27)
Treat.*Time Brand 2	**-0.19** (-0.37; -0.01)	**-0.44** (-0.76; -0.13)	**-0.37** (-0.75; -0.02)
Treat.*Time Brand 3	**0.41** (0.22; 0.6)	**0.63** (0.31; 0.96)	**0.54** (0.16; 0.93)
Treat.*Time Brand 4	-0.01 (-0.19; 0.17)	-0.13 (-0.44; 0.18)	-0.19 (-0.56; 0.15)
Treat.*Time Brand 5	-0.06 (-0.24; 0.12)	0.05 (-0.26; 0.35)	0.14 (-0.2; 0.5)
Treat.*Time PL	**0.47** (0.26; 0.68)	0.11 (-0.23; 0.45)	0.14 (-0.24; 0.53)
Time	2.01 (-0.24; 4.34)	1.78 (-0.2; 3.8)	2.09 (-0.3; 4.49)
Treatment	**0.27** (0.2; 0.34)	**0.44** (0.31; 0.57)	**0.44** (0.29; 0.59)
log Price per Unit	**-2.09** (-2.3; -1.88)	**-2.49** (-2.87; -2.12)	**-3.14** (-3.58; -2.69)
Intercept Brand 1	**5.99** (4.63; 7.28)	**5.70** (4.49; 6.93)	**6.50** (5.09; 7.93)
Intercept Brand 2	**2.87** (1.49; 4.18)	**1.96** (0.75; 3.15)	**2.57** (1.09; 3.97)
Intercept Brand 3	**8.26** (6.83; 9.62)	**7.29** (5.92; 8.72)	**7.85** (6.21; 9.54)
Intercept Brand 4	**4.61** (3.23; 5.89)	**3.40** (2.22; 4.58)	**5.22** (3.83; 6.61)
Intercept Brand 5	**3.90** (2.54; 5.18)	**3.16** (1.97; 4.37)	**4.82** (3.41; 6.25)
Intercept PL	**11.12** (9.66; 12.51)	**10.17** (8.73; 11.68)	**11.48** (9.74; 13.27)
Week 1	**2.21** (0.92; 3.58)	**1.82** (0.63; 3.02)	**2.00** (0.6; 3.48)
Week 2	**2.15** (0.85; 3.55)	**2.00** (0.81; 3.21)	**2.12** (0.71; 3.58)
Week 3	**2.16** (0.86; 3.54)	**1.94** (0.74; 3.14)	**1.95** (0.55; 3.41)
Week 4	**2.24** (0.94; 3.62)	**1.87** (0.67; 3.06)	**1.99** (0.56; 3.45)
Week 5	**2.17** (0.87; 3.55)	**1.90** (0.72; 3.11)	**2.12** (0.71; 3.57)
Week 6	**2.11** (0.82; 3.49)	**1.42** (0.22; 2.63)	**2.20** (0.79; 3.65)
Week 7	**2.14** (0.84; 3.53)	**1.87** (0.68; 3.06)	**2.12** (0.69; 3.58)
Week 8	**2.23** (0.93; 3.62)	0.99 (-0.2; 2.19)	**2.23** (0.82; 3.68)
Week 9	**2.11** (0.8; 3.49)	**1.78** (0.59; 2.98)	**2.15** (0.74; 3.6)
Week 10	**2.14** (0.84; 3.51)	**2.00** (0.82; 3.2)	**2.18** (0.75; 3.66)
Week 11	**2.14** (0.84; 3.53)	**2.01** (0.81; 3.22)	**2.38** (0.95; 3.85)
Week 12	-0.29 (-2.19; 1.62)	-0.22 (-1.84; 1.42)	-0.31 (-2.29; 1.67)
Week 13	-0.01 (-1.9; 1.92)	0.04 (-1.61; 1.69)	-0.15 (-2.11; 1.83)
Week 14	0.06 (-1.84; 1.97)	-0.19 (-1.82; 1.45)	0.01 (-1.97; 2)
Week 15	0.18 (-1.72; 2.09)	0.19 (-1.45; 1.82)	0.05 (-1.92; 2.02)
Week 16	0.15 (-1.75; 2.08)	0.11 (-1.51; 1.74)	0.13 (-1.86; 2.1)
Week 17	0.15 (-1.75; 2.07)	0.22 (-1.42; 1.86)	0.29 (-1.68; 2.26)
Week 18	0.05 (-1.85; 1.98)	0.02 (-1.63; 1.66)	-0.15 (-2.12; 1.84)
Week 19	-0.17 (-2.08; 1.75)	-0.21 (-1.84; 1.44)	-0.41 (-2.38; 1.56)
Week 20	0.00 (-1.91; 1.92)	0.08 (-1.56; 1.74)	0.21 (-1.74; 2.18)
Week 21	-0.05 (-1.95; 1.88)	-0.01 (-1.66; 1.62)	0.09 (-1.9; 2.08)
Week 22	-0.06 (-1.96; 1.85)	-0.24 (-1.88; 1.4)	-0.06 (-2.04; 1.92)
Week 23	-0.05 (-1.93; 1.88)	0.05 (-1.6; 1.69)	0.33 (-1.64; 2.31)
Week 24	**2.06** (0.75; 3.43)	**1.90** (0.71; 3.11)	**2.42** (1; 3.89)
Week 25	**2.01** (0.71; 3.4)	**1.76** (0.57; 2.97)	**2.29** (0.87; 3.76)
Week 26	**1.90** (0.6; 3.28)	**1.63** (0.44; 2.82)	**2.11** (0.68; 3.57)
Week 27	**1.79** (0.49; 3.17)	**1.63** (0.45; 2.83)	**2.00** (0.6; 3.47)
Week 28	**1.84** (0.55; 3.23)	**1.65** (0.47; 2.86)	**2.01** (0.6; 3.46)
Week 29	**1.54** (0.24; 2.92)	**1.57** (0.36; 2.77)	**2.14** (0.72; 3.6)
Week 30	**1.66** (0.37; 3.04)	**1.33** (0.14; 2.54)	**2.27** (0.85; 3.71)

Table 3.5: Results Difference-in-Difference with Week-Specific Intercept Estimation

Finally, we apply the method of synthetic group controls. The high variation in the dependent variables (see Table 3.2) may raise concerns regarding the suitability of the selected control product. The synthetic control groups address these concerns. Comparative case studies in social sciences have introduced the method of synthetic control groups (Abadie and Gardeazabal 2003). Instead of comparing the experimental group with one specific control group, the researchers build a synthetic control group from many potential control units (Abadie et al. 2010). We use the R-package "Synth" to construct the synthetic control group "based on a weighted combination of comparison units that approximates the characteristics of the unit that is exposed to the intervention" (Abadie et al. 2010). We use all other products available for sale in the same category as the experimental product. Figure 3.2 shows an example of a synthetic control group for one of our experimental products. The solid line represents sales of the experimental products, while the dashed line is the synthetic control group of 254 other products within the same category. The dotted vertical line shows the start of the manipulation phase. Across product categories, graphs remain inconclusive regarding the impact of the elimination of the advertised reference price (Figure 3.2) as well as the re-introduction of the advertised reference price (Figure 3.3, synthetic control group weighted combination of 287 products, dotted vertical line shows the re-introduction of advertised reference price). The graphs exhibit a high degree of variation in sales of the specific experimental products, which is not sufficiently reflected in the synthetic control groups. Consequently, the method of synthetic group controls is unsuitable for this analysis and therefore not further applied.

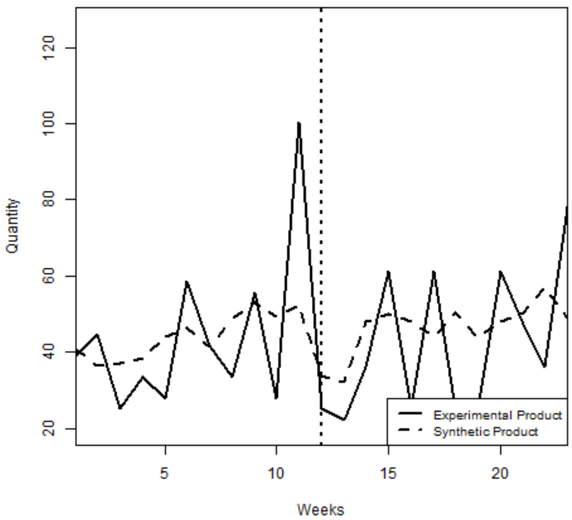


Figure 3.2: Example of Synthetic Control Group Pre-phase and Manipulation Phase

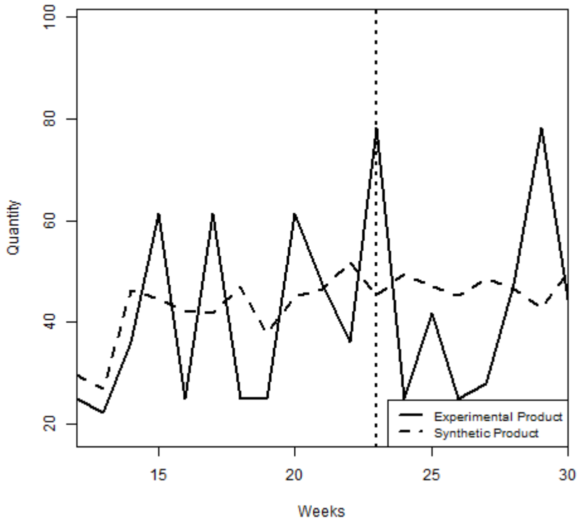


Figure 3.3: Example of Synthetic Control Group Manipulation Phase and Post-phase

In sum, study two does not support findings of study one. We do not find a consistent significant, negative impact of the elimination of advertised reference prices in this specific online shop on visits, cart additions, or sales. While we do not find consistency across brands, we do find mostly consistent results within brand. If the elimination of an advertised reference price decreases (increases) visits for one brand, this is reflected in a decrease (increase) in cart additions, as well as in quantity sold. The model is robust with respect to the time structure.

3.6 Study 3: Transaction Data

3.6.1 Data Collection and Description

In the third study, we analyze secondary transaction data from the same online retailer where we conduct the field experiment. We collect data on all the transactions on the German website in a five-year period from September 2012 until September 2017. We aggregate the transaction data to a weekly level to reduce intra-week variability. Of the entire sales data for this five-year period, for 35 percent of observations the retailer documents a manufacturer-suggested retail price. We reduce the data set accordingly. We restrict the remaining 915,921 observations to realistic cases, in which the retailer would display the manufacturer-suggested retail price. We define these cases as transactions, for which the actual selling price is smaller than the manufacturer-suggested retail price. For 99.4 percent of the remaining observations the manufacturer-suggested retail price is larger than the actual selling price. We remove articles that sold for less than 52 weeks within the five-year period, which reduces the data by a further 16 percent. We check for variation in prices over the weeks and eliminate 344 articles without variation in the actual selling price or the manufacturer-suggested retail price, reducing the data set by a further 4 percent. This still leaves us with an extensive data set of 732,903 observations covering seven categories with 58 subcategories, in total comprising 9.5 million units sold over the five-year period at a mean price of € 21 per article. Table 3.6 shows descriptive statistics per category. Standard deviations, as well as minima and maxima, exhibit a high degree of variety in the prices of articles within and across categories.

Category	**Subcategories**	**Unique articles**	**Articles sold**	**Price per article in €**		**MSRP**[24]	
				Average (SD)	Min Max	Average (SD)	Min/ Max
1	13	2,524	3,123,899	23.30 (24.52)	0.50/ 349.99	33.15 (35.23)	0.69/ 411.00
2	13	1,974	4,727,198	17.80 (23.57)	0.79/ 299.99	26.00 (36.00)	0.98/ 399.00
3	10	398	856,082	22.87 (39.99)	1.29/ 299.99	33.53 (58.77)	1.59/ 399.00
4	7	162	300,352	18.98 (37.52)	0.99/ 449.00	27.66 (54.37)	1.19/ 520.00
5	9	549	492,231	20.74 (27.85)	0.85/ 259.00	27.83 (37.77)	1.11/ 379.00
6	1	1	225	24.50 (2.93)	19.90/ 27.90	30.83 (0.22)	30.45/ 30.95
7	5	33	16,392	21.97 (10.39)	3.99/ 49.99	27.07 (13.55)	4.50/ 64.99
Total	58	5,641	9,516,379	20.97 (26.67)	0.50/ 449.00	29.98 (39.07)	0.69/ 520.00

Table 3.6: Descriptive Statistics – Transaction Data

3.6.2 Model

We analyze the impact of manufacturer-suggested retail prices on quantity sold based on weekly article data with a fixed-effects model. To control for article and week-specific variation, we include fixed effects α_{1j} for article j and α_{1t} for week t. We construct a quotient of manufacturer-suggested retail price per article j in week t divided by the regular price of article j in week t to capture the credibility of the manufacturer-suggested retail price. We call this quotient reference to regular ratio (R2R-ratio) (equation 5). We approximate the regular price, as denominator of the R2R-ratio, as the maximal price of the surrounding nine weeks, that is, four weeks prior to t and four weeks after t (equation 6). We choose the approximation of the regular price to exclude that temporary price reductions change the R2R-ratio. Figure

[24] MSRP = Manufacturer-suggested retail price

3.4 displays a histogram of the R2R-ratio. While the maximum R2R-ratio is at 6.61, most weekly R2R-ratios are below 3.

$$\text{R2R-ratio}_{jt} = \frac{\text{Manufacturer Suggested Retail Price}_{jt}}{\text{Regular Price}_{jt}} \tag{3.5}$$

$$\text{Regular Price}_{jt} = \max_{t-4}^{t+4}\left(\text{Actual Selling Price}_{jt}\right) \tag{3.6}$$

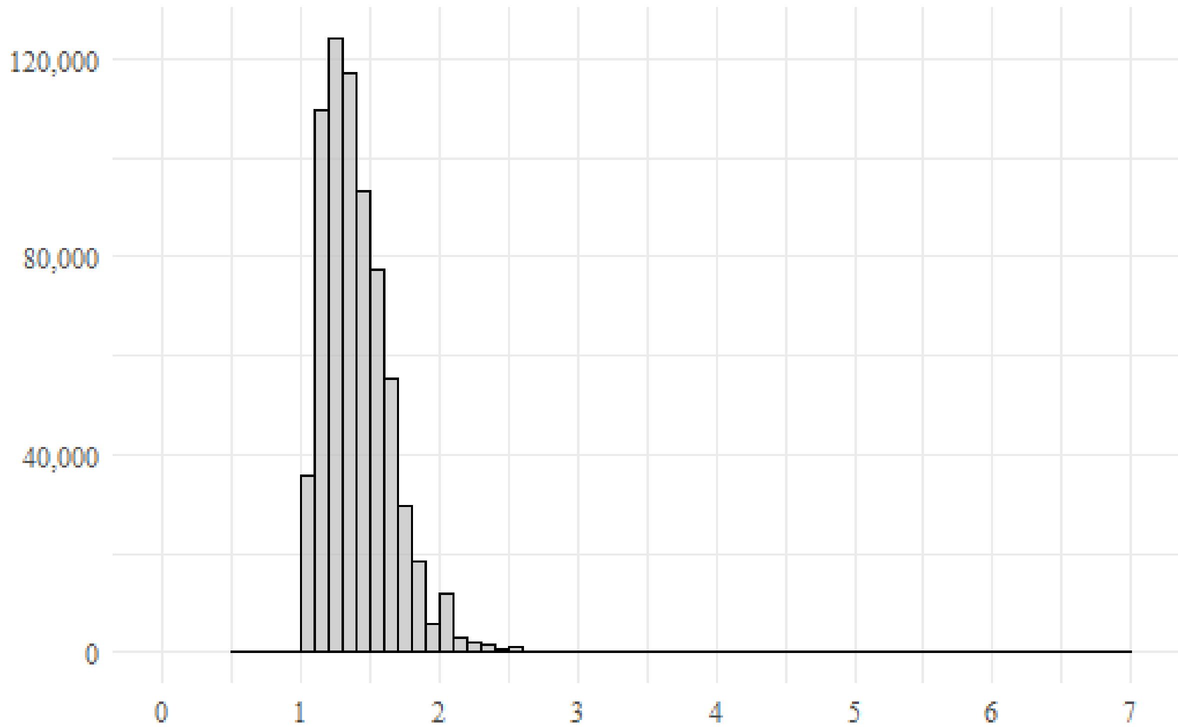


Figure 3.4: Histogram R2R-ratio

Assimilation-contrast theory suggests an inverted u-shape for the impact of advertised reference prices on purchase. Therefore, we include the main effect of the R2R-ratio (R2R), as well as the squared term of the R2R-ratio ($R2R^2$). We measure purchase as quantity sold in weight units per article and per week. For the dependent variable we take the logarithm of this quantity measure. Accordingly, price impact is measured in price per kg per article j in week t. To capture a potential moderation of the R2R-ratio the regression includes the interaction of the log price per kg and the R2R-ratio.

$$\log\left(Y_{jt}\right) = \alpha_{1j} + \alpha_{2t} + \beta_1 * R2R_{jt} + \beta_2 * R2R_{jt}^{\ 2} + \beta_3 * \log(\text{price})_{jt} + \beta_4 * \log(\text{price})_{jt} * R2R_{jt} + \epsilon_{jt} \tag{3.7}$$

We estimate the model in R using the "lfe" package (Gaure 2018).

3.6.3 Empirical Results and Functional Form

We examine the functional form of the R2R-ratio and the dependent variable. The traditional procedure to detect an inverted u-shape in a linear model is to add the squared termed of the independent variable and analyze the sign and significance of the coefficient. A significantly negative coefficient of the squared term indicates an inverted u-shape (Cohen et al. 2002). A subsequent test, on whether the values at which the sign of the coefficient flips are within the data, offers further robustness (Berman et al. 2002). Therefore, we initially build up the regression displayed in equation 3.7. We sequentially add independent variables as shown in equations 3.7a to 3.7f and analyze the significance and sign of the coefficient as well as the value at which the sign flips.

Simonsohn (2018a), however, criticizes these traditional procedures. His main points of concern are the high false-positive rates, such that traditional procedures, for example, derive that a logarithmic function is u-shaped (Simonsohn 2018a). While the author does not question the inclusion of quadratic terms in regressions to account for non-linear relations, he challenges the interpretation of the quadratic term as an indicator for a u-shaped relation.[25] Instead, a straightforward concept estimates two lines by splitting the independent variable under examination at a certain value into a high and low variable. A test of whether the two lines exhibit slopes with opposing, significant signs follows. The procedure of setting the splitting value of the independent variable is critical. The goal is high statistical power of the regression. Higher statistical power for the two lines has three potential sources, which the algorithm considers: "[…] the algorithm sets a break point that will increase the statistical strength of the weaker of the two lines, by placing more observations in that segment, without overly attenuating its slope" (Simonsohn 2018a, p. 546)[26]. We apply the approach suggested by Simonsohn (2018a) to our data set. We use the results from the proposed algorithm as guiding information for a simplified procedure that considers our fixed-effects setting, including thousands of intercepts. We regress the dependent variable on low and high values of the R2R-ratio, the logarithm of price, as well as the interactions in a fixed-effects setting.

[25] Visual inspection of the functional form is not feasible because of the high number of products (5,671).

[26] Three potential sources for high statistical power: (1) out of the two lines, focus on the statistically weaker line; (2) steeper lines with (3) more observations (smaller standard error) have more power (Simonsohn 2018a, p. 546).

Analysis of the Squared Term

We initially follow the traditional approach and regress the dependent variable on the R2R-ratio (R2R) and sequentially add the squared R2R-ratio ($R2R^2$) to test for a potential inverted u-shape as well as the logarithm of price and the interaction of price and R2R-ratio, while accounting for article heterogeneity and time impact with fixed effects. Equations 3.7a to 3.7f build up equation 3.7. Due to testing the inverted-u shape, we do not include the R2R-ratio as the logarithm of the R2R-ratio. Hence, β_1, the coefficient of the main effect of the R2R-ratio may not be interpreted as elasticity. Rather, a one unit increase in the R2R-ratio translates to an average change in the dependent variable quantity of 100 * (exp(β_1) - 1) %.

$$\log(Y_{jt}) = \alpha_{1j} + \alpha_{2t} + \beta_1 * R2R_{jt} + \epsilon_{jt} \tag{3.7a}$$

$$\log(Y_{jt}) = \alpha_{1j} + \alpha_{2t} + \beta_1 * R2R_{jt} + \beta_2 * \log(price)_{jt} + \epsilon_{jt} \tag{3.7b}$$

$$\log(Y_{jt}) = \alpha_{1j} + \alpha_{2t} + \beta_1 * R2R_{jt} + \beta_2 * \log(price)_{jt} + \beta_3 * \log(price)_{jt} * R2R_{jt} + \epsilon_{jt} \tag{3.7c}$$

$$\log(Y_{jt}) = \alpha_{1j} + \alpha_{2t} + \beta_1 * R2R_{jt} + \beta_2 * R2R^2_{jt} + \epsilon_{jt} \tag{3.7d}$$

$$\log(Y_{jt}) = \alpha_{1j} + \alpha_{2t} + \beta_1 * R2R_{jt} + \beta_2 * R2R_{jt}^2 + \beta_3 * \log(price)_{jt} + \epsilon_{jt} \tag{3.7e}$$

$$\log(Y_{jt}) = \alpha_{1j} + \alpha_{2t} + \beta_1 * R2R_{jt} + \beta_2 * R2R_{jt}^2 + \beta_3 * \log(price)_{jt} + \beta_4 * \log(price)_{jt} * R2R_{jt} + \epsilon_{jt} \tag{3.7f}$$

Table 3.7 shows the results of Equations 3.7a to 3.7f indicated as models a to f. The R2R-ratio (R2R) has a positive impact on quantity sold; in other words, the further away the manufacturer-suggested retail price from the regular price, the more the retailer sells. In this respect, this study corroborates the findings of study one since the advertised reference price being larger than the regular price has a positive impact on sales. In the simplest model, 7a, with only the main effect of the R2R-ratio, increasing the R2R-ratio by one unit leads to a surge in quantity by 75 percent. In models d, e, and f we add the squared R2R-ratio. The coefficient of the squared R2R-ratio (R2R²) is significant and negative, describing an inverted u-shape in all three model constellations. Hence, in line with assimilation-contrast theory, there is an end to the positive impact of the R2R-ratio on sales. The price elasticity is negative and close to -2 which is in the expected region (Bijmolt et al. 2005). The interaction of the R2R-ratio and price is negative, such that with a higher R2R-ratio the price elasticity is stronger. The further away the manufacturer-suggested retail price from the regular price, the stronger the impact of the actual selling price.

The explained variance (R^2) of the fixed-effects model reveals a strong impact of article and time. For model f the adjusted R^2 of the full model including fixed effects is 0.90, while the model without fixed effects shows an adjusted R^2 of 0.04. Hence, the fixed-effects model is suited to accounting for considerable heterogeneity across articles and time.

	a	**b**	**c**	**d**	**e**	**f**
R2R	0.56 ***	0.05 ***	0.34 ***	1.17 ***	0.18 ***	0.55 ***
R2R squared				-0.17 ***	-0.04 ***	-0.05 ***
Log (price)		-1.90 ***	-1.77 ***		-1.89 ***	-1.74 ***
Log (price)* R2R			-0.10 ***			-0.11 ***
Observations	690,970					
Dependent variable	Log (quantity)					
Mult. R² full model	0.90	0.90	0.90	0.90	0.90	0.90
Mult. R² proj. model	0.01	0.04	0.04	0.01	0.04	0.04

*** *<0.001*

Table 3.7: Fixed-Effects Model on Article Level

Algorithm by Simonsohn (2018a)

The introduction of a squared term supports an inverted u-shape relation between R2R-ratio and the dependent variable in all model settings. However, following Simonsohn (2018a), testing significance and sign of the squared term is not sufficient. The author suggests an algorithm consisting of five steps to estimate two lines. The procedure relies on cubic splines to estimate the relation between x and y. After identifying the most extreme internal fitted value $\hat{y}_{max}$ and the set of $\hat{y}$ values within a standard error of $\hat{y}_{max}$ (this set is referred to as $\hat{y}_{flat}$)[27], the author estimates an interrupted regression. Here, the breakpoint is critical. The breakpoint is the median value of x within the $\hat{y}_{flat}$. The two resulting t-test statistics t_1 and t_2 set the

[27] Simonsohn (2018a) argues for $\hat{y}_{flat}$ as most inverted u-shapes are rather Us than Vs, i.e., displaying a region with a flat maximum.

breakpoint at the $t_2/(t_1+t_2)$ percentile of x associated with $\hat{y}_{flat}$ (Simonsohn 2018a, p. 546). The estimation is based on the interrupted regression displayed in equation 3.8, where x_c is the value splitting the R2R-ratio (R2R). ZB_z is the matrix with covariates, here price and the interaction of price and R2R-ratio. In a u-shape relation, β_1 and β_2 have opposing signs (Simonsohn 2018a).[28]

$$\log(Y_{jt}) = \alpha_1 + \beta_1 {*} R2R_{low_{jt}} + \beta_2 {*} R2R_{high_{jt}} + \beta_3 {*} high + ZB_z + \epsilon_{jt} \quad (3.8)$$

R2Rlow = R2R – xc if R2R ≤ xc, 0 otherwise

R2Rlow = R2R – xc if R2R ≥ xc, 0 otherwise

High = 1 if R2R ≥ xc, 0 otherwise.

Unlike the fixed-effects model, we do not account for differences between articles and between weeks. We use the R-Code provided by Simonsohn (2018b) for estimation. Table 3.8 shows the results. We provide graphs of data and estimated functional form in the Appendix in Figure 6.10, Figure 6.11, and Figure 6.12. In model a1 opposing signs document an inverted u-shape. In models b1 and c1, after adding price and its interaction, the sign of the coefficient of the high R2R-ratio values also turns positive. However, across all models the slope of the high R2R-ratio is smaller than the slope of the low R2R-ratio.[29] The further away the manufacturer recommended retail price from the regular price of an article the smaller, but still positive, the impact on sales. In line with previous models, the price elasticity remains negative and the interaction of price and R2R-ratio exhibits a negative coefficient.

	a1	**b1**	**c1**
Intercept	1.74 ***	5.49 ***	5.81 ***
R2R low	0.60 ***	1.25 ***	2.14 ***
R2R high	-0.31 ***	0.06 .	1.11 ***
Log (price)		-1.24 ***	-0.78 ***
Log (price)* R2R			-0.34 ***
High	0.01 .	-0.14 ***	-0.11 ***
Split value	1.40	1.71	1.71
Dependent variable	Log(quantity)		

*** <*0.001*

Table 3.8: Results Algorithm by Simonsohn (2018a)

[28] As weak inequalities are involved, for discrete values the break point is included in the high and low equation (Simonsohn 2018a).

[29] Results are robust for elimination of R2R >6.

We introduce a reduced panel-like structure to the model. To control for time impact and article heterogeneity we introduce a linear trend over weeks and 58 dummies on subcategory level.[30] The results displayed in Table 3.9[31] all point in the same direction as before, albeit with smaller magnitude. We again find a less positive slope for high R2R-ratio values while the slope does not turn negative. Price elasticity and interaction with R2R-ratio remain negative. We provide graphs of data and estimated functional form in the Appendix in Figure 6.13 to Figure 6.15.

	a2	b2	c2
Intercept	1.35 ***	6.38 ***	6.51 ***
R2R low	1.35 ***	0.70 ***	1.15 ***
R2R high	0.31 ***	0.05	0.54 ***
Log (price)		-1.30 ***	-1.08 ***
Log (price)* R2R			-0.16 ***
High	0.09 ***	-0.09 ***	-0.08 ***
Weekly trend	-0.001 ***	-0.001 ***	-0.001 ***
Split value	1.39	1.71	1.71
Dependent variable	Log(quantity)		

*** *<0.001*

Table 3.9: Results Algorithm by Simonsohn (2018a) with Linear Weekly Trend and Subcategory Dummies

Finally, we combine the fixed-effects approach and the split of the variable (equation 9).

$$\log(Y_{jt}) = \alpha_{1j} + \alpha_{2t} + \beta_1 * R2R\_low_{jt} + \beta_2 * R2R\_high_{jt} + \beta_4 * \log(price)_{jt} + \beta_5 * \log(price)_{jt} * R2R\_low_{jt} + \epsilon_{jt} \tag{3.9}$$

To assess the results dependent on different splitting values for dividing the R2R-ratio into low and high, we provide a sensitivity analysis of the resulting coefficients β1 and β2, as shown in Figure 3.5. We plot β_1 (R2R-ratio low) and β_2 (R2R-ratio high) coefficients resulting from different splitting values in relation to the respective R2R-ratio-split[32]. From a split value of 1.8 onward, the coefficient of the lower R2R-ratio values is stronger positive than for the higher R2R-ratio values. The algorithm proposed by Simonsohn (2018a) suggests a splitting value in the same region of 1.71. At an R2R-ratio of 2.9, the coefficients of the higher R2R-ratio turn negative (insignificant). Hence, we again find a stronger impact of lower R2R-ratio values on the dependent variable than for higher R2R-ratio values. Table 3.10 shows exemplary results

[30] Due to calculation constraints, the introduction of several thousand intercepts is not feasible.

[31] The results for 57 dummy coefficients are not displayed here.

[32] We split the R2R-ratio variable into two variables; R2R low and R2R high. We split the variable along a splitting value x, such that all observations < x are assigned to the new variable "R2R low", otherwise 0. All observations ≥ x are assigned to the new variable "R2R high", otherwise 0.

for the splitting value of two. The R2R-ratio low variable contains all R2R-ratios smaller than two, while the R2R-ratio high variable contains all R2R-ratio observations larger or equal to two. Again, low R2R-ratio values have a stronger impact on the dependent variable than higher R2R-ratio values.

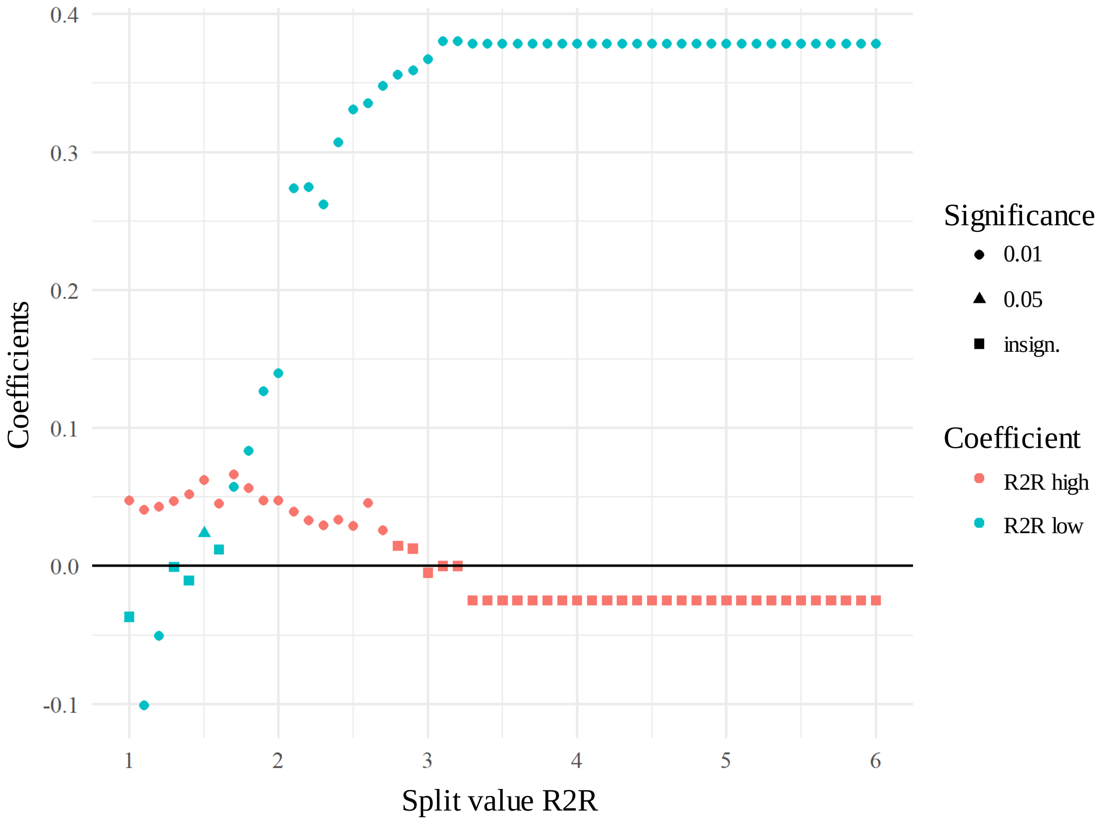


Figure 3.5: Sensitivity Analysis R2R-ratio Split

	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**
R2R low < 2	0.14	0.01	10.73	< 0.000***
R2R high ≥ 2	0.05	0.01	6.50	< 0.000***
Log (price)	-1.86	0.01	-141.17	< 0.000***
Log (price)* R2R	-0.03	0.00	-8.37	< 0.000***
Dependent variable	Log (quantity)			
Multiple R^2 full model	0.90			

*** *<0.001*

Table 3.10: Example Estimates for R2R-ratio Split Value of 2

In conclusion, the sign and significance of the price elasticity as well as the interaction of price and R2R-ratio, remain untouched by the specified functional form of the main effect of the R2R-ratio. The main effect of the R2R-ratio is positive in all specifications, highlighting a positive impact of displaying a manufacturer-suggested retail price which is higher than the regular price on sales. With respect to the functional form and the main effect of the R2R-ratio, the introduction of a squared term supports an inverted-u relation. Further assessment of the relation supports stronger impact of lower R2R-ratio values on the dependent variable than for higher R2R-ratio values, but no strictly inverted-u relation. Thus, with increasing distance of the advertised reference price from the regular price, the impact on sales increases, albeit with diminishing strength. Consequently, our research extends offline research. Even exaggerated reference prices have a positive impact on sales.

3.6.4 Robustness of Results

To further test the robustness of the results, we estimate the models described in equation 3.7a to 3.7f on different hierarchical levels. First, we estimate a simple linear model without fixed effects controlling for heterogeneity. Afterwards, we include a hierarchical level that is higher than in the initial model. We estimate fixed effects for product landing pages instead of unique articles. As a further robustness check, we introduce an additional control variable to control for the potential impact of promotional activities. We include a dummy variable signaling whether or not an item is on promotion.

Model without Fixed Effects

The simple linear model without any fixed effects, meaning that we do not account for article or time structure, produced the results displayed in Table 3.11. Signs remain the same, while price induces a surge in explained variance, supporting previous findings.

	a	**b**	**c**	**d**	**e**	**f**
Intercept	1.63 ***	3.91 ***	2.41 ***	1.15 ***	2.84 ***	1.38 ***
R2R	0.03 ***	0.82 ***	1.93 ***	0.64 ***	2.22 ***	3.29 ***
R2R squared				-0.20 ***	-0.44 ***	-0.43 ***
Log (price)		-1.24 ***	-0.71 ***		-1.24 ***	-0.72 ***
Log (price)* R2R			-0.38 ***			-0.38 ***
Dependent variable	Log (quantity)					
Mult. R^2 full model	0.00	0.64	0.64	0.00	0.64	0.64

**** <0.001*

Table 3.11: Linear Model Without Fixed Effects

Model on Product Level

To test the impact of the choice of the hierarchical level of the article-specific fixed effects, instead of 5,641 single articles we use the corresponding 3,385 product landing pages. A product landing page includes, e.g., different sizes and flavors of an article. The remaining variables are specified on article level. Table 3.12 displays the results. The signs and significance of the coefficients remain comparable on different hierarchical levels. The R^2 of the full model remain conclusive, including a surge after the introduction of price as an independent variable.

	a	b	c	d	e	f
R2R	0.32 ***	0.12 ***	0.18 ***	0.93 ***	0.58 ***	0.70 ***
R2R squared				-0.17 ***	-0.13 ***	-0.13 ***
Log (price)		-1.79 ***	-1.76 ***		-1.78 ***	-1.73 ***
Log (price)* R2R			-0.02 ***			-0.04 ***
Dependent variable	Log (quantity)					
Mult. R² full model	0.83	0.88	0.88	0.84	0.88	0.88
Mult. R² proj. model	0.003	0.25	0.25	0.004	0.25	0.25

*** <*0.001*

Table 3.12: Fixed Effects on Product Landing Page Level

Model with Control Variable Promotional Activity

As a final robustness check we introduce a fixed effect, flagging up whether an item is on promotion, which might have an impact on sales. Table 3.13 shows that the results are robust with respect to the introduction of a promotional factor in the example of the article level model.

	a	b	c	d	e	f
R2R	0.56 ***	0.05 ***	0.34 ***	1.16 ***	0.18 ***	0.55 ***
R2R squared				-0.17 ***	-0.04 ***	-0.05 ***
Log (price)		-1.90 ***	-1.77 ***		-1.89 ***	-1.74 ***
Log (price)* R2R			-0.10 ***			-0.11 ***
Observations	687,775					
Dependent variable	Log (quantity)					
Multiple R² full model	0.90	0.91	0.91	0.90	0.90	0.91
Multiple R² proj. model	0.01	0.04	0.04	0.01	0.04	0.04

*** <*0.001*

Table 3.13: Fixed Effects on Article Level Including Promotion

In summary, the hierarchical level of the fixed effects neither drives the sign nor significance of the price elasticity nor the interaction of price and R2R-ratio. Price and the interaction of price and R2R-ratio have a negative impact on the dependent variable in all the tested settings.

3.6.5 Profit Assessment

The main effect of the R2R-ratio is positive, while the interaction of the actual selling price and the R2R-ratio is negative across all robustness checks and functional forms. These results highlight the role of credibility in using advertised reference prices. For the retailer, increasing the R2R-ratio, ceteris paribus, increases sales, at the same time it strengthens the impact of price changes on sales. In the following, we show the revenue and profit impact for three scenarios: an increase in the R2R-ratio, a temporary price decrease in the actual selling price[33], and the combination of the two. We use a three-step procedure to quantify the impact for the retailer.[34]

First, we derive the predictions of the quantity for each article in each week based on the articles' actual price, R2R-ratio. Based on these quantities we use article- and week-specific prices and margins to calculate revenue and profit.[35] Second, we introduce different simulations: we assess the absolute sales impact of a change in the R2R-ratio by 0.01, of a change in actual selling price by 1 percent, and of the combination of different R2R-ratio increases with an actual selling price decrease, ceteris paribus, per week and article. We then cumulate over all weeks and articles and again calculate revenues and profits. Third, we derive the deltas in sales, revenue and profit between predictions and simulations.

In total, an increase in the R2R-ratio in each week for each article by 0.01 increases cumulated sales by 34,000 units, associated revenue by €104,000 and profit by €21,000. Figure 3.6 displays the profit per article cumulated across weeks. Temporary price reductions underline that even manufacturer-suggested retail prices, that are not credible, affect sales. While a price reduction by 1 percent, ceteris paribus, increases sales by 308,000 units and revenue by €873,000, it induces a profit decrease of €480,000, when compared to the predictions. The same price reduction, in combination with an increase in the R2R-ratio, changes profitability advantageously. Figure 3.7 displays the delta in profit of a price reduction in combination with different increases in the R2R-ratio compared to the profit of the predictions. The delta for each value of the R2R-ratio is the sum across all articles and weeks. Increasing the R2R-ratio value by 0.3 units changes the negative profit delta of a 1 percent price decrease to a positive profit impact. Thus, this simulation highlights that for the retailer using less credible manufacturer-suggested retail price is beneficial.

[33] We assess a price reduction independent of a change in the R2R-ratio since the R2R-ratio includes the regular price. The price reduction is supposed to be temporarily limited and therefore should not impact the R2R-ratio.

[34] As we do not find clear support for an inverted-u shape, we assess the impact of changes in the reference to regular ratio on profit based on model c, i.e., equation 3.7c using article and week-specific prices and profit margins.

[35] We must reduce the data set by 173 articles for which profit margin information is missing, leading to a reduction in observations from 690,970 to 662,220.

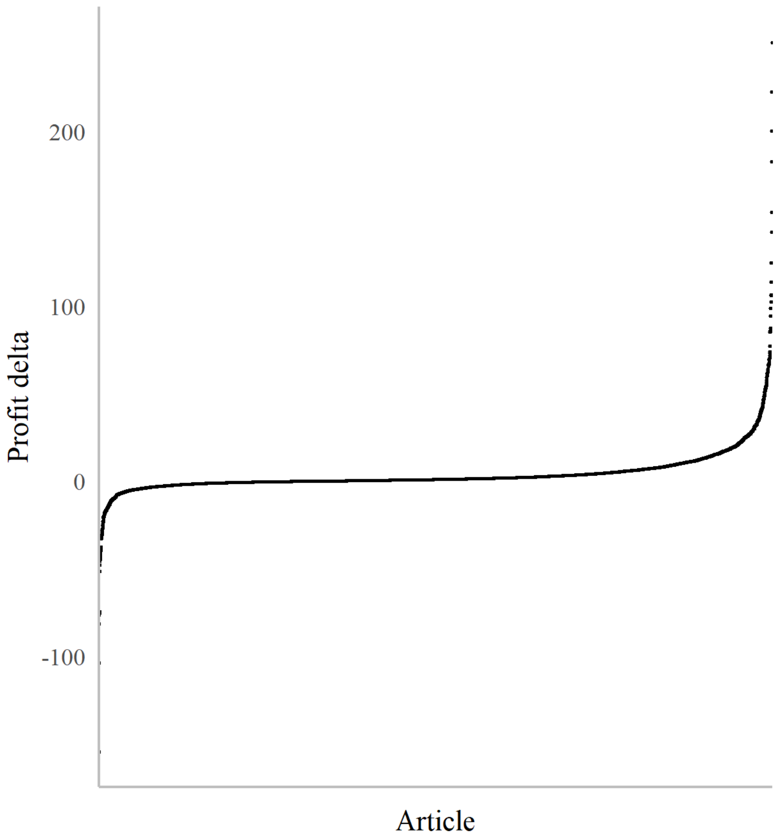


Figure 3.6: Absolute Change in Profit Given R2R-ratio Increase by 0.01 Cumulated per Article

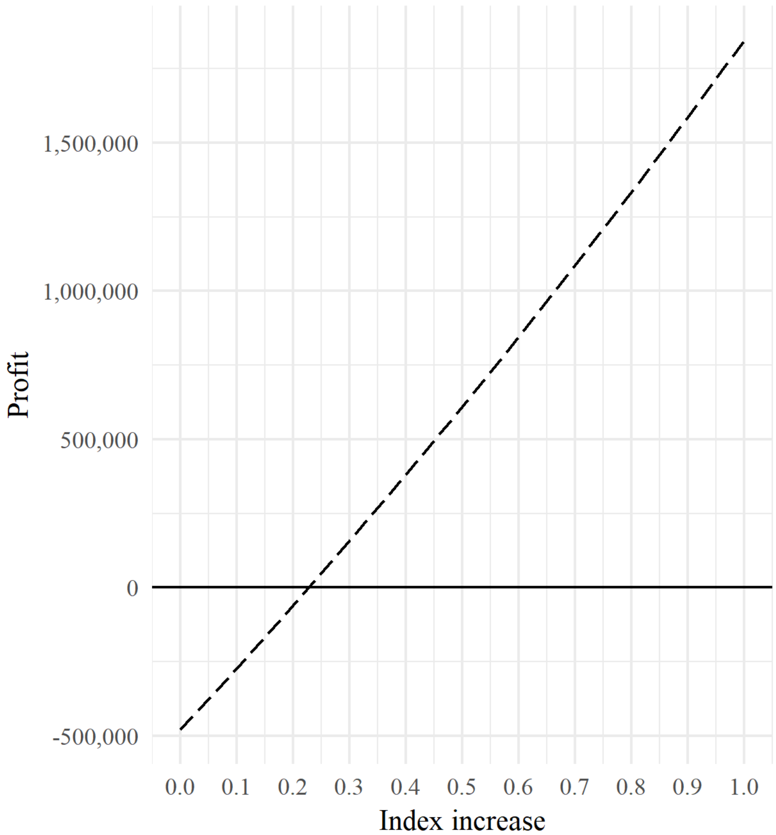


Figure 3.7: Absolute Change in Profit Based on R2R Increase

3.7 Discussion and Managerial Implications

The aim of this study was to shed light on the performance of advertised reference prices in online settings. We identified five avenues to contribute to the large field of research on advertised reference prices.

First, the impact of advertised reference prices in online environments is largely unknown, although the theory suggests substantial changes in the informational environment (Bakos 1997). As online pricing nevertheless seems to follow offline pricing by offering advertised reference prices on a great share of products in online shops, we add to the limited existing research on the performance of advertised reference prices in online environments.

Second, research in the field of advertised reference prices reports a positive impact of advertised reference prices on purchasing (Compeau and Grewal 1998). This effect might diminish from a long-term perspective, as research on promotions reports that frequent promotions have less impact on purchase decisions (Alba et al. 1994; Alba et al. 1999).

We addressed both avenues with experimental studies assessing whether advertised reference prices have an impact on online sales. Study one, an online experiment, revealed a positive impact of advertised reference prices on purchasing and sales. Study two, a field experiment, however, did not find a significant impact.

The online experiment exhibited a positive effect of displaying an advertised reference price on purchase intentions. Hence, this experimental study supports the existing findings on advertised reference prices. However, while high in internal validity, the laboratory setting of the study potentially limited the access to information by subjects. It is likely that the subjects did not search for other price information online while answering the survey. Thus, although we framed the experiment as an online shopping experience, this study was potentially limited with respect to the information search conducted by the respondents. To challenge this finding and to add external validity, we conducted a field experiment. In this natural environment, displaying an advertised reference price is the default mode, meaning that the products' landing pages usually display an advertised reference price. Furthermore, customers were more likely to be familiar with the product they were buying and aware of, or accessing, additional price information compared to the online experiment. Here, we were not able to replicate the findings from the online survey. We did not find a consistent effect of advertised reference prices on visits, cart additions, or sales. In sum, we did not find empirical evidence justifying advertised reference prices online; nor did we find the opposite scenario. In this field setting, eliminating the advertised reference price did not decrease sales strongly and significantly.

Third, we analyzed whether, and how, the impact of the credibility of an advertised reference price, operationalized as the ratio of manufacturer-suggested retail price and regular price, impacts sales. The focal aspect was the analysis of the functional form of the relation, for which we used a large transaction data set. We did not find full support for an inverted u-shape. However, different approaches to accessing the functional form underlined a diminishing positive impact of the credibility of advertised reference prices for high values on sales: the larger the distance between the manufacturer-suggested retail price and the regular selling price, i.e., the less credible the manufacturer-suggested retail price, the less positive the impact on sales. Nevertheless, even manufacturer-suggested retail prices that were substantially higher than the regular price still had a positive impact on sales.

Fourth, we assessed whether the actual selling price becomes a stronger signal the less credible the manufacturer-suggested retail price, namely, whether the R2R-ratio moderates price elasticity negatively. We found a negative relation. Thus, the further away the manufacturer-suggested retail price from the regular price, i.e., the less credible the manufacturer-suggested retail price, the stronger the impact of the actual selling price on sales.

Finally, based on the same data set, we conducted a profit simulation. We found that using less credible advertised reference prices in combination with price reductions can balance the negative profit impact of temporary price reductions.

Displaying advertised reference prices comes at a cost for retailers since advertised reference prices must adhere to legal requirements. Therefore, retailers need to generate, update, or validate advertised reference prices, resulting in personnel costs. Furthermore, if legal requirements are violated, the penalties are a potential cost factor. Therefore, from a managerial perspective it is of interest to analyze whether displaying advertised reference prices increases sales. While we did not find a consistent positive impact of advertised reference prices across all three studies, we also did not find the opposite to be true. Hence, as a first step, displaying advertised reference prices in online shops, even if they have a notion of an inflated advertised reference price, does not seem to harm sales. The field experiment, however, highlights that in a realistic purchasing environment, the advertised reference price might not be as strong a cue when in competition with other information and when displayed by default. Based on the field experiment, we cannot provide robust estimates of the sales impact of the elimination of advertised reference prices; thus, we do not find evidence to suggest retailers should not continue with the status quo, as it does not harm sales. Furthermore, studies one and three point in the direction of a positive impact of advertised reference prices in online environments.

The analysis of the credibility of advertised reference prices provides interesting insights. This analysis revealed that for less credible advertised reference prices online, customers tend to re-focus on the actual selling price. Thus, retailers must manage the constellation of three price cues, namely, the manufacturer-suggested retail price, the regular price, and the actual selling price. However, we want to underline the responsibility of retailers with respect to the legal requirements. As study three highlights the positive profit impact of using less credible manufacturer-suggested retail prices, it is evident that there is the potential to trick customers into buying with less credible or inflated reference prices. When providing a manufacturer-suggested retail price with the intention of highlighting the offer value of the product, the manufacturer-suggested retail price has to be true. Otherwise, although customers can easily access additional price information online, the online shop is deceiving its customers and may face financial penalties and loss of image.

3.8 Limitations and Future Research

We note several limitations that might guide future research. In both the online experiment and the field experiment, we model the advertised reference price as a dichotomous variable. As we chose the manufacturer-suggested retail price as advertised reference price for the field experiment, we could not manipulate the distance of the advertised reference price and the regular price by adjusting the advertised reference price. Future research might address this relation in further experiments.

The field experiment revealed a high level of variance in weekly sales of the selected products. Repeating this experiment in an environment exhibiting less natural variation might lead to more structured and more conclusive results. Furthermore, we focused on a limited sample of products per brand, which might also impact the generalizability of our findings.

We gathered data from one company in one European market, which limits the generalizability of our findings. Future research might address this aspect and analyze the performance of advertised reference prices for different categories and multiple retailers.

4 Reach for the Stars – the Interplay of Product Reviews and Price in Online Retailing

4.1 Introduction

In recent years, the ascent of the Internet has disrupted retailing. Online shopping has provided customers with easy access to information, lower search costs for information, and new forms of information. The Internet has, in particular, changed the scope of providing information from customer to customer by the means of online product reviews. Online product reviews are "peer-generated product evaluations posted on company or third party web sites" (Mudambi and Schuff 2010, p. 186). While traditionally customers would exchange information among their peers only, posting a product review online, makes it accessible to anyone (Dellarocas 2003). With the ascent of the Internet such online product reviews "have become one of the most popular information sources for modern consumers" (Racherla et al. 2012, p. 94). Today, online product reviews are ubiquitous. In recent years, major retailers have accumulated an enormous number of reviews, such that showing product reviews is increasingly becoming standard practice for retailers; for example, on Amazon.com in 2014 more than 140 million product reviews were available (McAuley et al. 2015).[36] According to recent surveys, for 93 percent of respondents[37] reviews have an impact on their purchase decisions (Podium 2017), and online peer and expert reviews are the top two influencers in purchase decisions, while advice from family and friends is relegated to third place (Stine and Sethi 2014).[38] The reason for product reviews playing a key role for customers is that customers perceive risk when purchasing products. They buy in markets that are characterized by information asymmetry that is disadvantageous to customers because sellers typically know the quality of their products better than customers, meaning that customers will pay the price of the product while being uncertain about its performance (Forsythe et al. 2006). To facilitate purchase decisions, sellers try to reduce uncertainty by providing information on their products (Kirmani and Rao 2000), while customers counteract these perceived risks by searching for information, e.g., by consulting product reviews. Reviews reduce the risk involved in the purchase decision, as they provide signals on the quality of products. These signals on the quality of the products are of particular importance for pricing. Quality is inherent to pricing literature, since it is assumed to influence the impact of price on sales, e.g., for larger brands price elasticities are less strong potentially stemming from the higher quality of these large brands (Fok et al. 2006). Thus, as

[36] The data crawled by McAuley spans the period from May 1996 until July 2014.

[37] A total of 2,005 respondents took part in the survey (Podium 2017).

[38] A total of 1,174 customers took part in the survey, and the sample is representative of the United States broadband population by age, income, and region.

online product reviews signal quality they may also moderate the impact of price on sales. For example, in the presence of many positive reviews, there are strong signals for high quality of the product, so that the perceived risk of the purchase decreases and price might become a less relevant factor. Consequently, positive product reviews might dampen the impact of price on sales. This potential impact of reviews on price is substantial, as price is of outstanding importance for retailers. Existing marketing research has identified price as the most powerful instrument steering demand in offline shopping. A comparison of meta-analyses on marketing instruments reveals that the impact of price on sales is substantially stronger than the impact of other marketing instruments. For example, the impact of price on sales is ten times greater than the impact of advertising (Bijmolt et al. 2005; Sethuraman et al. 2011).[39]

Therefore, this study has the primary goal of understanding whether and how online product reviews affect the impact of price on sales, i.e., price elasticities, online.

In order to obtain granular insights, we follow existing research and analyze the impact of product reviews via three dimensions (Chintagunta et al. 2010). The first dimension of a review is valence. Valence is the average rating of a product and illustrates the level of satisfaction that other customers derive from the product (Chevalier and Mayzlin 2006; Duan et al. 2008; Kostyra et al. 2016). Valence is typically provided on a five-star scale (e.g., the three largest US online retailers accounting for 45 percent of traffic, Amazon.com, ebay.com, and Walmart.com (Miller and Washington 2017), ask for reviews on a five-star scale). The second dimension is volume, which captures the amount of reviews that other customers have provided for this specific product (Chevalier and Mayzlin 2006; Duan et al. 2008; Kostyra et al. 2016). And the last dimension is variance within the reviews. Variance captures the spread in average reviews, i.e., the disagreement or agreement among reviewers (Godes and Mayzlin 2004; Sun 2012). According to existing research, these three dimensions, individually and collectively, impact the purchase decisions of customers in online retail settings.

So far, however, research on the interactions between valence, volume, variance, and price is very scarce. Two existing studies have discuss these relations and highlight the relevance of product reviews for pricing (Kostyra et al. 2016; Maslowska et al. 2017). While Kostyra et al.

[39] The meta-analysis by Sethuraman et al. (2011) assesses 56 studies published between 1960 and 2008. They report a short-term advertising elasticity based on 751 individual elasticities of 0.12 and a long-term advertising elasticity based on 402 elasticities of 0.24. Bijmolt et al. (2005) report a price elasticity of -2.62 based on 1,851 individual price elasticities from 81 studies.

(2016) do not include distinct interactions, Maslowska et al. (2017) assess interactions but exclude variance from their analysis. Given this scarcity of empirical findings, we pose the first research question:

(3.1) Do valence, volume, and variance moderate the impact of price on sales?

On top of that, product reviews might influence sales directly since they increase customers' trust in an online shop by signaling that other customers have already made purchases from the shop (Dellarocas 2003); they also indicate quality and customer satisfaction with the product (Floyd et al. 2014; Kostyra et al. 2016; Maslowska et al. 2017). In line with the growing relevance of product reviews in practice, many research publications focus on the role of product reviews in online shopping. In particular, studies examine the effects of product reviews on sales and provide guidance for companies to leverage reviews to their advantage. While most researchers have found that review valence positively influences purchase decisions (e.g., Chintagunta et al. 2010), other empirical results downplay the relevance of valence and stress the impact of review volume (e.g., Amblee and Bui 2011). One reason for these mixed findings may be that studies show a strong focus on a limited number of product categories, as well as data sources (Trenz and Berger 2013; Babić Rosario et al. 2016). The meta-analysis by Babić Rosario et al. (2016) highlights this concentration. Of the total 1,532 effect sizes in their study, 59 percent originate from books and movies. The same analysis reveals that 44 percent of studies are based on Amazon data (Babić Rosario et al. 2016). In addition, the interactions between review dimensions, i.e., the role of the number of reviews in combination with valence, as well as the interaction of valence and variance, have only recently emerged as a further fruitful aspect in research (Kostyra et al. 2016). While Chintagunta et al. (2010) do not find a significant moderation of valence by volume for movies, other contextual settings provide opposing results. Park et al. (2012), in analyzing camera products, Maslowska et al. (2017) for health and beauty products, and Kostyra et al. (2016) for e-readers, provide evidence for a moderation. Only three studies so far have analyzed the interaction between valence and variance. Sun (2012) finds a significant interaction between valence and variance for books: for books with low average rating, high variance increases demand. For a highly rated book, higher variance reduces demand. Kostyra et al. (2016) corroborates the findings of Sun (2012) in a choice experiment, whereas Chintagunta et al. (2010) report the interaction to be insignificant for movies.

Overall, research findings on product reviews and their effects on sales show mixed empirical results regarding the relevance of the three review dimensions, and they show very limited findings on the interactions of such. One possible reason for these mixed findings is that a comprehensive perspective, including the moderation among review dimensions (Kostyra et al. 2016; Maslowska et al. 2017), as well as the moderation of price, has mostly been ignored. Thus, the second objective of this paper is to address those mixed findings and assess the impact of review dimensions, as well as their interactions on sales:

(3.2) Do valence, volume, and variance – individually and comprehensively – have an impact on sales?

Hence, this study sets out to comprehensively integrate research on product reviews and pricing research. We propose that the assessment of the moderation of the impact of price on sales by the above-mentioned review dimensions, as well as the inclusion of the relevant interactions between review dimensions, will lead to a clearer picture of product reviews and contribute to findings that are currently mixed. Furthermore, adding knowledge to the relation of reviews and price may provide useful guidance for the complex task of setting and changing product prices for retailers. To the best of our knowledge, we are the first to analyze the interaction between all three review dimensions and price (see Table 4.1 for an overview of existing studies that consider sales or sales-related variables as the dependent variable, and which include all three dimensions of reviews, or at least two dimensions of reviews in combination with price.)

We test the effects with transaction data collected from a large European online retailer over the course of three years. We focus on retailer-based product reviews, i.e., the retailer provides a platform that enables customers to review the product. This type of review provides a direct link between reviews and purchases, as customers can only review products that they have bought. With this data set we combine data on review dimensions, prices, and sales. We further include the profit margin to assess the impact on profit. To overcome the limitations in product categories in the extant literature, we collect data on a broad product range of roughly 45,000 products in 88 product categories from seven countries.

The next chapter outlines the conceptual framework of the study and develops the hypotheses in detail. Subsequent to presenting the methodology, we describe the study's results and test their robustness. We further use the results to illustrate pricing decisions based on product reviews, as well as the impact on sales, revenue, and profit. Afterwards, we discuss the results and derive managerial implications. Finally, the limitations and future research recommendations are put in focus.

	Valence	**Volume**	**Variance**	**Price**	**Interact. with Price**	**Dependent Variable**	**Results**
Chintagunta et al. (2010)	Yes	Yes	Yes	-	-	Box office sales	Only valence significant
Sun (2012)	Yes	Yes	Yes	Yes	-	Books sales rank	Interactions significant[40]
Kostyra et al. (2016)	Yes	Yes	Yes	Yes[41]	-	E-readers' choice	Interactions significant
Maslowska et al. (2017)	Yes	Yes	-	Yes	Yes	Health and beauty sales	Interactions significant
Our Study	Yes	Yes	Yes	Yes	Yes	Consumer goods sales	Interactions significant

Table 4.1: Overview of Existing Empirical Findings on Product Reviews Including Interactions

4.2 Contribution and Conceptual Framework

As outlined above, in this study we focus on retail, which is commonly characterized by information asymmetry that is disadvantageous to the customer. Such information asymmetries have an impact on demand (Stiglitz 2000). Signaling theory addresses the uncertainty originating from information asymmetry (Spence 1978). With the provision of signals parties seek to reduce information asymmetry (Connelly et al. 2011). In order to reduce uncertainty, retailers and manufacturers steer marketing mix variables as quality signals, for example, by building brands or granting warranties (Kirmani and Rao 2000). In the presence of positive quality signals, the perceived risk of the purchase decreases and price might become a less relevant factor, so that the impact of price on sales diminishes.

Product reviews are a unique type of signal for the retailer. In contrast to other signals, retailers decide whether to provide the platform that enables customers to review the product, whereas they cannot directly steer the product reviews that are then posted on their website. We concentrate on such retailer-hosted product review platforms that provide a direct link between reviews and purchases. Furthermore, we focus on quantitative product-specific reviews, which ask the customer to evaluate a specific product based on a pre-defined rating scale. We follow the existing research by differentiating online reviews along three dimensions (Chintagunta et al. 2010): valence (Chevalier and Mayzlin 2006; Duan et al. 2008; Kostyra et al. 2016), volume

[40] Higher variance increases sales for low-valence books and decreases sales for high-valence books (Sun 2012).

[41] The importance of price decreases when product reviews are present (Kostyra et al. 2016).

(Chevalier and Mayzlin 2006; Duan et al. 2008; Kostyra et al. 2016), and variance (Godes and Mayzlin 2004; Sun 2012). Much research has been conducted on these dimensions with respect to different dependent variables, e.g., sales (Maslowska et al. 2017), sales rank (Chevalier and Mayzlin 2006; Amblee and Bui 2011), or helpfulness (Mudambi and Schuff 2010). In the following, to derive our hypotheses we review the existing literature on these three dimensions of product reviews and their relation to price with respect to sales-related dependent variables.

4.2.1 Review Dimension: Valence

Valence refers to the preference conveyed with the review, which can be positive, neutral, or negative (Liu 2006). The average number of stars that previous reviewers have assigned to the product indicates its valence. It is an indicator of the product's quality and customers' satisfaction with the product (Floyd et al. 2014; Kostyra et al. 2016; Maslowska et al. 2017; Watson et al. 2018). According to social impact theory, people affect one another, to the point that one individual's actions influence another individual's motives, values, and behaviors (Latané 1981). Latané (1981) defines such effects as social impact. As such, product reviews have a social impact. The exposure to product reviews, i.e., to another customer's satisfaction with a product, can generate, support, or change a customer's preference for the product. Thus, product reviews have a persuasive effect (Rui et al. 2013), as they move customers' preferences toward the preference (positive, neutral, negative) given in the review and thereby affect customers' purchase decisions (Rui et al. 2013).

Research on the impact of valence on sales has so far been consistent in its positive direction of the effect but mixed regarding its significance. The majority of studies find a significantly positive effect of valence on sales (Chintagunta et al. 2010; Gopinath et al. 2014; Maslowska et al. 2017), sales rank (Chevalier and Mayzlin 2006), and choice in experimental settings (Kostyra et al. 2016). However, some studies find valence to be an insignificant driver of sales (Duan et al. 2008) and sales rank (Amblee and Bui 2011; Park et al. 2012).

In recent years conceptional literature reviews (Cheung and Thadani 2012; Trenz and Berger 2013; King et al. 2014), as well as meta-analyses (Floyd et al. 2014; You et al. 2015; Babić Rosario et al. 2016), have started to summarize and analyze the existing research on product reviews. We concentrate on the three meta-analyses analyzing sales-related dependent variables: Floyd et al. (2014), You et al. (2015), and Babić Rosario et al. (2016). All three meta-analyses find a positive impact of valence on sales. Floyd et al. (2014) analyze 26 articles on how valence influences the elasticity of retailer sales. They find a positive mean sales elasticity with a valence of 0.69. The meta-analysis by You et al. (2015) corroborates this positive impact of valence based on 51 articles. They report an average valence elasticity of 0.42. Babić Rosario et al. (2016) review research with a broader scope, including 96 studies. They also report a positive correlation between valence and sales. Hence, following the majority of findings, we test the following hypotheses:

H_{1a}: *Positive valence, i.e., four- and five-star reviews, has a positive impact on sales compared to a neutral valence of three stars.*

H_{1b}: *Negative valence, i.e., one- and two-star reviews, has a negative impact on sales compared to a neutral valence of three stars.*

4.2.2 Review Dimension: Volume

Volume is the total number of reviews that one product has received (Floyd et al. 2014). Many studies name customer awareness as reason why volume without any information on valence has an impact on sales. With an increasing number of reviews, the probability of gaining information on the product increases, i.e., awareness of the product (Liu 2006; Chen et al. 2011; Cui et al. 2012; Park et al. 2012). Awareness, in turn, is a necessary condition for purchasing, thus resulting in higher sales (Godes and Mayzlin 2004). However, for reviews that are posted on retailer websites the creation of awareness is a questionable reason, as customers only see the review after searching for the product (Duan et al. 2008). For reviews on retailer websites, the bandwagon effect offers a more suitable explanation. The bandwagon effect describes diffusion behavior, in which the probability of adoption increases with the number of people who have already adopted (Babić Rosario et al. 2016). As many review systems require a verified purchase in order to write a review, e.g., Amazon.com, a high number of reviews implies a high number of people who have bought the product. Social impact theory also underlines that the impact of other people on an individual's behavior is, among other things, based on the number of other people exerting an impact (Latané 1981). As the volume of reviews represents the number of people, the more reviews there are, the higher the incentive there is to imitate previous behavior.

Most empirical studies report a positive impact of volume on sales (Maslowska et al. 2017) and sales rank (Chevalier and Mayzlin 2006; Amblee and Bui 2011). Others find the impact to be insignificant: Gopinath et al. (2014) report that volume does not impact the sales of cellular phones while valence does. Chintagunta et al. (2010) support this finding for the box-office performance of movies.

Meta-analytical findings, however, support a positive impact of volume on sales. Floyd et al. (2014) find a positive mean sales elasticity of volume of 0.35. You et al. (2015) report an average volume elasticity of 0.24. However, the meta-analyses present different results on which dimension is more influential. Babić Rosario et al. (2016) choose a more differentiated approach. They introduce the composite valence–volume metric to differentiate between absolute and relative volume. They add to existing meta-analyses that volume and the composite valence–volume are most important with respect to sales. Furthermore, analyzing the results of these meta-analyses, the relation between volume and sales is more robust than the one between valence and sales (Schoenmueller et al. 2018). Following meta-analytical results, we hypothesize:

H_2: *An increasing volume of reviews has a positive impact on sales.*

4.2.3 Review Dimension: Variance

Variance is the variation in reviews and captures the heterogeneity among reviews (Sun 2012). Different interpretations of the impact of variance include, on the one hand, that, as customers are risk-averse, heterogeneity in evaluations should decrease demand; and, on the other hand, that heterogeneous reviews induce curiosity, which increases demand. Additionally, a high dispersion of reviews might make customers deduce that the product is a niche product which induces extreme evaluations (Sun 2012). Research mainly focuses on volume and valence, while only a few studies pay attention to variance, with mixed findings (Babić Rosario et al. 2016). Clemons et al. (2006) and Sun (2012) report a significant correlation of the variance of reviews and sales, and Kostyra et al. (2016) corroborate these insights with a choice experiment. In contrast, Chintagunta et al. (2010) find no significant impact of variance.

Babić Rosario et al. (2016) provide the only meta-analysis that includes variance. They derive that polarized evaluations increase risk and uncertainty, causing customers to avoid the product. Hence, variance reduces customers’ reliance on reviews (Babić Rosario et al. 2016). Following these findings, we hypothesize:

H_3: *Increasing variance decreases sales.*

4.2.4 Interactions Between Review Dimensions

Despite strong growth in the field, we do not yet have a clear picture of product reviews. One potential reason for the mixed findings might be the omission of interactions among review dimensions (Kostyra et al. 2016; Maslowska et al. 2017).

Besides the direct impact of volume on sales, volume might moderate the effect of valence on sales. Higher volume increases the trustworthiness of the reviews' valence, as the overall rating converges to the true value of valence with an increasing number of reviews. While Chintagunta et al. (2010) find no significant impact of this interaction in the field of movies, Park et al. (2012) stress the relevance of the interaction of valence and volume and report that valence is positively interacted with volume in the category of camera products. Both Maslowska et al. (2017), for a high number of fast-moving consumer-goods categories, and Kostyra et al. (2016), in a choice experiment, support the notion that a high number of reviews, i.e., high volume, strengthens the positive sales impact of positive valence, as well as the negative sales impact of negative valence. Therefore, we hypothesize the following interaction between valence and volume:

H_{4a}: *Volume moderates the impact of four- and five-star reviews positively, leading to a more positive impact on sales.*

H_{4b}: *Volume moderates the impact of one- and two-star reviews negatively, strengthening their negative sales impact.*

Sun (2012) provides reasons for the inclusion of the interaction of valence and variance. High variance is associated with a niche product, i.e., with extreme evaluation, as some love and others hate the product. The author finds a significant interaction between valence and variance: for a product with low valence, higher variance increases demand. For high-valence products, higher variance reduces demand. These findings are not supported by Chintagunta et al. (2010). Another interpretation of the impact of the variance of reviews relates to risk aversion or the trustworthiness of the review. Low variance in reviews reduces risk and increases trustworthiness, while high variance increases the risk involved in the purchase. Kostyra et al. (2016) find support for the idea that higher variance decreases the positive impact of high valence and decreases the negative impact of low valence. Hence, we hypothesize moderation of the impact of valence on sales by variance:

H_{5a}: *For high valence, higher variance decreases sales, i.e., increasing variance decreases the positive impact of high valence on sales.*

H_{5b}: *For low valence, higher variance increases demand, i.e., increasing variance weakens the negative impact of low valence on sales.*

4.2.5 Price

An extensive stream of research on pricing reflects that changing the price of a product is one of the most important topics in marketing (Gijsbrechts 1993). Two influential meta-analyses by Tellis (1988) and Bijmolt et al. (2005) summarize the research on price elasticities. Both meta-analyses focus on offline pricing; consequently, they do not contain product reviews. However, the construct linking product review and price is quality, as product reviews are an indicator of the quality of the product, respectively, of customers' satisfaction with the product (Floyd et al. 2014; Kostyra et al. 2016; Maslowska et al. 2017). Both Tellis (1988, p. 334) and Bijmolt et al. (2005, p. 150) assess whether the inclusion of a quality indicator influences price elasticity under the hypothesis that not including quality would bias price elasticities positively. The results are mixed: while Tellis (1988) finds support for the omitted variable bias, Bijmolt et al. (2005) do not. Several studies explicitly focus on the determinants of price elasticities or price-promotion elasticities. Fok et al. (2006) provide a selection of such studies on price elasticities. The focus is on category, brand, and product features to explain the differences in price elasticities. Fok et al. (2006) find, among others, that brand size as a share of sales moderates price elasticities. Quality as an underlying construct plays an important role in the reasoning for this determinant of price elasticities. For brand size, the hypothesis based on previous empirical studies is enhanced by the idea "that large brands tend to have higher quality; in turn, this could lead to lower price elasticities" (Fok et al. 2006, p. 448). Hence, although meta-analyses provide opposing results, quality is inherent to pricing literature, meaning that increasing quality might shift price elasticity closer to zero.

In research on product reviews, while there are studies that control for price (You et al. 2015; Babić Rosario et al. 2016)[42], that analyze the impact of reviews on price (Shin et al. 2008), as well as the impact of price on reviews (Li and Hitt 2010), research on the moderation of the impact of price on sales by dimensions of product reviews is scarce. Kostyra et al. (2016)[43] and Maslowska et al. (2017) are two exceptions. Only Maslowska et al. (2017) include interactions among the dimensions of product reviews and price, while Kostyra et al. (2016) do not assess interactions directly but use a dichotomous control-group approach. Kostyra et al. (2016) conduct a conjoint analysis including all three dimensions of product reviews, as well as

[42] Two of the existing meta-analyses on product reviews, review the inclusion of price as a control variable and provide a mixed picture. While Babić Rosario et al. (2016) report that not controlling for price systematically biases the impact of word-of-mouth information, You et al. (2015) find no significant impact.

[43] Kostyra et al. (2016) do not assess interactions directly but use a dichotomous control-group approach.

product attributes, including price. They compare the relevance of price when product reviews are present as opposed to when they are not. The relevance of price and all other product attributes decreases when product reviews are available. Maslowska et al. (2017) provide the only empirical study analyzing interactions of the product review dimensions valence and volume with price. However, the authors reduce price to a factor variable and exclude variance from the analysis. They find a stronger impact of valence and volume, as well as the moderation of valence by volume for high-priced products.

Valence and volume, and their interaction, signal the quality of the products. Providing information on the quality of the product changes the risk involved in the purchase (Erdem et al. 2002; Kostyra et al. 2016).Therefore, following the quality assumptions in the pricing literature, product reviews may moderate price elasticities. For high-valence products, the risk involved in the investment decreases as a result of the positive reviews, such that price is a less relevant factor, i.e., decreasing the impact of price on sales. Following insights on interactions among review dimensions, the weakening of the price elasticity by high valence should be enhanced by high volume, resulting in a less negative impact of price. The more positive reviews a product has, the less important is the price of the product. For low-valence products, negative reviews increase the perceived risk, which makes price a more relevant factor, thereby increasing absolute price elasticity (more negative). High volume then intensifies this relation, i.e., price elasticity is stronger negative. Thus, we hypothesize:

H_{6a}: *The higher the volume for positive valence reviews, the closer to zero the price elasticity.*

H_{6b}: *The higher the volume for negative valence reviews, the further away from zero the price elasticity.*

Finally, increasing variance in reviews augments uncertainty about the review, while low variance in reviews increases trustworthiness. For positive valence, high variance makes the review less informative and should strengthen the role of price. Positive valence shifts price elasticity closer to zero, as positive reviews reduce the perceived risk for the customer. The stronger the variance in positive reviews, the less trustworthy the product review. Increasing variance thus counteracts the positive signal in the positive valence, meaning that customers are less sure about the review. Consequently, with increasing variance in positive valence, price should regain importance, pushing the price elasticity further away from zero. We assume that this effect changes with the direction of valence. Negative valence shifts price elasticity further away from zero, as negative reviews increase the perceived risk of the purchase. The stronger the variance, the less trustworthy the negative reviews, i.e., the weaker the informational value. Hence, variance counteracts the shift by negative valence, meaning the more variance there is in the negative reviews, the less sure customers are about the negative statement. With decreasing trust in information on low quality, price should play a less important role compared to low valence and low variance. Therefore, we hypothesize the following moderation of the impact of valence on sales by variance:

H_{7a}: *The more variance there is in positive valence, the stronger, i.e., the further away from zero, the price elasticity.*

H_{7b}: *The more variance there is in negative valence, the less strong, i.e., the closer to zero, the price elasticity.*

In summary, the primary objective of this paper is to analyze the interactions between review dimensions and price, which we capture with hypotheses H_{6a} to H_{7b}. Additionally, we assess the impact of review dimensions and interactions among review dimensions on sales with hypotheses H_{1a} to H_{5b}, since existing literature provides mixed findings and lacks a comprehensive model. In order to close this gap in terms of a comprehensive analysis, we follow the conceptual framework displayed in Figure 4.1.

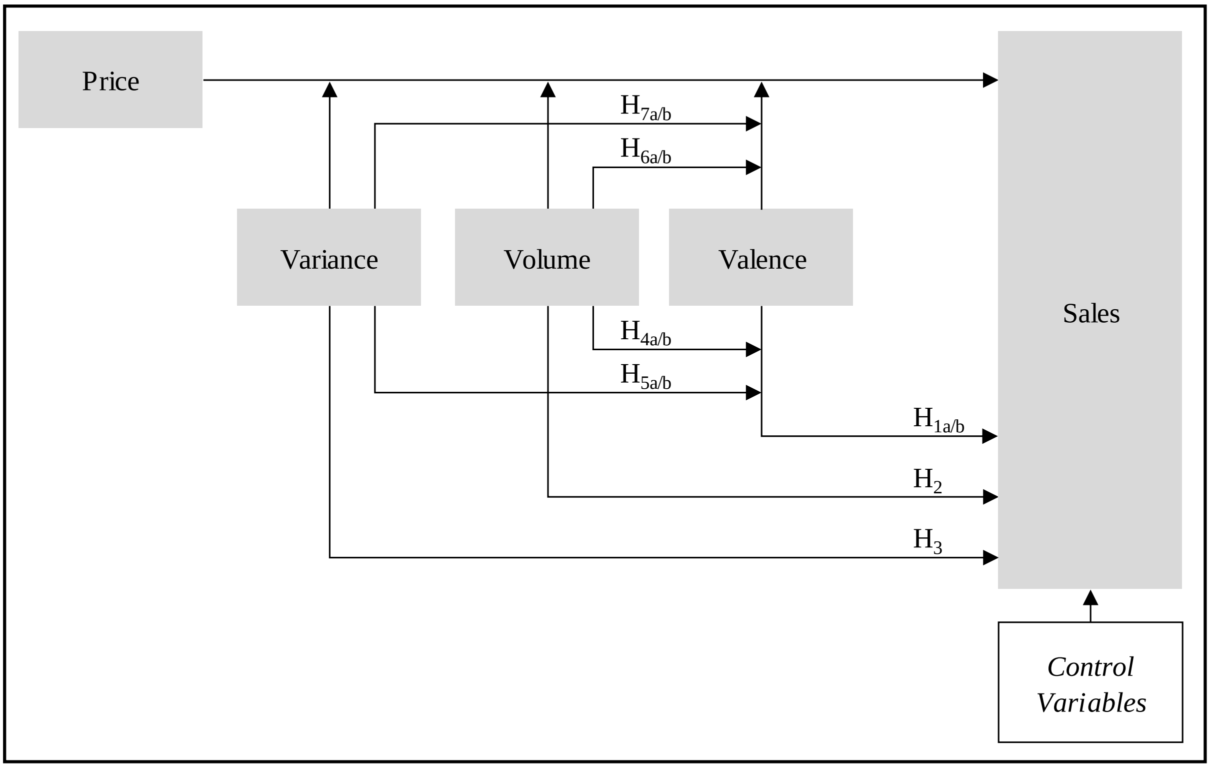


Figure 4.1: Conceptual Framework

4.3 Empirical Study

4.3.1 Product Review Process

We focus on reviews provided on the websites of a large, European online retailer with more than five million active customers and more than one billion euros in revenue in 2017. The retailer sells a large variety of goods including, groceries, accessories, and electronic goods. The product review platform is part of the retailer-hosted website and asks for product reviews for specific products sold on the retailer's website. In this online shop, a standard process to review products is established. Customers see the average review valence and the number of reviews (volume) next to the product picture. The online shops display valence as the average review rounded to full stars from one to five, with the total number of reviews (volume) next to it. Figure 4.2 and Figure 4.3 show two representations of product reviews in the online shop. All product pages include the review information in one of these formats. Consequently, customers always see the average review and the number of reviews, meaning that every buying decision is influenced by the review information.[44] They do not need to search for this aggregated information. Individual product reviews are available by clicking on the stars or the number of reviews. A bar chart providing the number of reviews (volume) for each valence option (one to five stars) illustrates the variance, as displayed in Figure 4.4.

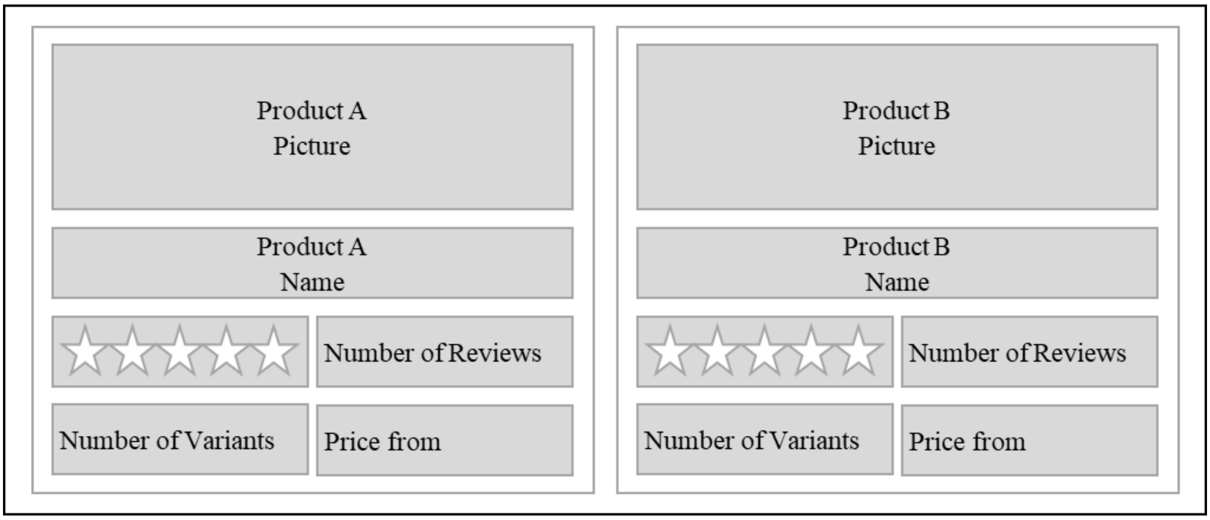


Figure 4.2: Product Information on Overview Website

[44] Promotions on landing pages only show the rating and not the number of reviews. Clicking on the respective product on promotion directs the customer to a product detail view, which shows both review valence and volume.

Figure 4.3: Product Information on Product Detail Website

Figure 4.4: Variance of Product Reviews

The online shop invites customers to provide reviews via a process typical for current retail websites. To increase barriers to submitting manipulated reviews, the online shop includes quality measures in the process of review submission. We describe these in the following. The process of submitting a product review starts with a guiding remark that reviews should be relevant and helpful. Next, the customer must provide a review rated from one to five, add a title for the review, and complement the review with further details edited in a free text field. The customer is then asked to provide some personal information, i.e., name and email address. Without this information submission of the review is not permitted, while the customer can decide whether the review is shown with or without his or her name displayed. Finally, the customer needs to agree to the terms of participation. These include the fact that the product review becomes the property of the online shop, that the personal data may be saved and used to contact the reviewer regarding the review, and that the online shop can adapt the written evaluations if these do not correspond to its etiquette.

4.3.2 Data Collection and Description

We collect transaction data from a large European pure online retailer over the period of four years from October 2012 until September 2016. The data set comprises roughly 93,000 products, of which 78 million pieces have been sold, and includes products both with and without reviews. We reduce the data to those products that have attracted product reviews according to the process described in Chapter 4.3.1, i.e., in the data set used for subsequent analyses only products with at least one review are included. This reduces the number of unique products by 50 percent, so that the data set comprises 52 million sold pieces. Of this data set, we use the first 12 months as the initialization phase. This reduction leaves us with data on products in 88 product categories[45] across seven European countries. The final data set includes roughly 45,000 products,[46] with 204,904 individual reviews. The number of products sold over the course of the three years adds up to 44 million pieces at an average price of €23.76 per piece or 180 million weight units at an average price of €32.64 per weight unit. The average star-rating displayed with a product over the three years was 4.46, with an average number of reviews per product of 9.34. Table 4.2 displays the descriptive statistics of the data set.[47]

Variable	Mean	SD	Min.	25% Q.	Median	75% Q.	Max.
Weekly Price per Product €	23.76	27.80	0.25	5.99	13.32	32.25	1,439.00
Average Valence	4.46	0.76	1.00	4.00	5.00	5.00	5.00
Average Volume	9.34	18.02	1.00	2.00	4.00	10.00	860.00
Average Variance	0.51	0.59	0.00	0.00	0.29	0.95	2.83
Weekly Number of Products Sold	15.80	40.1	0.00	2.00	6.00	15.00	2,879.00

Table 4.2: Descriptive Statistics – Product Reviews

The quantiles of valence exhibit a strongly positively skewed distribution, with 50 percent of the data points having an average of five stars. Figure 4.5 shows the frequency of each valence option based on the individual product reviews over the course of the three years. In line with

[45] Categories comprise a wide range of product types, for example, fast-moving consumer goods, durables, and electronic products.

[46] Products are country-specific. The same product sold in two countries (with different packaging as a result of different languages) is counted as two products.

[47] We provide details of the calculation of valence, volume, and variance in the subsequent chapter.

the existing literature, the frequency distribution is positively skewed (J-shaped) (Hu et al. 2017).

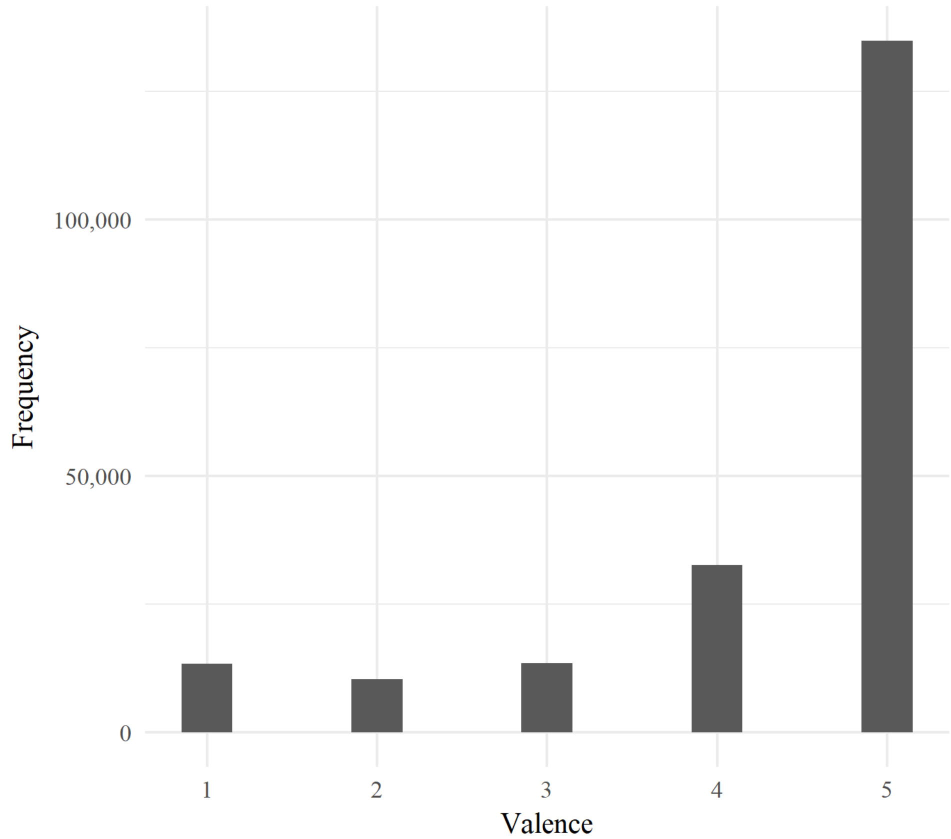


Figure 4.5: J-shape of Online Product Reviews (n = 204,904 Unique Reviews)

4.3.3 Model

We analyze the effects of product reviews on sales with a fixed-effects model on weekly product level. The dependent variable is sales, which we operationalize as the logarithm of the sum of weight units sold of product j in week t and aggregate over all variants of the same product, for example, flavors, sizes, and colors. We use the terms sales and quantity interchangeably to refer to the amount of weight units sold. For product reviews, we consider the three dimensions valence, volume, and variance, as outlined above. $Valence_{jt}$ is the average rating of product j in week t based on all reviews for j up to week t, meaning that for a given week all previous reviews, as well as the new reviews for that week, are reflected in the valence score. We use the first twelve months of data to generate a starting value for the valence variable, i.e., an average star rating for the product. We then aggregate the individual product reviews into weekly averages, cumulate, and round to the nearest star-rating.

$$\text{Valence}_{jt} = \frac{\sum_{t=1}^{t} \text{Weekly Valence}_j}{\text{Volume}_{jt}} \tag{4.1}$$

Volume_{jt} is the number of all reviews submitted for product j up to week t. We add up the number of individual reviews per week to a week-specific volume score and cumulate this number with proceeding weeks. We include the logarithm of the mean-centered variable as volume.[48]

$$\text{Volume}_{jt} = \sum_{t=1}^{t} \text{Number Weekly Reviews}_{jt} \tag{4.2}$$

Variance is the standard deviation of the cumulated valence of reviews. We include the mean-centered cumulated standard deviation for each product based on each week's average valence.[49]

$$\text{Variance}_{jt} = \text{sd}(\text{Valence}_{jt}) \tag{4.3}$$

A product may include different variants, e.g., different sizes, flavors, and colors. We derive the price of a product as price per kilogram. With this definition of price per weight unit across all product categories we account for different variants of the same product. The price is the mean-centered logarithm of the average weekly price per weight unit for product j in week t.

We interact each of the three dimensions of product reviews separately with price. Furthermore, we include the three-way interaction between valence, volume, and price on sales, as well as valence, variance, and price on sales. With respect to interactions between review dimensions, we include the two-way interactions between valence and volume, and valence and variance.

We control for promotional activity, with the variable Promo_{jt} equaling 1 if product j is promoted in week t, and 0 otherwise. We further include the dependent variable lagged by one week to capture dynamic effects and to remove autocorrelation. Finally, the sum of quantity sold in the entire shop controls for shocks in the country. To account for product- and week-specific variation, we include fixed effects α_{1j} for product j and α_{1t} for week t. It is very likely that products differ in quality; however, the quality is not completely observable. Products of

[48] Whenever mean-centering is applied we use the grand mean for centering purposes. For logged variables we first take the logarithm and then subtract the grand mean of the logged variable from the logged variable.

[49] We do not take the logarithm of variance because of data constraints. Variance equals 0 in 45 percent of observations, which would result in considerable data loss.

high quality may generate more sales, be higher priced, and exhibit higher valence. This may lead to the price, review, and error term being correlated. With the product-specific time-invariant fixed effects we address potential endogeneity due to unobserved quality difference between products.

$$\begin{aligned}\log(Y_{jt}) = {} & \alpha_{1j} + \alpha_{2t} + \beta_1 * \log(\text{Price})_{jt} + \beta_2 * \log(\text{Volume})_{jt} + \beta_3 * \text{Valence}_{jt} + \beta_4 * \text{Variance}_{jt} \\ & + \beta_5 * \log(\text{Price})_{jt} * \log(\text{Volume})_{jt} + \beta_6 * \log(\text{Price})_{jt} * \text{Valence}_{jt} + \beta_7 * \log(\text{Price})_{jt} * \text{Variance}_{jt} \\ & + \beta_8 * \text{Valence}_{jt} * \log(\text{Volume})_{jt} + \beta_9 * \text{Valence}_{jt} * \text{Variance}_{jt} + \beta_{10} * \log(\text{Price})_{jt} * \text{Valence}_{jt} * \log(\text{Volume})_{jt} \\ & + \beta_{11} * \log(\text{Price})_{jt} * \text{Valence}_{jt} * \text{Variance}_{jt} + \beta_{12} * \log(Y_{jt-1}) + \beta_{13} * \log(\text{Shop Quantity})_t + \beta_{14} * \text{Promo}_t + \epsilon_{jt}\end{aligned} \quad (4.4)$$

We estimate the model in R using the “lfe” package (Gaure 2018). The unit root test reveals that the dependent variable is stationary.[50]

4.3.4 Empirical Results

This chapter presents the empirical results of the study. Table 4.3 displays the estimates of the fixed-effects model described in Equation 4.4. Price, volume, and variance are mean-centered. Valence is a factor variable with reference level three. Thus, for interpretation purposes, we assume mean-centered variables at the mean and valence at the reference level of three stars. We do not display individual product and time fixed effects because of the high number.

First, the focus is on the impact of the three review dimensions, valence, volume, and variance, on sales, regardless of price, i.e., hypotheses H_{1a}–H_3. Afterwards we analyze the interactions between valence and volume (hypotheses H_{4a} and H_{4b}), as well as valence and variance (hypotheses H_{5a} and H_{5b}). Finally, we concentrate on the moderation of price by review dimensions (hypotheses H_{6a}, H_{6b}, H_{7a} and H_{7b}). For visualization purposes, we calculate scenarios, which are different combinations of the independent variables. We combine the five levels of valence (one to five stars) with three levels of volume, variance, and price. For these continuous, mean-centered variables we choose the mean, as well as one standard deviation above and below the mean as levels for visualization. These level definitions result in 135 scenarios (5 levels of valence* 3 levels of volume* 3 levels of variance * 3 levels of price = 135 scenarios).[51]

[50] We test whether the dependent variable is stationary with the Augmented Dickey-Fuller Test. The null hypothesis that a unit root is present in the time series can be rejected.

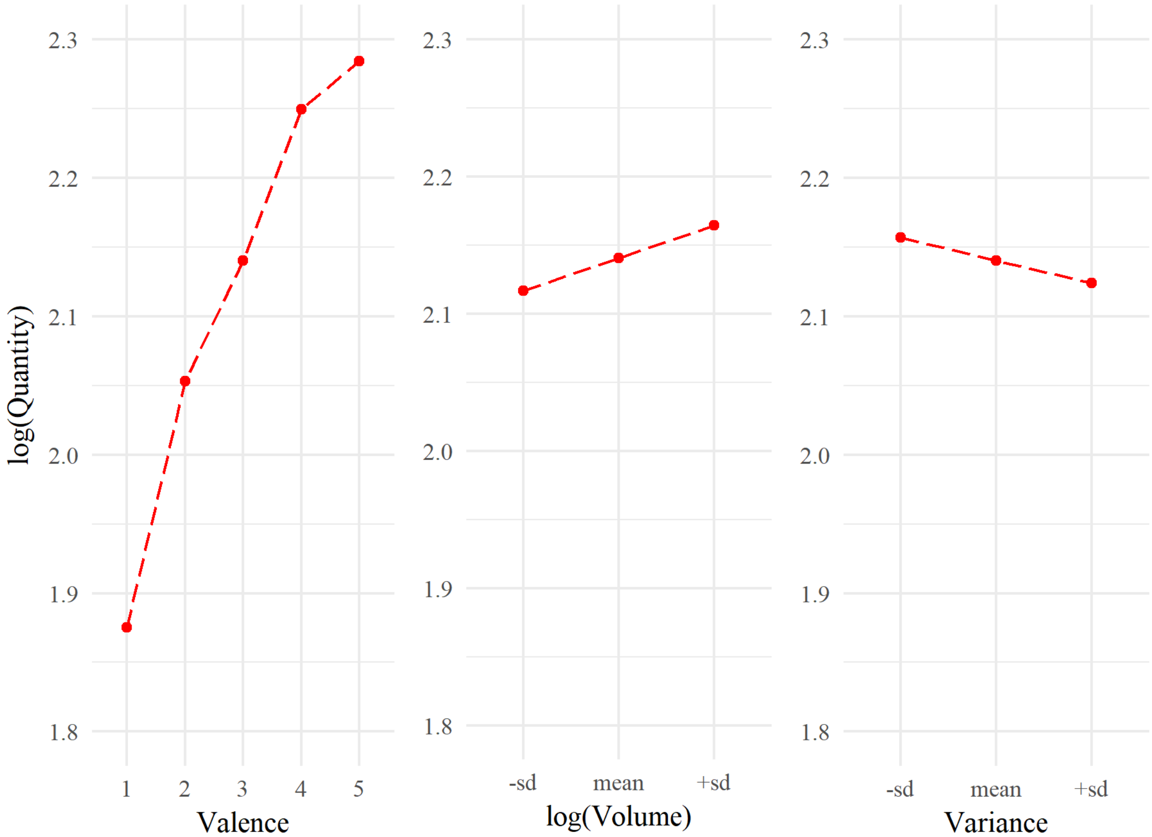
[51] Table 6.3 in the Appendix presents the levels of the independent variables, with the resulting quantities and price elasticities and intercepts. All insignificant terms are set to zero.

		Estimate	Std. Error	t value	Pr(>|t|)
β_1	log(Price)	-1.678	0.005	-351.891	0.0000 ***
β_2	log(Volume)	0.021	0.003	6.532	0.0000 ***
$\beta_{3.1}$	Valence 1	-0.265	0.037	-7.186	0.0000 ***
$\beta_{3.2}$	Valence 2	-0.087	0.010	-9.028	0.0000 ***
$\beta_{3.3}$	Valence 4	0.109	0.005	23.135	0.0000 ***
$\beta_{3.4}$	Valence 5	0.144	0.005	29.458	0.0000 ***
β_4	Variance	-0.028	0.005	-5.792	0.0000 ***
β_5	log(Price) * log(Volume)	-0.020	0.002	-9.599	0.0000 ***
$\beta_{6.1}$	log(Price) * Valence 1	0.084	0.026	3.265	0.0011 **
$\beta_{6.2}$	log(Price) * Valence 2	-0.003	0.007	-0.488	0.6259
$\beta_{6.3}$	log(Price) * Valence 4	0.011	0.003	3.018	0.0025 **
$\beta_{6.4}$	log(Price) * Valence 5	0.014	0.004	3.781	0.0002 ***
β_7	log(Price) * Variance	0.003	0.003	0.803	0.4220
$\beta_{8.1}$	Valence 1 * log(Volume)	-0.098	0.026	-3.706	0.0002 ***
$\beta_{8.2}$	Valence 2 * log(Volume)	-0.038	0.008	-4.544	0.0000 ***
$\beta_{8.3}$	Valence 4 * log(Volume)	0.058	0.003	18.764	0.0000 ***
$\beta_{8.4}$	Valence 5 * log(Volume)	0.103	0.003	32.087	0.0000 ***
$\beta_{9.1}$	Valence 1 * Variance	-0.051	0.088	-0.576	0.5648
$\beta_{9.2}$	Valence 2 * Variance	0.031	0.011	2.855	0.0043 **
$\beta_{9.3}$	Valence 4 * Variance	-0.033	0.005	-6.389	0.0000 ***
$\beta_{9.4}$	Valence 5 * Variance	-0.035	0.006	-5.846	0.0000 ***
$\beta_{10.1}$	log(Price) * Valence 1 * log(Volume)	-0.056	0.015	-3.792	0.0001 ***
$\beta_{10.2}$	log(Price) * Valence 2 * log(Volume)	-0.008	0.006	-1.450	0.1471
$\beta_{10.3}$	log(Price) * Valence 4 * log(Volume)	0.014	0.002	6.682	0.0000 ***
$\beta_{10.4}$	log(Price) * Valence 5 * log(Volume)	0.013	0.002	5.741	0.0000 ***
$\beta_{11.1}$	log(Price) * Valence 1 * Variance	0.347	0.063	5.492	0.0000 ***
$\beta_{11.2}$	log(Price) * Valence 2 * Variance	0.000	0.008	-0.038	0.9696
$\beta_{11.3}$	log(Price) * Valence 4 * Variance	-0.009	0.004	-2.390	0.0169 *
$\beta_{11.4}$	log(Price) * Valence 5 * Variance	-0.009	0.005	-2.066	0.0389 *
β_{12}	log(Quantity$_{t-1}$)	0.188	0.001	329.708	0.0000 ***
β_{13}	log(Shop Quantity)	0.606	0.003	186.048	0.0000 ***
β_{14}	Promotion	0.221	0.019	11.534	0.0000 ***
Dependent variable					log(Quantity in kg)
Observations					2,788,753
Multiple R^2 full model					0.9179
Multiple R^2 proj. model					0.1483

**** <0.001; ** <0.01; * <0.05*

Table 4.3: Results of Fixed-Effects Model

The effects of each review dimension separately with the other variables at the mean respectively reference level support hypotheses H_{1a} –H_3. The valence of four ($\beta_{3.3}$) and five stars ($\beta_{3.4}$) increases sales, while one ($\beta_{3.1}$) and two stars ($\beta_{3.2}$) have a negative impact compared to the three-star reference level.[52] The left panel in Figure 4.6 displays the impact of valence on log quantity for mean price, mean volume, and mean variance. Hence, we find support for hypotheses H_{1a} and H_{1b}. The results further support hypothesis H_2. Volume per se has a positive impact on sales (β_2), as high volume increases trust in the product and signals that other customers have already bought the product (Figure 4.6, middle panel). Hypothesis H_3 is also supported as with increasing variance sales decrease (β_4) (Figure 4.6, right panel).[53]



Note: In each panel, all remaining variables are at the mean or reference level.

Figure 4.6: Effects of Valence, Volume, and Variance on Sales

Our analysis of the interaction of valence and volume supports prior studies (e.g., Park et al. 2012 and Maslowska et al. 2017). Volume moderates the positive impact of four- and five-star reviews (positive valence) positively ($\beta_{8.3}$ and $\beta_{8.4}$), leading to higher sales. A high number of

[52] A positive coefficient does not mean that the effect is positive; rather that it is larger than for three-star reviews (the selected reference point).

[53] In all figures insignificant terms are set to zero.

positive reviews strengthens the positive impact of positive reviews on sales, while a lower number of reviews weakens the positive impact on sales. For one- and two-star reviews volume strengthens the negative impact on sales. The more negative reviews, the stronger the negative impact of the negative reviews ($\beta_{8.1}$ and $\beta_{8.2}$). If fewer reviews form the negative review, the negative impact of negative valence on sales is less strong. Thus, in line with existing research (Park et al. 2012; Kostyra et al. 2016; Maslowska et al. 2017), we find support for hypotheses H_{4a} and H_{4b}. Figure 4.7 highlights this two-way interaction with price and variance at the mean.

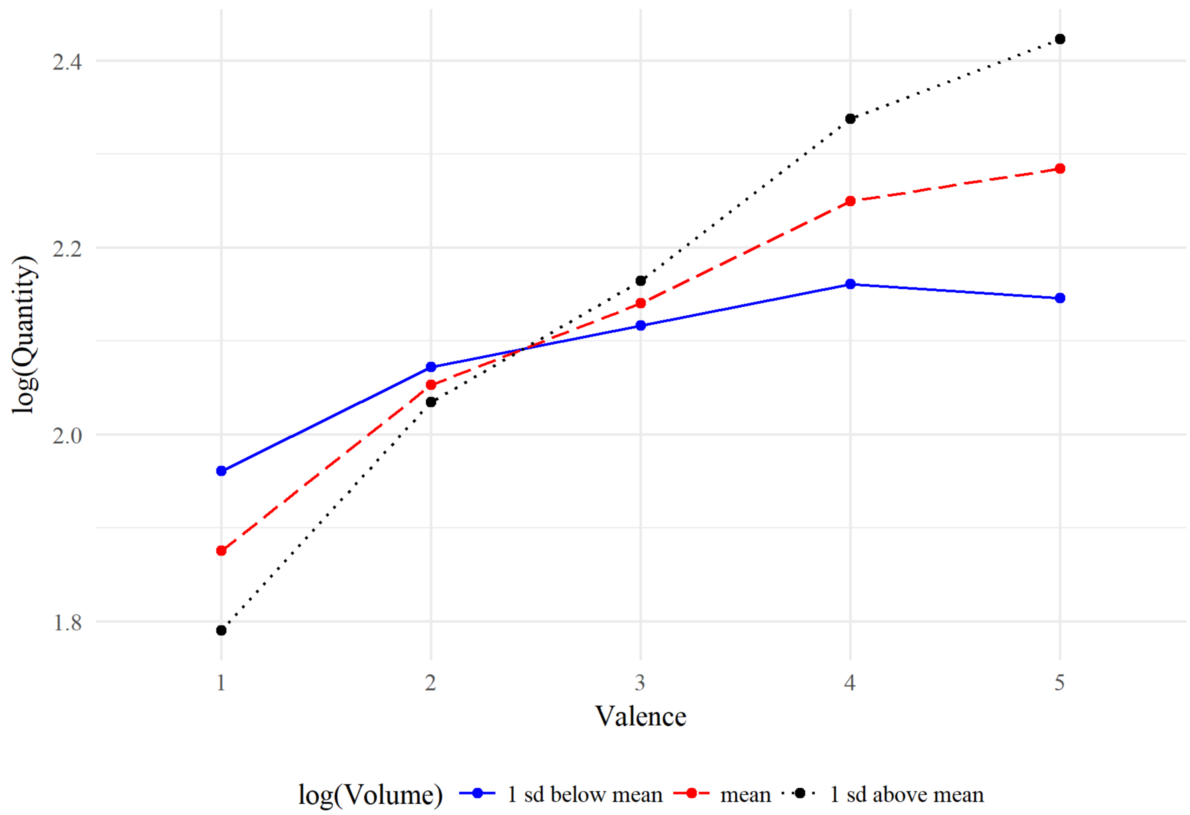


Figure 4.7: Interaction of Volume and Valence at Mean Price and Mean Variance

Finally, we derive the moderation of valence by variance in reviews. Increasing variance decreases the positive sales impact of positive valence ($\beta_{9.3}$ and $\beta_{9.4}$). More variance makes reviews less trustworthy and therefore reduces the sales impact of high valence. For two-star reviews, increasing variance weakens the negative sales impact of negative valence and makes the sales impact of low-valence product reviews less negative, i.e., variance moderates two-star reviews positively ($\beta_{9.2}$). For one-star reviews, the moderation is insignificant ($\beta_{9.1}$). Figure 4.8 displays the sales impact of valence dependent on variance. As a result of the insignificance of the moderation of one-star reviews, Figure 4.8 shows the main effect of variance on sales for valence of one. For valence of two the moderation ($\beta_{9.2}$ = 0.031) balances the main effect of variance (β_4 = -0.028). Figure 4.8 includes this small remaining difference for two-star reviews. For four- and five-star reviews the moderation of valence by variance reduces the sales impact. Hence, we find partial support for hypothesis H_5. Increasing variance causes decreasing sales for positive valence. For two-star reviews, variance moderates valence positively, thus, increasing sales for low valence, while for one-star reviews the moderation is insignificant.

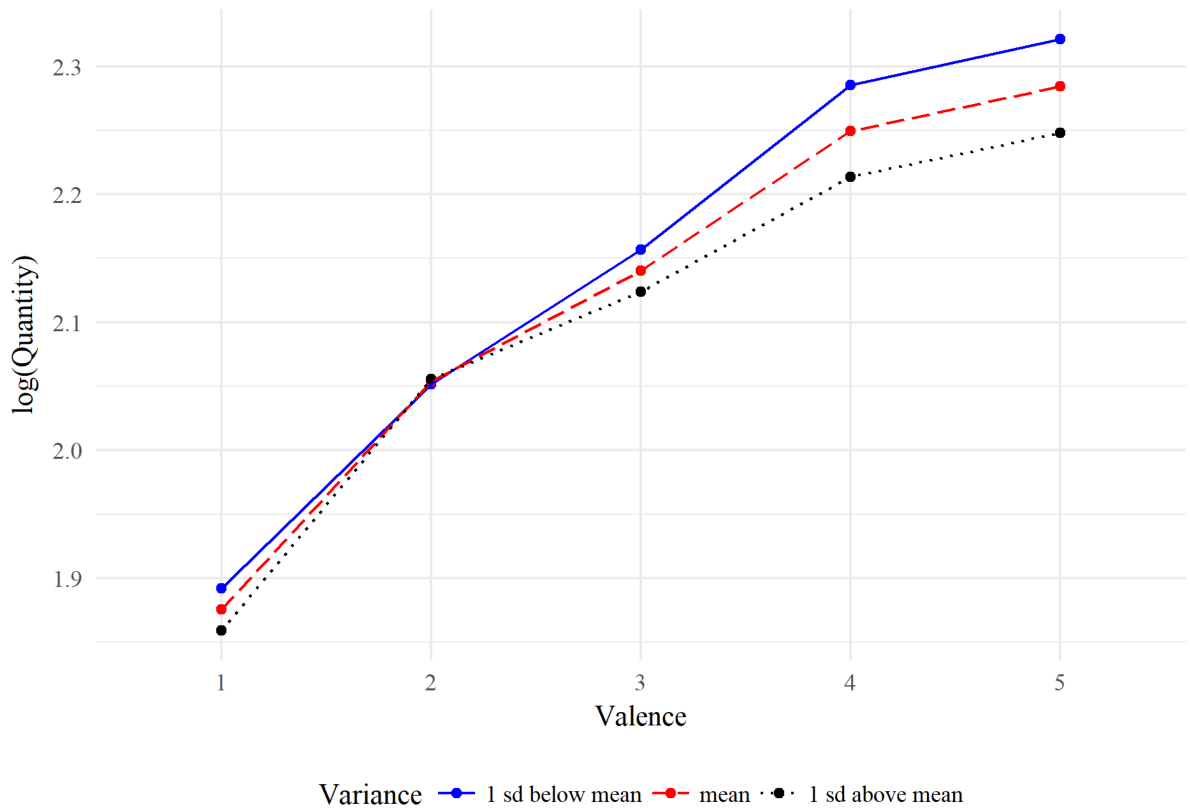


Figure 4.8: Interaction of Variance and Valence at Mean Price and Mean Volume

Figure 4.9 combines hypotheses H_{4a}, H_{4b}, and H_5 by showing the moderation of valence by variance with increasing volume. With increasing valence, increasing volume and decreasing variance, the sales of positive valence products increase, i.e., many positive reviews with little variation result in the highest sales. The role of volume and variance switches for two-star reviews: for few reviews with high variance, sales are the strongest. Thus, customers do not assume the negative reviews to be trustworthy as a result of high variance. Vice versa, the more reviews with low variance, the lower the resulting sales, as customers believe in the low quality of the product. However, the difference is barely visible in Figure 4.9, as it only changes the third decimal in logs, i.e., the effect is very small. Table 4.4 displays the relevant extract of the scenario table (Appendix Table 6.3) for mean price and valence of two. The fourth and fifth columns clarify the differences between the scenarios in the logarithm of quantity and quantity.

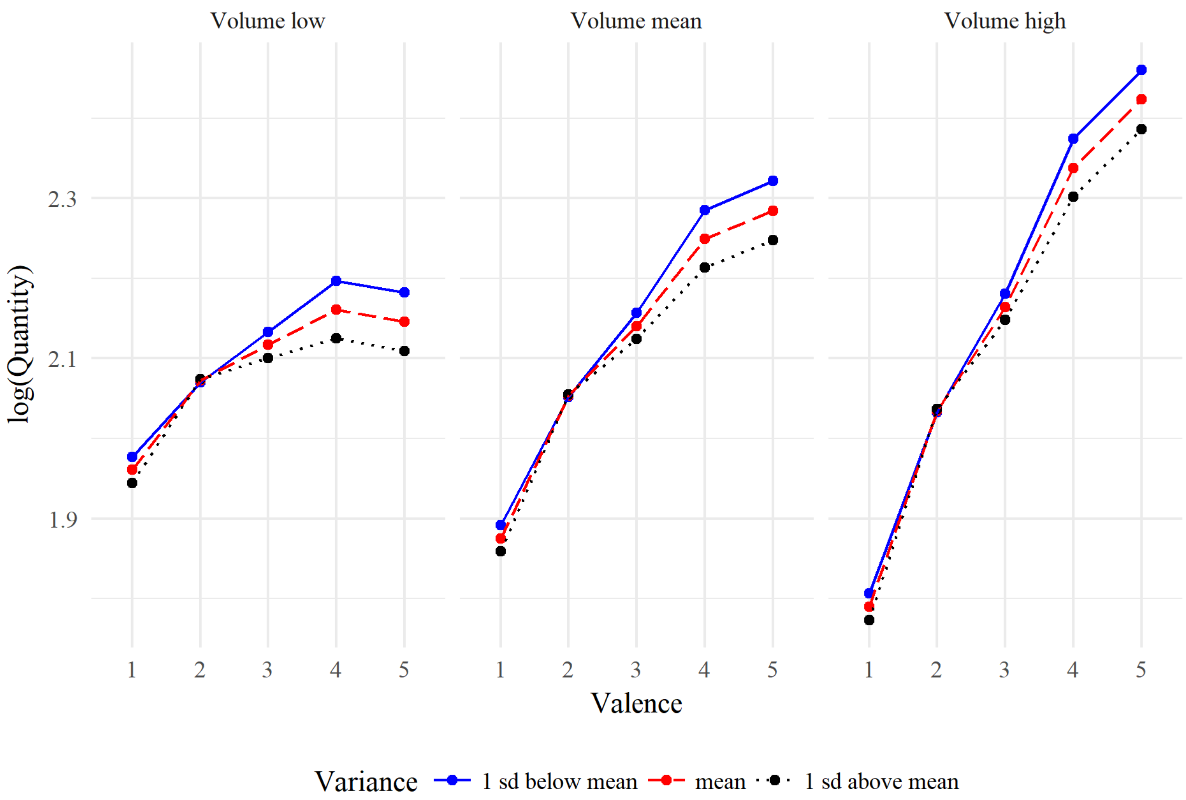


Figure 4.9: Interaction of Valence and Variance at Mean Price by Volume

Scenario	**Volume**	**Variance**	**log(Quantity)**	**Quantity in Weight Units**
47	low	high	2.0743	7.96
38	low	mean	2.0724	7.94
29	low	low	2.0704	7.93
50	mean	high	2.0553	7.81
41	mean	mean	2.0533	7.79
32	mean	low	2.0514	7.78
53	high	high	2.0363	7.66
44	high	mean	2.0343	7.65
35	high	low	2.0324	7.63

Table 4.4: Detailed Impact of Variance on Sales for Valence of Two Stars

In the following, we focus on the moderation of price. For visualization purposes, we derive the price elasticity for each of the scenarios presented in Table 6.3 in the Appendix. We rearrange Equation 4.4 into those parts that are independent of price changes (left side of the equation) and those that are dependent on price changes (right side of the equation):

$$
\begin{aligned}
&\log\left(\widehat{Y}_{jt}\right) - (\alpha_{1j} + \alpha_{2t} + \beta_2 * \log(\text{Volume})_{jt} && \beta_1 * \log(\text{Price}) \\
&+ \beta_3 * \text{Valence}_{jt} + \beta_4 * \text{Variance}_{jt} && + \beta_5 * \log(\text{Price}) * \log(\text{Volume}) \\
&+ \beta_8 * \text{Valence}_{jt} * \log(\text{Volume})_{jt} && + \beta_6 * \log(\text{Price}) * \text{Valence} \\
&+ \beta_9 * \text{Valence}_{jt} * \text{Variance}_{jt} \quad = && + \beta_7 * \log(\text{Price}) * \text{Variance} \\
&+ \beta_{12} * \log(Y_{jt-1}) + \beta_{13} * \log(\text{Shop Quantity})_t && + \beta_{10} * \log(\text{Price}) * \text{Valence} * \log(\text{Volume}) \\
&+ \beta_{14} * \text{Promo}_t) && + \beta_{11} * \log(\text{Price}) * \text{Valence} * \text{Variance}
\end{aligned}
\tag{4.5}
$$

As volume is a continuous variable, we insert the mean volume, one standard deviation above the mean and one standard deviation below the mean. Hence, for mean-centered variables the mean is zero. We further set insignificant coefficients to zero (the italics below indicate insignificance). We use the right-hand side of Equation 4.5 to generate the coefficient displaying price elasticity. For example, for a review with valence of four, mean volume and mean variance, the price elasticity is -1.668 (Scenario 95 in Table 6.3 in the Appendix):

$$
\begin{aligned}
&= \log(\text{Price}) * (\beta_1 + \beta_5 * \log(\text{Volume}) \\
&+ \beta_{6.4} * \text{Valence } 4 + \mathit{\beta_7 * Variance} \\
&+ \beta_{10.4} * \text{Valence } 4 * \log(\text{Volume}) \\
&+ \beta_{11.4} * \text{Valence } 4 * \text{Variance})
\end{aligned}
\tag{4.6}
$$

$$
\begin{aligned}
&= \log(\text{Price}) * (-1.678 + (-0.020 * 0) \\
&+ (0.010 * 1) + \mathit{(0.011 * 0.5)} \\
&+ (0.014 * 1 * 0) + (-0.009 * 1 * 0)\ ) \\
&= -1.668 * \log(\text{Price})
\end{aligned}
$$

The price elasticities across all scenarios range from -1.84 to -1.35, characterizing elastic goods. It is closer to zero but in a credible range of a recent meta-analysis study conducted by Bijmolt et al. (2005).

In line with hypothesis *H6a*, the three-way interaction effect of price, valence, and volume is significant for positive valence (four- and five-star reviews, i.e., $\beta_{10.3}$ and $\beta_{10.4}$). Hence, these three variables are interdependent in their effect on sales. With increasing volume, positive valence has a stronger impact on price elasticity, i.e., high volume strengthens positive valence in shifting price elasticity closer to zero. For negative valence, the picture is more complex. The three-way interaction is only significant and negative for one-star reviews, while the two-way interaction of price and valence of level one is positive. The more reviews there are, the further away from zero the price elasticity for one-star reviews. For two-star reviews both the two-way and the three-way interaction are insignificant. Hence, hypothesis *H6b* is only partially supported. Figure 4.10 displays the changes in price elasticities (setting insignificant terms to zero).

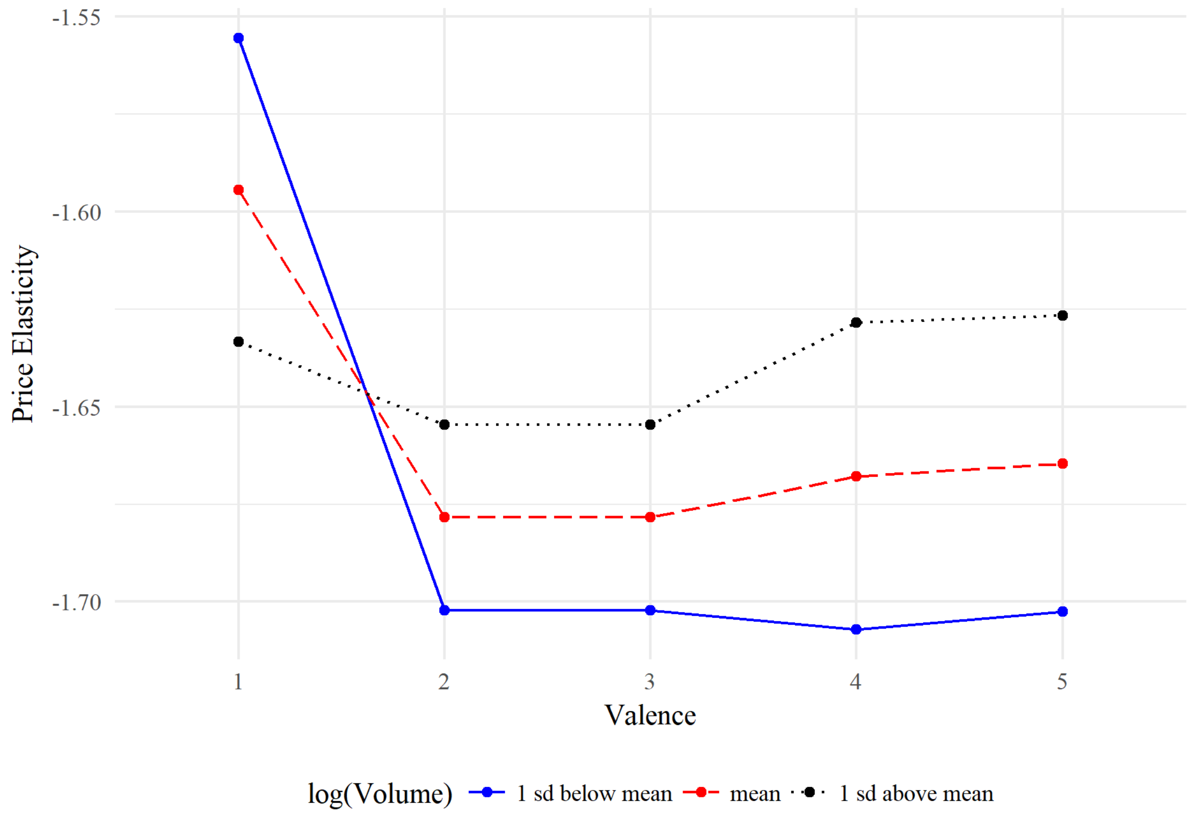


Figure 4.10: Three-way Interaction of Price, Valence, and Volume at Mean Variance

In the following, we assess the role of variance. We hypothesize that increasing variance in reviews augments uncertainty about the review, while low variance in reviews increases trustworthiness. The stronger the variance in positive reviews, the less trustworthy the product review for the customer. Hence, increasing variance counteracts the positive signal of positive valence, so that customers are less sure about the review. While positive valence shifts price elasticity closer to zero, high valence should balance this movement. Thus, the more variance there is in positive valence, the stronger, i.e., the further away from zero, the price elasticity. Thus, we expect the three-way interaction to be negative for positive valence ($\beta_{11.3}$ and $\beta_{11.4}$). Figure 4.11 displays this relation at mean volume. Hence, we find support for hypothesis *H7a* at low levels of significance and with low size. In contrast, we hypothesize that negative valence shifts price elasticity further away from zero, as negative reviews increase the purchasing risk. Variance then counteracts this movement: the more variance there is in the negative reviews, the less trustworthy they are. Interestingly, we find price elasticity to be closer to zero for one-star reviews, which contradicts the first part of this hypothesis. However, the moderation of variance functions as hypothesized. Strong variance shifts price elasticity closer to zero, while low variance shifts price elasticity further away from zero. Thus, we cannot completely support hypothesis *H7b*. It is further noteworthy that the impact of variance for low valence is larger than for high-valence reviews.

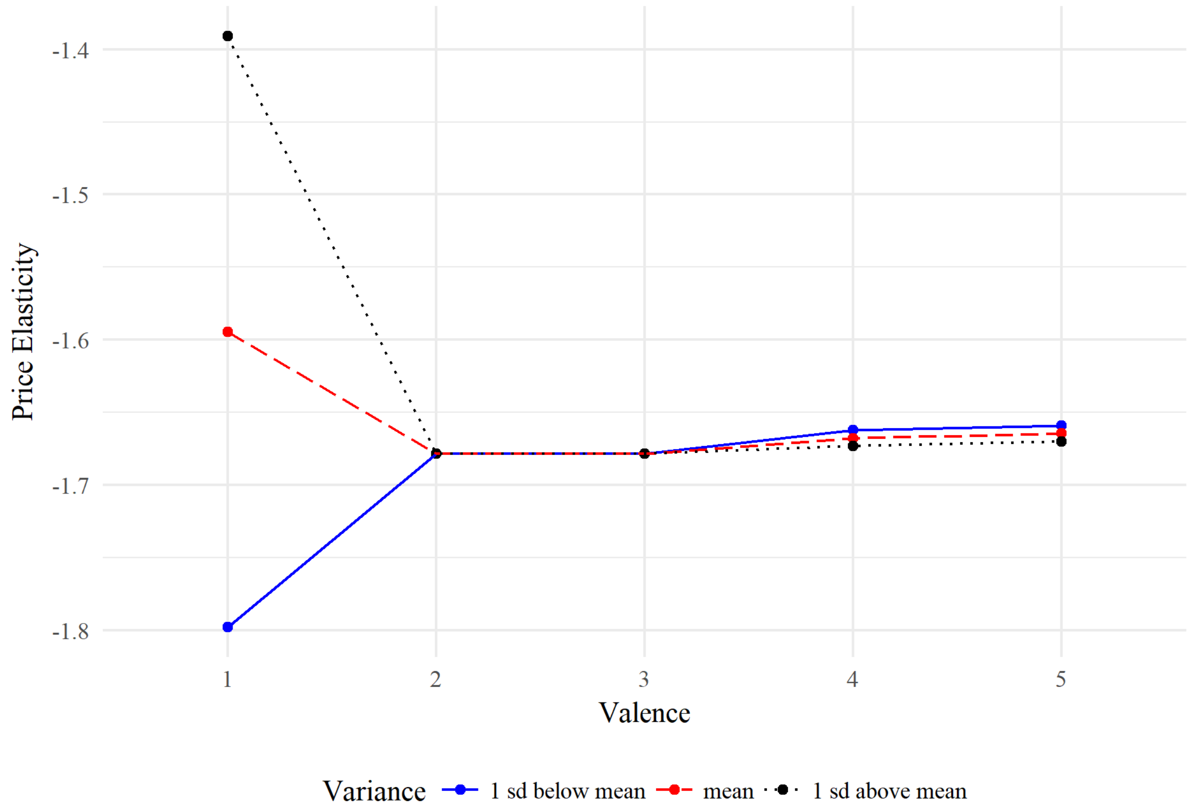


Figure 4.11: Three-way Interaction of Price, Valence, and Variance at Mean Volume

Finally, we adopt a comprehensive perspective combining both three-way interactions on price elasticity. Figure 4.12 depicts price elasticities dependent on low, mean, and high values of valence, volume, and variance. We find the strongest negative price elasticities for reviews with one-star, high volume, and low variance. Hence, if many customers agree about having low satisfaction with the product, the signal of price is most important. In this case, a price reduction generates the highest sales impact. The high impact of variance and valence of one star is based on the size of $\beta_{11.1}$ compared to the other coefficients. Interestingly, one star-reviews are also accompanied by price elasticity closest to zero. If customers disagree on the low quality of a product, the signal of price is least important. For five-star reviews, variance has a very small impact, while higher volume shifts the price elasticity of positive volume closer to zero. Thus, the higher the number of reviews for positive valence, the less important the price signal, with variance playing a minor role. We summarize our results with respect to the hypotheses in Table 4.5.

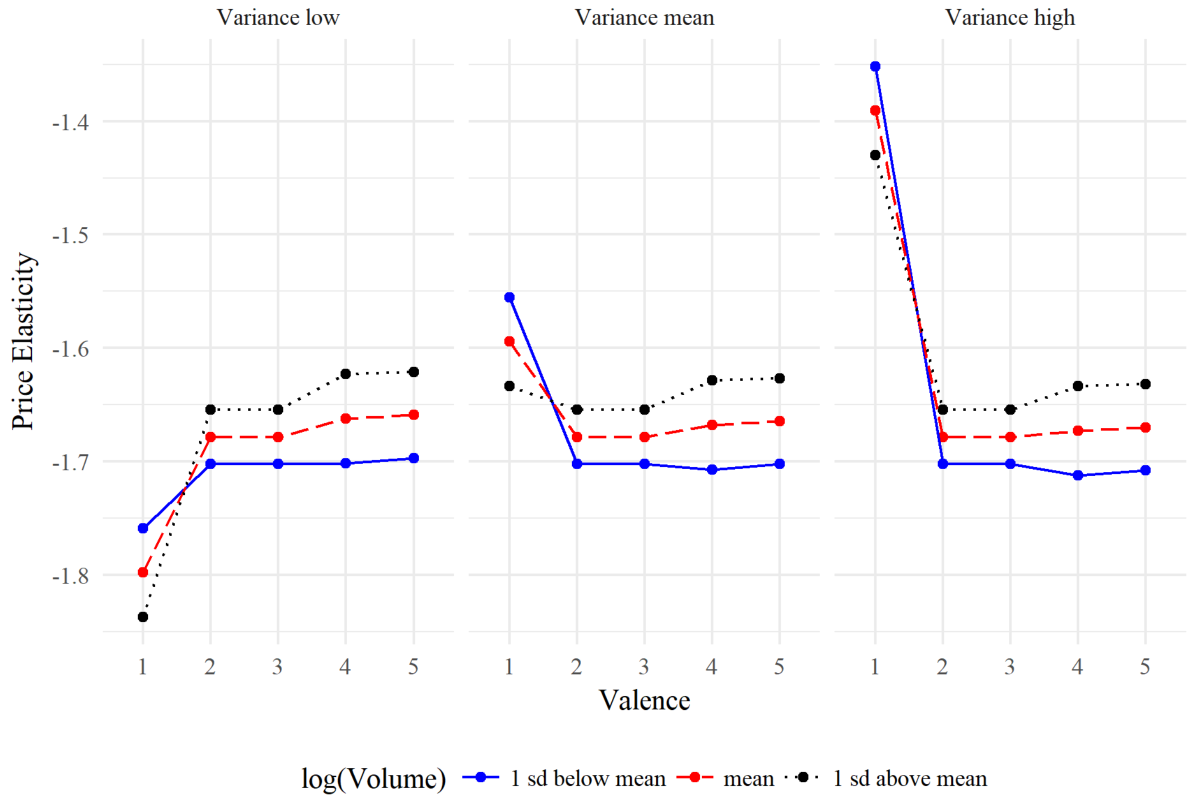


Figure 4.12: Three-way Interactions on Price Elasticity

Hypotheses		**Result**
Impact of valence, volume, and variance on sales		
H_{1a}:	*Positive valence, i.e., four- and five-star reviews, has a positive impact on sales compared to a neutral valence of three stars.*	Support
H_{1b}:	*Negative valence, i.e., one- and two-star reviews, has a negative impact on sales compared to a neutral valence of three stars.*	Support
H_2:	*Increasing volume has a positive impact on sales.*	Support
H_3:	*Increasing variance decreases sales.*	Support
Interactions among valence, volume, and variance		
H_{4a}:	*Volume moderates the impact of four- and five-star reviews positively, leading to a more positive impact on sales.*	Support
H_{4b}:	*Volume moderates the impact of one- and two-star reviews negatively, strengthening their negative sales impact.*	Support
H_{5a}:	*For high valence, higher variance decreases sales, i.e., increasing variance decreases the positive impact of high valence on sales.*	Support
H_{5b}:	*For low valence, higher variance increases demand, i.e., increasing variance weakens the negative impact of low valence on sales.*	Partial Support
Interactions of valence, volume, and variance with price		
H_{6a}:	*The higher the volume for positive valence reviews, the closer to zero the price elasticity.*	Support
H_{6b}:	*The higher the volume for negative valence reviews, the further away from zero the price elasticity.*	Partial Support
H_{7a}:	*The more variance there is in positive valence, the stronger, i.e., the further away from zero, the price elasticity.*	Support
H_{7b}:	*The more variance there is in negative valence, the less strong, i.e., the closer to zero, the price elasticity.*	Partial Support

Table 4.5: Overview of Hypotheses

4.3.5 Robustness Check

To assess the robustness of the results outlined in the previous chapter, we test whether our model is robust against the inclusion of lagged review dimensions. Previous research has based models on lagged predictors generating a better model fit (Godes and Mayzlin 2004; Kübler et al. 2018). In our model specification, sales per product and week is the dependent variable, while valence, volume, and variance are cumulative measures. Consequently, reviews are not necessarily posted in the same week as the sales number is reported. These cumulative measures, as opposed to measures of the same week, are less likely to encounter endogeneity issues.[54] In time-series data, the cumulated review dimensions would have to systematically match unobserved demand shocks (Berger et al. 2010). However, if review dimensions were influenced by past sales, model estimates would change for lagged review dimensions. Hence, we test the robustness of our model against review dimensions being affected by sales of past weeks. Thus, we estimate Equation 4.4 with valence, volume, and variance lagged by one week instead. Table 4.6 displays the results, and significant differences are in bold. Coefficients remain roughly the same. The only notable differences are in the significance of the three-way moderation of price by valence of two and volume, as well as price by valence of five and variance. Following our hypothesis, for valence of two, the three-way interaction of price, valence, and volume ($\beta_{10.2}$) turns significant at low levels of significance. Furthermore, for valence of five, the three-way interaction of price, valence, and variance ($\beta_{11.4}$) is now insignificant. In the main model, the relation is significant at low levels. Figure 4.13 shows the moderation of valence by volume at different levels of variance based on the lagged model. In line with previous findings, high volume increases sales of high-valence products and decreases sales of low-valence products, while low volume increases sales of low-valence products and decreases sales of high-valence products. Figure 4.14 shows the impact on price elasticity.[55]

In sum, the model is robust against changes in the time structure of the variables.

[54] Product review dimensions may be both the cause of sales and the outcome of sales. Please refer to Chapter 4.6 regarding potential endogeneity concerns.

[55] The data points for valence of two seem to be identical; however, they differ in the fourth decimal.

		Estimate	Std. Error	t value	Pr(>|t|)
β_1	log(Price)	-1.676	0.0048	-349.513	0.0000 ***
β_2	log(Volume $_{t-1}$)	0.011	0.0033	3.367	0.0008 ***
$\beta_{3.1}$	Valence 1_{t-1}	-0.260	0.0372	-6.990	0.0000 ***
$\beta_{3.2}$	Valence 2 $_{t-1}$	-0.083	0.0097	-8.531	0.0000 ***
$\beta_{3.3}$	Valence 4 $_{t-1}$	0.107	0.0047	22.627	0.0000 ***
$\beta_{3.4}$	Valence 5 $_{t-1}$	0.144	0.0049	29.381	0.0000 ***
β_4	Variance $_{t-1}$	-0.027	0.0049	-5.559	0.0000 ***
β_5	log(Price) * log(Volume $_{t-1}$)	-0.020	0.0021	-9.545	0.0000 ***
$\beta_{6.1}$	log(Price) * Valence 1 $_{t-1}$	0.077	0.0260	2.963	0.0030 **
$\beta_{6.2}$	log(Price) * Valence 2 $_{t-1}$	-0.007	0.0070	-0.965	0.3347
$\beta_{6.3}$	log(Price) * Valence 4 $_{t-1}$	0.009	0.0035	2.673	0.0075 **
$\beta_{6.4}$	log(Price) * Valence 5 $_{t-1}$	0.013	0.0037	3.417	0.0006 ***
β_7	log(Price) * Variance $_{t-1}$	0.002	0.0035	0.464	0.6425
$\beta_{8.1}$	Valence 1 $_{t-1}$ * log(Volume $_{t-1}$)	-0.081	0.0265	-3.046	0.0023 **
$\beta_{8.2}$	Valence 2 $_{t-1}$ * log(Volume $_{t-1}$)	-0.033	0.0085	-3.865	0.0001 ***
$\beta_{8.3}$	Valence 4 $_{t-1}$ * log(Volume $_{t-1}$)	0.056	0.0031	17.984	0.0000 ***
$\beta_{8.4}$	Valence 5 $_{t-1}$ * log(Volume $_{t-1}$)	0.103	0.0032	31.912	0.0000 ***
$\beta_{9.1}$	Valence 1 $_{t-1}$ * Variance $_{t-1}$	-0.083	0.0892	-0.933	0.3510
$\beta_{9.2}$	Valence 2 $_{t-1}$ * Variance $_{t-1}$	0.027	0.0110	2.414	0.0158 *
$\beta_{9.3}$	Valence 4 $_{t-1}$ * Variance $_{t-1}$	-0.029	0.0052	-5.501	0.0000 ***
$\beta_{9.4}$	Valence 5 $_{t-1}$ * Variance $_{t-1}$	-0.035	0.0060	-5.915	0.0000 ***
$\beta_{10.1}$	log(Price) * Valence 1 $_{t-1}$ * log(Volume $_{t-1}$)	-0.066	0.0149	-4.416	0.0000 ***
$\beta_{10.2}$	**log(Price) * Valence 2 $_{t-1}$ * log(Volume $_{t-1}$)**	**-0.012**	**0.0058**	**-2.000**	**0.0455** *
$\beta_{10.3}$	log(Price) * Valence 4 $_{t-1}$ * log(Volume $_{t-1}$)	0.014	0.0021	6.765	0.0000 ***
$\beta_{10.4}$	log(Price) * Valence 5 $_{t-1}$ * log(Volume $_{t-1}$)	0.012	0.0022	5.482	0.0000 ***
$\beta_{11.1}$	log(Price) * Valence 1 $_{t-1}$ * Variance $_{t-1}$	0.369	0.0640	5.764	0.0000 ***
$\beta_{11.2}$	log(Price) * Valence 2 $_{t-1}$ * Variance $_{t-1}$	0.000	0.0076	-0.044	0.9652
$\beta_{11.3}$	log(Price) * Valence 4 $_{t-1}$ * Variance $_{t-1}$	-0.008	0.0038	-2.190	0.0286 *
$\beta_{11.4}$	**log(Price) * Valence 5 $_{t-1}$ * Variance $_{t-1}$**	**-0.007**	**0.0046**	**-1.593**	**0.1111**
β_{12}	log(Quantity $_{t-1}$)	0.188	0.0006	328.022	0.0000 ***
β_{13}	log(Shop Quantity)	0.609	0.0033	185.299	0.0000 ***
β_{14}	Promotion	0.225	0.0192	11.715	0.0000 ***
Dependent variable					log(Quantity in kg)
Observations					2,744,918
Multiple R^2 full model					0.918
Multiple R^2 proj. model					0.148

**** <0.001; ** <0.01; * <0.05*

Table 4.6: Robustness Check – Results of Fixed-Effects Model with Lagged Valence, Volume, and Variance

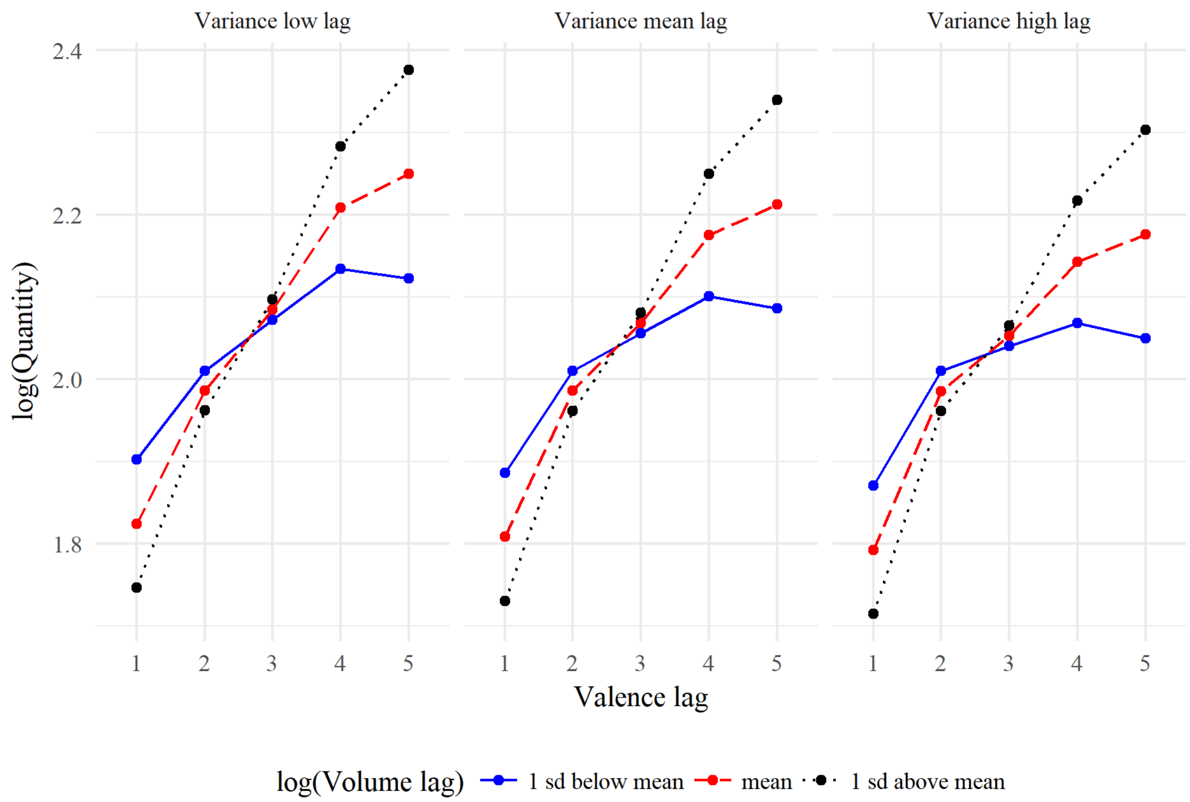


Figure 4.13: Robustness Check – Interaction of Volume and Valence at Mean Price by Variance

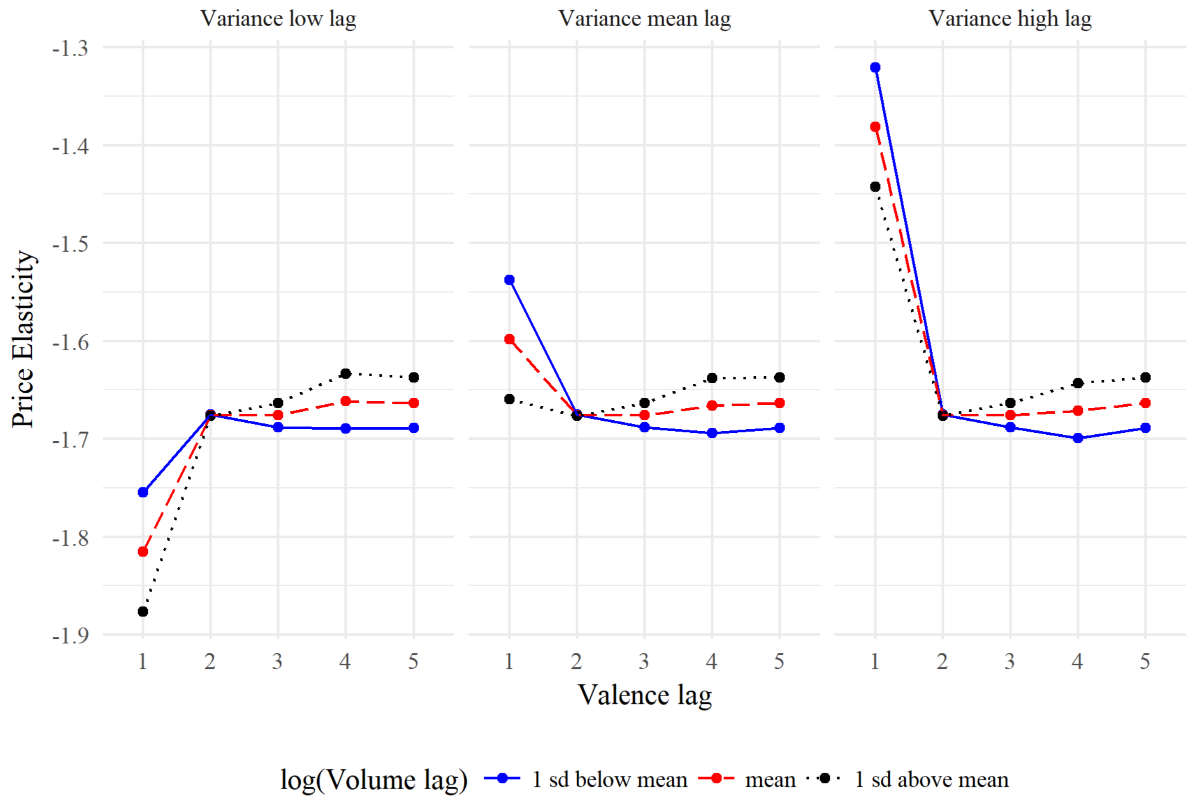


Figure 4.14: Robustness Check – Three-way Interaction on Price Elasticity

4.4 Pricing Decisions and Product Reviews

Our previous analyses show that valence, volume, variance, and price have an interdependent impact on sales. While retailers cannot precisely steer but only facilitate and induce product reviews, they can strategically manage price. In their pricing strategy, product reviews provide important signals. In the following, we analyze the impact of price changes as reactions to a decrease in valence with respect to sales, revenue, and profit. We assess the scenario of losing one star in reviews. The analysis in the previous chapter revealed that decreasing valence decreases sales. In such a case, different price changes can compensate for the impact on sales, revenue, or profit induced by lower valence. Hence, we assess the inclusion of product reviews in retailers' pricing strategy and analyze the monetary impact.

The predicted quantities serve as a base case, i.e., we derive the predicted quantity for each product in each week using the products' actual price, valence, volume, and control variables in that specific week, as well as the coefficients displayed in Table 4.3 (predicted values). With these quantities we derive the associated revenue (as quantity multiplied by product- and week-specific price) and profit based on product- and week-specific prices and margins. We display this base case of sales, revenue, and profit as horizontal dotted red lines in Figure 4.15 to Figure 4.18. We assess the impact on sales, revenue, and profit across all 45,000 products and seven countries.

We analyze the absolute sales impact of a valence reduction by one star,[56] ceteris paribus, per week and present the average over all weeks. The sales, revenue, and profit resulting from a decrease in valence are indicated by horizontal dashed black lines in Figure 4.15, Figure 4.16, and Figure 4.17. Cumulated over the course of the three years, losing one star on every product in every week decreases the quantity sold by 14 million weight units, €90 million in revenues and €16 million in profit. In order to counteract the impact in sales, revenue, or profit, retailers have the option to change the price. Each corporate objective, i.e., sales, revenue, and profit, requires different price changes. In Figure 4.15 we present the corporate objective sales (as weekly average) dependent on price changes. This illustration allows us to compare the sales in the base case without any changes in valence or price (horizontal red dotted line), with sales in the case of a valence reduction (horizontal dashed black line), and in combination with different levels of price reduction (solid black line). The intersection between the red line and the black solid line is the price change that compensates for the sales decrease due to the

[56] We reduce valence for each product in each week by one star, while we do not change one-star ratings.

valence loss (a price reduction of about 5 percent on average). With the decrease in sales due to losing one star in the reviews, the retailer loses the associated revenue. Figure 4.16 depicts the price reduction to compensate for the revenue decrease due to a loss in valence. Again, the intersection between the red dotted line and the solid black line highlights the price change to compensate for the loss, i.e., on average the price needs to be reduced by 11 percent to generate the same revenue as prior to the loss in valence. Finally, the lost revenue translates to decreased profits. Figure 4.17 shows the change in price to prevent a loss in profit when valence is decreased by one star. In order to keep profit at the same level as prior to the valence decrease, prices must increase by 2 percent.

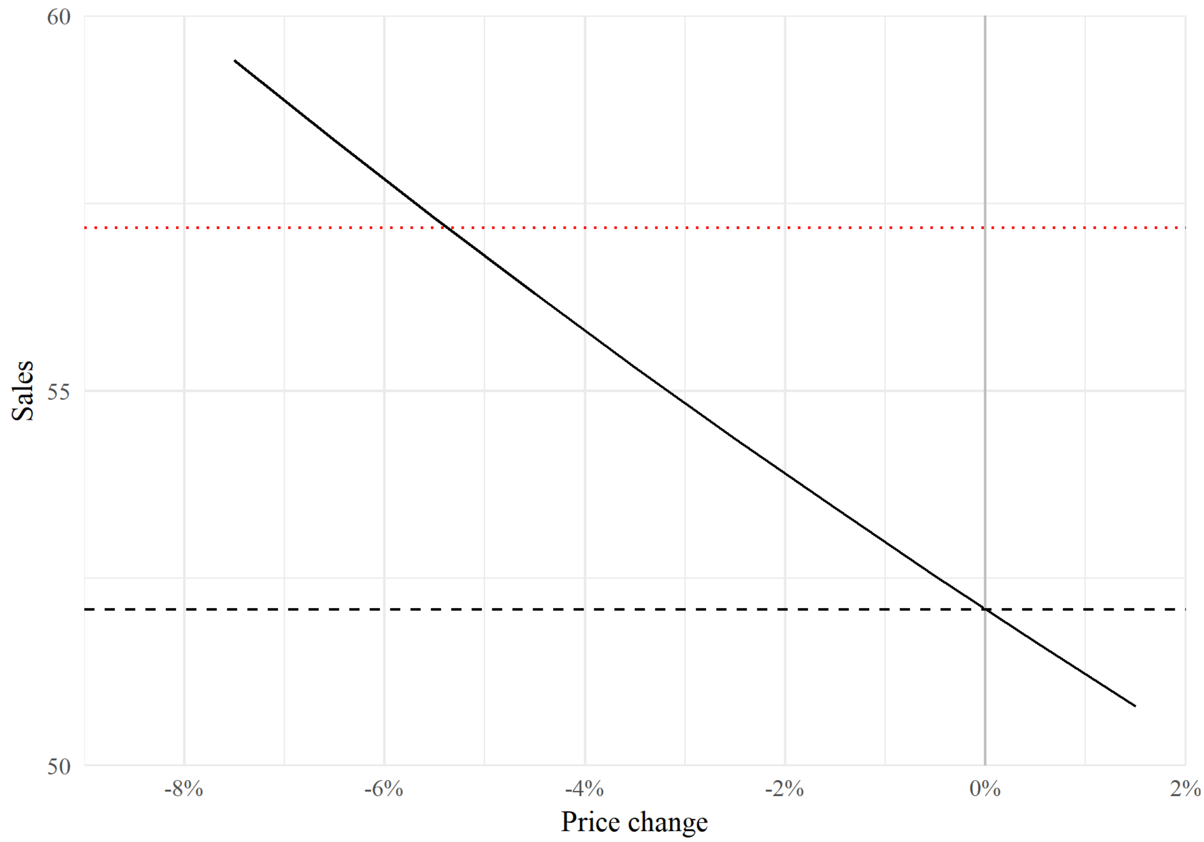


Figure 4.15: Price Reduction to Compensate for the Sales Impact of a Decrease in Valence

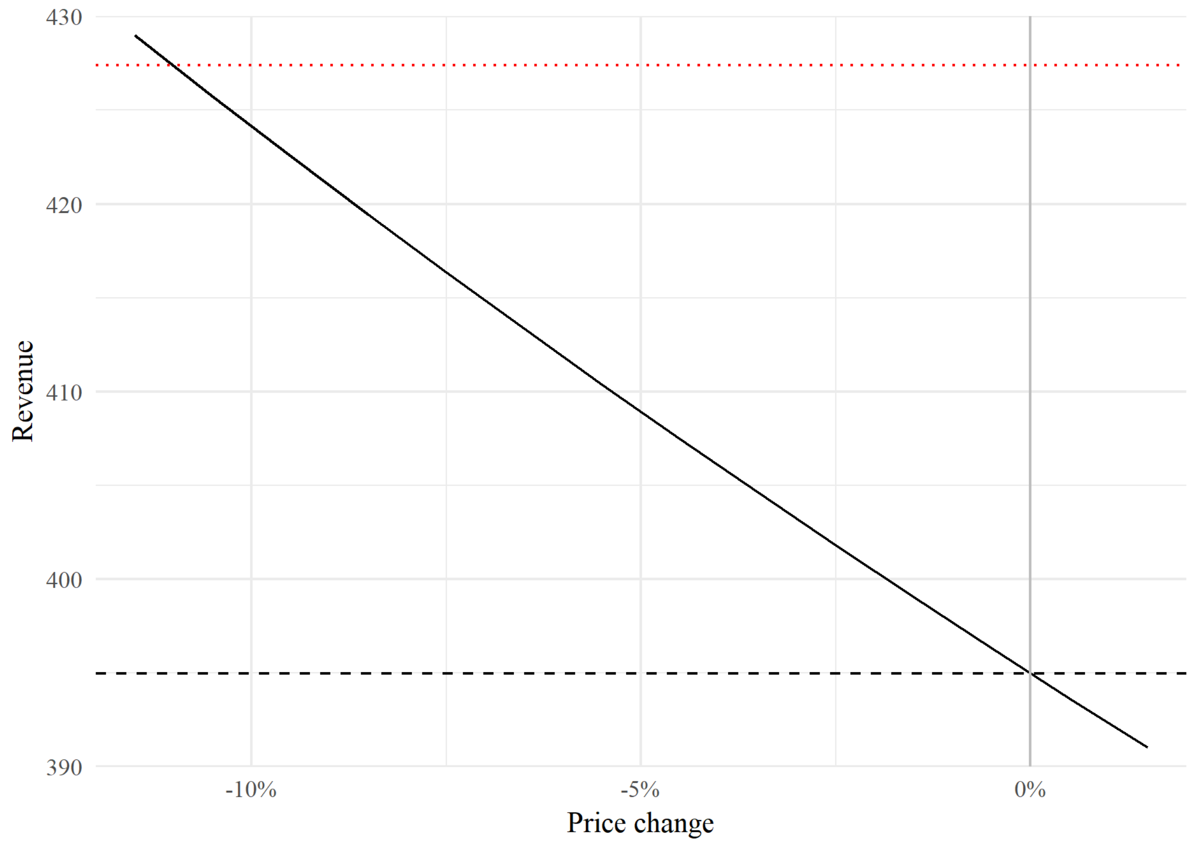


Figure 4.16: Price Reduction to Compensate for the Revenue Impact of a Decrease in Valence

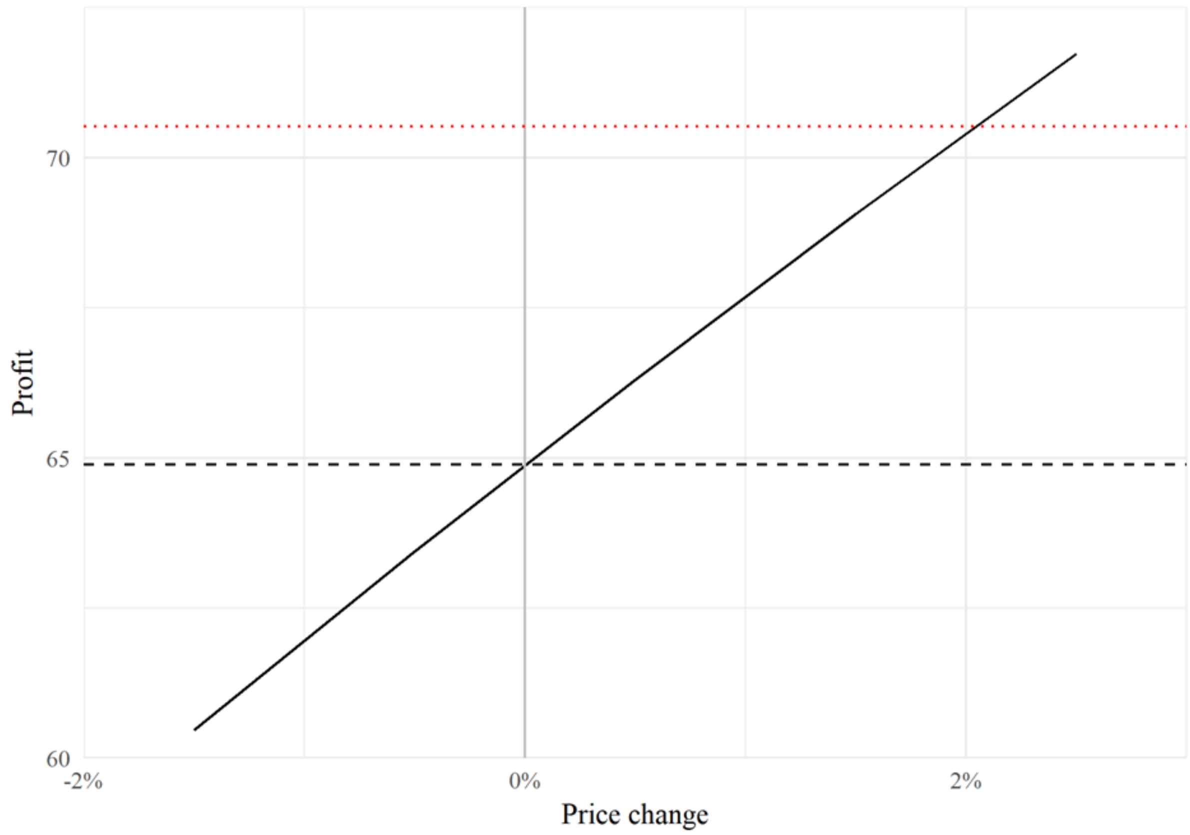


Figure 4.17: Price Increase to Compensate for the Profit Impact of a Decrease in Valence

Thus, to balance a loss in valence, retailers must initially decide on the corporate objective, since price changes differ in direction and size for the three objectives. If the retailer operates under the corporate objective of maximizing sales or revenue, price reductions compensate for the sales (revenue) loss. Figure 4.18 depicts a sensitivity analysis for price changes ranging from -12 percent to +12 percent, which illustrates that the prioritization of one objective is detrimental to the other. The green vertical line in Figure 4.18 highlights the example of decreasing the price by 11 percent to counteract a loss in revenue. While this decrease in price overcompensates for the sales loss, it strengthens the detrimental impact on profit, since the increase in sales does not compensate for the loss in profit margin due to the price reduction. Moreover, vice versa, increasing price by 2 percent to counteract the profit loss results in decreased sales and revenue (blue vertical line in Figure 4.18).

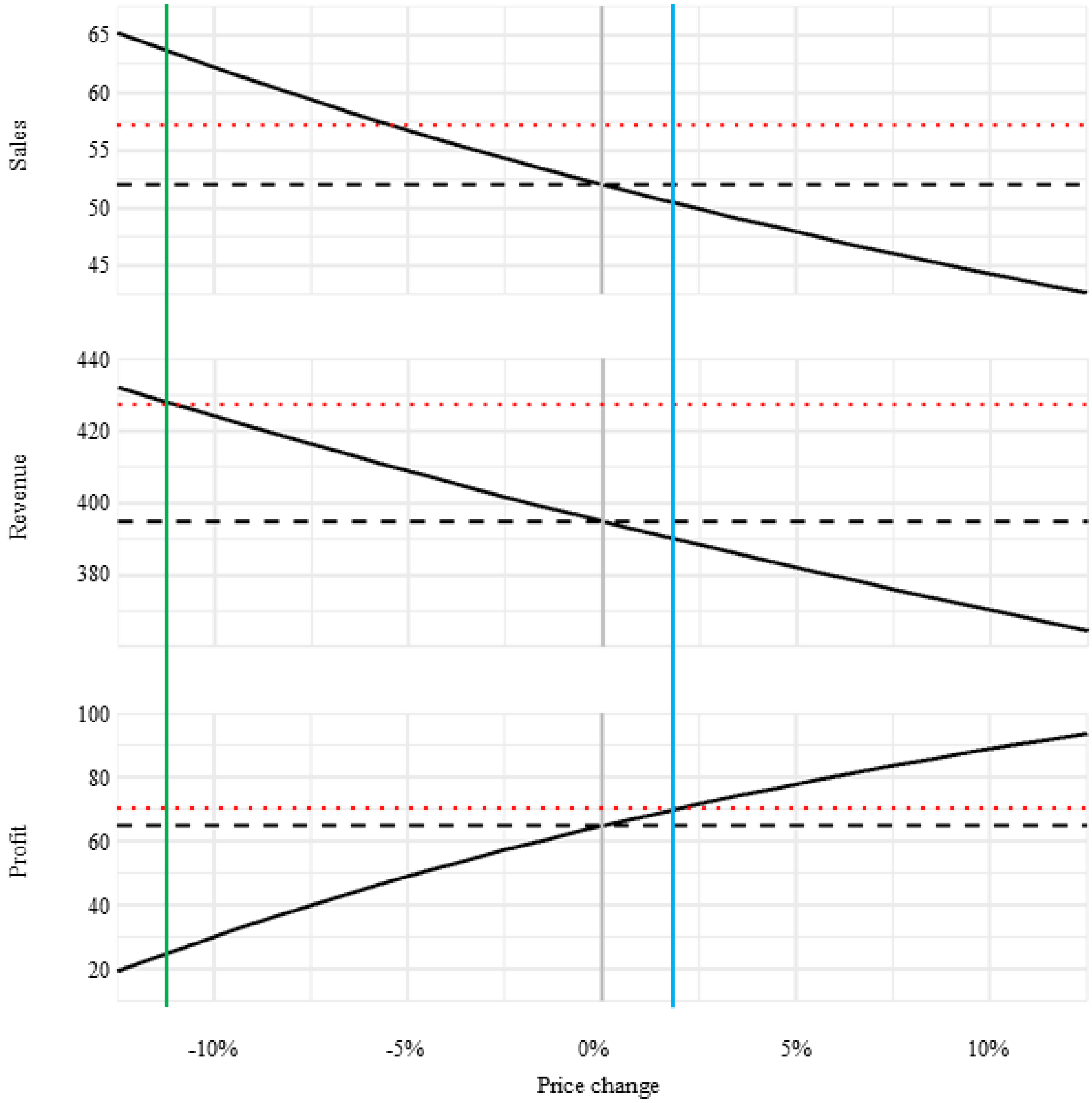


Figure 4.18: Impact of Price Changes on Corporate Objectives

4.5 Discussion and Managerial Implications

Customers perceive risk when they are in a purchase situation (Cox and Rich 1964; Murray 1991). As a consequence, they search for information to reduce this risk (Stern et al. 1977). In offline settings, word-of-mouth has long been established as a method to reduce the risk involved in purchase decisions (Arndt 1967). Product reviews are the widespread resemblance of word-of-mouth online and are, thus, supposed to signal quality. Hence, providing more information about the quality of the product should reduce the risk involved in the purchase (Erdem et al. 2002; Kostyra et al. 2016). Therefore, following the findings on the relation of quality and price, product reviews, as a signal of quality, may moderate price elasticities. For example, for products with many, positive, and agreeing reviews, the perceived risk of the investment for the customer decreases, so that price is a less relevant factor, and consequently the impact of price on sales decreases. However, research on product reviews so far has mainly excluded interactions of product reviews and price. To the best of our knowledge, only two previous studies have paid attention to the moderation of price by review dimensions. Those two studies highlight the relevance of product reviews for price elasticities. Hence, the primary goal of this study was to understand whether product reviews affect price elasticities.

Furthermore, findings on the effects of review dimensions and their interactions on sales are still mixed. We hypothesized that a possible reason for these mixed findings is that a comprehensive perspective, including the moderation among review dimensions and price, has mostly been ignored (Kostyra et al. 2016; Maslowska et al. 2017). Therefore, we applied a comprehensive analysis of all three relevant review dimensions, valence, volume, and variance, the interactions among these dimensions, as well as the moderation of the impact of price on sales by those review dimensions. Our study makes the following contributions.

First and foremost, we find strong support for the moderation of price by product review dimensions. Dependent on the characteristics of the product review (valence, volume, and variance), the impact of price on sales changes.

For high valence, i.e., products with which other customers are satisfied, the risk of investment decreases and price is less relevant, i.e., the price elasticity moves closer to zero. High volume enhances the weakening of the price elasticity, so that an even less negative impact of increasing prices on sales results. Hence, if more customers provide a positive review, price is a less strong driver. Our results also reveal that the size of this effect is rather small. In particular, in the case of high valence, the moderation of price by variance is significant but very small. For high-valence products, increasing variance makes price a slightly stronger signal. Increasing variance in positive reviews creates uncertainty about the review, while low variance in such reviews increases trustworthiness. Increasing variance therefore counteracts the positive signal in positive valence, meaning that customers are less sure about the review, strengthening the signal of price, however, in very small size.

We cannot mirror these findings for negative valence. For two-star reviews, interactions are insignificant. On the contrary, one-star reviews reveal the strongest reactions, which partly oppose our hypothesis. Low volume strengthens this effect, while high volume counteracts it. Hence, for a high number of reviews with an average of one star the price elasticity is further away from zero for a lower number of reviews. Thus, the more customers share their low satisfaction, the stronger the impact of price on sales. While the direction of the moderation by volume is in line with our hypotheses, the level of the price elasticity is not. Surprisingly, for one-star reviews with mean variance and mean volume price elasticity is closer to zero than in the case of high-valence reviews. However, for one-star valence, variance is the strongest moderator. While the two-way interaction of variance and price remains insignificant, the three-way interaction of variance, valence, and price reveals an interesting interplay. As described above, one-star reviews shift price elasticity closer to zero. Low variance strongly counteracts this effect. For one-star reviews, on which customers agree (low variance), the price elasticity is by far the strongest, which is in line with our hypotheses. On the contrary, for mean and high variance, i.e., with increasing disagreement among reviewers of one-star reviews, the impact of price on sales strongly decreases. The size of the effect is somewhat surprising. For one-star reviews with mean variance or high variance price elasticity is closer to zero than in the case of high-valence reviews. Thus, for one-star reviews, our analysis reveals the importance variance. While when ignoring variance, the most prompting question would be, why sales react less strong to price changes of products with one-star reviews, the inclusion of variance provides some guidance. For the moderation of price by one-star reviews the agreement or disagreement of reviewers is substantial. Even average disagreement among reviewers of one-star products leads to a strongly decreasing impact of price on sales, while high disagreement results in the smallest impact of price on sales identified in our model. However, it is somewhat surprising that the impact of price on sales for products with disagreeing one-star reviews is lower than for products with agreeing five-star reviews. An explanation for the strong moderation by variance in the case of one-star reviews might be that variance has only one direction, i.e., positive divergence from one star, since more negative ratings than one star are not possible. For one-star reviews, with increasing variance more reviewers rate the product positive among a strong majority of negative reviews. This might send the signal to the customer that the product is a specific niche product which only satisfies a very specific need. Therefore, only those customers for whom consumption goals and the product performance match would buy the product. For these customers, price is less important due to the satisfaction of their specific need.

Following our second research objective, we analyze the impact of valence, volume, and variance, and their interactions on sales. We find that the average rating, i.e., the review's valence, has a significant impact on sales. In line with social impact theory (Latané 1981) and the persuasive effect of product reviews (Rui et al. 2013), we find that the preferences of other individuals for products affect an individual's preference, i.e., in our data set, positive valence increases sales, whereas negative valence decreases sales when compared to a neutral review. Hence, we add further evidence to the majority of studies that find a significant positive effect of valence on sales (Chintagunta et al. 2010; Gopinath et al. 2014; Maslowska et al. 2017). Furthermore, the effect of one-star reviews on sales is much stronger than that of any other valence level, which highlights the role of negative reviews. Our simulation in the previous chapter further illustrates a strong sales decrease following a loss of one star.

We further add to the existing finding that volume, per se – without the direction of valence – has an impact on sales. Awareness has often been given as a reason for increasing sales with increasing review volume, as awareness of a product is a necessary condition for purchasing (Godes and Mayzlin 2004; Liu 2006; Chen et al. 2011; Cui et al. 2012; Park et al. 2012). However, for reviews that are posted on retailer websites, as in this study, the creation of awareness is a questionable reason, because customers only see the review after searching for the product (Duan et al. 2008). However, the bandwagon effect offers a relevant explanation for the direct impact of volume on sales, i.e., the probability of adoption increases with the number of people who have already adopted the product (Babić Rosario et al. 2016). Thus, the more reviews there are, the higher the incentive to imitate previous behavior and buy the product. We add to the majority of existing studies with a significant positive impact of volume on sales (Chevalier and Mayzlin 2006; Amblee and Bui 2011; Maslowska et al. 2017). Irrespective of the direction of valence, the number of reviews induces customers to imitate others' behavior.

Most studies on product reviews exclude variance and focus instead on valence and volume only (Babić Rosario et al. 2016). Nevertheless, variance has been found to have a significant impact on sales in several studies (Sun 2012; Kostyra et al. 2016) and has been interpreted from different perspectives. For risk-averse customers, higher variance in reviews introduces risk and should therefore decrease demand. On the contrary, more heterogeneous reviews could induce curiosity, thereby increasing demand. As most of the studies rely on experiential goods (i.e., books and movies), we add to research on rather non-experiential goods with a broad data set. We find that variance significantly affects sales, meaning that more diverse reviews weaken the impact on sales. Hence, we add to the findings that polarized evaluations increase risk and uncertainty and induce the customer to avoid the product (Babić Rosario et al. 2016).

For a comprehensive picture, we analyze the moderation of valence by volume and variance. The findings provide important information, since the omission of the interactions might bias results in existing studies. For the moderation of valence by volume, we oppose findings by Chintagunta et al. (2010) for the movie industry and add support to the studies by Maslowska et al. (2017), Kostyra et al. (2016), and Park et al. (2012). We find a significant interaction of valence and volume. In our data set covering seven countries and 88 categories, high volume strengthens the positive impact of high-star reviews on sales, while it also strengthens the negative impact of low-star reviews on sales.

Variance of reviews relates to risk aversion, as it displays the trustworthiness of the review. Low variance in reviews increases trustworthiness and reduces risk, while high variance increases risk in the purchase. We find support for this relation. High variance decreases demand for products with positive valence and increases demand for products with negative reviews. Products with two-star reviews benefit from the uncertainty about this negative review introduced by high variance, while one-star reviews remain untouched (insignificant relation). For the same reason, for four- and five-star reviews, high variance is detrimental, as it introduces uncertainty about the positive average valence.

In sum, the effects of product review dimensions remain relatively small in size compared to the price elasticity; however, product reviews comprise new, additional, or reassuring information for the customer. Valence, volume, and variance transport information and interact in multiple ways with the price of the product. Therefore, it is highly recommendable for retailers to include product review information in pricing decisions and to actively manage product reviews. With respect to managing product reviews it is important to differentiate between the objectives of retailers and manufacturers. While manufacturers are interested in positive reviews of specific brands, retailers must take on a more comprehensive perspective. The decision about whether to provide a review platform affects all categories and all brands. Unlike manufacturers, retailers have the sales, revenue, and profit of the entire category or shop as a corporate objective, not just the performance of a specific brand. Hence, retailers must assess whether the upsides of providing a review option for their customers will outweigh the downsides. On the one hand, reviews provide the opportunity to increase sales based on high valence or high volume, or a combination of both. Consequently, by providing a review option for their customers, retailers gain further measures to manage demand. Although the effect is small, review stimulation strategies should be considered, for example, at least reminding the customer to leave a review after purchase, as a high volume of reviews alone – independent of valence – increases sales. More active strategies, for example, providing discounts or samples for reviews, could be assessed. Analogous to the simulation in Chapter 4.4, an increase in volume can provide room for price increases at constant sales. For positively perceived products, such an increase in volume even decreases the role of price and therefore weakens the negative impact of price increases on sales. At the same time, retailers can use this information for price changes. For example, since the impact of price on sales is weaker for products with many, agreeing, and positive reviews, retailers could increase the prices for such products or reduce the frequency of price promotions or price reductions. In this context, our findings on one-star reviews must be mentioned. As one-star reviews characterized by high variance generate the weakest impact of price changes on sales, price increases on these products will result in the smallest sales loss for the retailer. On the contrary, one-star reviews characterized by low variance induce the strongest impact of price changes on sales, i.e., price reductions on these products will result in a strong sales increase.

On the other hand, the most impactful downside for the retailer of providing a product review platform, is the probability of receiving low-valence reviews, which decrease sales, revenues, and profits. However, reviews with low valence also have the strongest price elasticities, meaning that price reductions on these products will strongly increase sales. Hence, even negative information might be valuable for retailers, since this information provides an opportunity to adjust the pricing strategies according to customers' interests and thereby to boost demand or adjust the product portfolio, e.g., de-list low-valence products. Furthermore, in price negotiations with manufacturers, negative information provided by product reviews can complement price and sales data to decrease the price at which retailers by the product from manufacturers. Such price decreases in supply would allow for price reductions to offset valence reductions while limiting profit deterioration (Figure 4.18, bottom panel). Finally, retailers can use product review information for an enhanced perspective on the product portfolio. A categorization along valence, volume, and variance can serve as additional information for pricing strategies.

4.6 Limitations and Future Research

Although our analysis provides important findings, we acknowledge several limitations to it. We cannot capture missed sales opportunities, i.e., non-purchases that might be due to negative reviews, as we focus on those products that have sold and for which product reviews have been submitted. Therefore, deriving insights on the impact of a change from zero to one review could be a fruitful avenue for future studies.

Furthermore, future research could address potential endogeneity via different routes. Theoretically, there are two potential sources of endogeneity in our setting: unobserved product quality and endogenous predictors. With the product- and week-specific fixed effects included in our main model, we address potential endogeneity due to unobserved quality difference between products, i.e., products differ in quality, which may lead to the price, review, and error term being correlated. High-quality products may be sold more frequently at a higher price and with higher valence. Furthermore, product review dimensions may be both the cause of sales and the outcome of sales. The sales of each product in each week are the dependent variable, while valence, volume, and variance are cumulative measures. Consequently, reviews are not necessarily posted in the same week as the sales number is reported. These cumulative measures, as opposed to measures of the same week, are less likely to encounter endogeneity issues. In the time-series structure of our data set, the cumulated review dimensions would have to systematically match unobserved demand shocks (Berger et al. 2010). Furthermore, we use the data-rich approach described by Germann et al. (2015) and include the promotion variable to control for other marketing actions. However, valence, volume, and variance may not be fully exogenous. In theory, reviews might already have an impact on pricing, meaning that the retailer or manufacturer increase prices for products with high valence and volume and decrease prices for products with low valence. In this case, the variables might be endogenous, and estimating through instrumental variable estimation would be a common approach (Papies et al. 2017). Past research has included instrumental variables to address endogeneity concerns (Chintagunta et al. 2010; Kübler et al. 2018), with the meta-analysis by Babić Rosario et al. (2016) showing that the impact of product reviews does not change substantially when using instrumental variables. However, future research could apply an instrumental variable approach for the three review dimensions.

Additionally, the common J-shape of product review frequencies (Figure 4.5) is based on two self-selection biases: an acquisition bias, i.e., those who buy and are able to review have a more positive attitude toward the product; and an underreporting bias, i.e., the probability to submit a review is higher for those customers with extreme evaluations (Hu et al. 2017). Future research could address these selection biases by modeling the selection process separately.

Finally, we include data from seven countries and control for the difference via product-specific fixed effects, which also differentiate products across countries, i.e., because of different packaging, among other things, the same product has different fixed effects across countries. However, we do not dive deeper into the differences between the countries. Following Kübler et al. (2018), the inclusion of country as moderator of both price elasticities and product reviews might be a fruitful avenue for future research. The decision to have the large data set further restrains us from estimating product- or category-specific price elasticities. In this context, future research could provide a more granular perspective by estimating, for example, category-specific price elasticities.

5 Conclusion

5.1 Main Research Findings and Managerial Implications

The ascent of the Internet means that research is needed to re-evaluate retailers' traditional pricing measures to steer demand and to assess new, true online phenomena. Given the limited empirical studies on pricing in online retailing, this dissertation set out to contribute to current research priorities by analyzing the central impact of price on three corporate objectives: sales, revenue, and profit. We further assessed this central relation in the light of two different information sources: first, information provided by the retailer in the form of advertised reference prices; and, second, information provided by customers in online reviews. Building on online and offline literature, we asked research questions addressing the gaps in the current literature. To answer these questions, we collected unique transaction data from an online retailer, conducted a field study and an online experiment, and analyzed data with both Bayesian and frequentist models to answer the research models. Table 5.1 illustrates the scope of these studies. In the following, this chapter gives a brief overview of the findings of each study[57] and afterwards provides a holistic discussion and unique conclusions based on the constellation of the three studies.

	Chapter 2	**Chapter 3**	**Chapter 4**
Central Independent Variable	Price	Advertised reference price	Review valence Review volume Review variance
Dependent Variables	Sales Revenue Profit	Sales (Revenue) Profit	Sales Revenue Profit
Data	Transaction data	Transaction data Field experiment Online experiment	Transaction data
Method	Bayesian multilevel analysis	Bayesian regression Fixed-effects model	Fixed-effects model

Table 5.1: Scope of Individual Chapters

Chapter 2 assesses the central relation of this dissertation, the impact of price changes, in the form of temporary price reductions, on sales, revenue, and particularly profit. Online price reductions increase the focal brands' sales and revenue. Although theory expects stronger price competition online, we found price elasticities in the range of offline elasticities. Furthermore, stockpiling does not reduce sales and revenue for the online retailer, i.e., price reductions in the past do not influence current sales significantly. While a robustness check revealed parameters pointing in the direction of stockpiling, these were not unambiguous. At the same

[57] Chapters 2 to 4 provide more detailed discussions of the respective findings.

time, price reductions decrease the sales and revenue of the other brands in the category based on cross-price elasticities, revealing strong competition among brands. In sum, the impact of price reductions on category sales and revenue are still positive, whereas this net category impact turns negative for profit. The negative profit impact results from the increase in demand for the brands, which is too weak to balance the lower profit margins of the focal brand. Additionally, the reduced demand for the remaining brands strengthens the negative profit impact for the category. However, results include substantial brand-specific heterogeneity, such that decisions on promotions are strategic decisions for retailers. Online retailers cannot increase the sales, revenue, and profit of a category with the same promotional action across all brands. However, certain characteristics of the brands can be used to guide promotions, e.g., the size of the brands. An interesting finding of this study is that regular price changes, compared to promotional price changes, are a relatively strong signal and should therefore be managed carefully.

In sum, Chapter 2 offers a granular perspective on the central relation of price reductions and profit for online retailers, while analyzing the impact of price reductions, as well as the key correlates of differences in the reductions' impact on sales, revenue, and profit.

Chapter 3 explores whether displaying advertised reference prices impacts online purchases. We conducted three empirical studies to answer the exploratory research questions, which offer partly contradictory insights. First, two experimental studies compare whether displaying an advertised reference price has an advantage over not displaying such a price with respect to sales. While the online experiment supports a positive impact of displaying an advertised reference price on sales, the field experiment did not add empirical evidence to this finding. In the field experiment, eliminating the advertised reference price did not decrease sales strongly and significantly. Subsequent to the impact of displaying versus not displaying an advertised reference price we assess whether the credibility of advertised reference prices impacts sales. Different approaches to analyzing the functional form of the relation of manufacturer-suggested retail price, regular price, and sales underline that for a larger distance between the manufacturer-suggested retail price and the regular price, meaning a less credible advertised reference price, the impact on sales is still positive, but less positive than for more credible advertised reference prices. Thus, even manufacturer-suggested retail prices that are substantially higher than the regular price increase sales. Finally, we analyze the interaction with price. The further away the manufacturer-suggested retail price from the regular price, meaning the less credible the reference price, the stronger the impact of the actual selling price on sales. Hence, the actual selling price becomes a stronger signal for the customer. With respect to profit, increasing the distance between the manufacturer-suggested retail price and the regular price weakens the negative profit impact of a price reduction.

In summary, Chapter 3 explores the performance of advertised reference prices and highlights the role of the actual price when advertised reference prices are not credible.

Chapter 4 assesses the relation of price and online product reviews as a true online phenomenon. We focus on the established review dimensions of valence, volume, and variance and their price and sales relations. First, we find strong support for the moderation of price by product review dimensions. Dependent on the characteristics of the product review (valence, volume, and variance), the price impact on sales changes. For products with positive reviews, i.e., products with which customers are satisfied, price is less relevant, i.e., the price elasticity moves closer to zero. With an increasing number of reviews this relation strengthens: if more customers provide a positive review, price is a less strong driver. However, increasing variance among reviews counteracts the positive signal in positive valence, meaning that customers are less sure about the review and price becomes a stronger signal. Hence, in order to make price less relevant, many positive reviews with low variance are beneficial. Negative reviews, however, do not mirror these findings: for a high number of reviews with an average of one star the price elasticity is further away from zero when compared to lower volume. Thus, the more customers share their low satisfaction, the stronger the price impact. Moreover, for one-star valence, variance is the strongest moderator. For one-star reviews, on which customers agree (low variance), price elasticity is the strongest. If customers disagree about one-star reviews, this seems to reduce risk strongly, leading to the lowest price elasticity. Therefore, products with one-star reviews might be niche products that some customers love and others hate. In addition to the moderating role this dissertation corroborates the existing literature with respect to the effect of valence, volume, and variance on sales: positive reviews (valence) increase sales, whereas negative reviews decrease them. Furthermore, with increasing volume, i.e., a growing number of reviews, sales increase. Variance also significantly impacts sales, so that more diverse reviews weaken sales. For a comprehensive assessment, the moderation of valence by volume and variance is included. Both interactions are relevant. We find a significant interaction of valence and volume: high volume strengthens the positive impact of high-star reviews on sales, while it also strengthens the negative impact of low-star reviews on sales, making it more negative. High variance decreases demand for products with positive valence and increases demand for products with negative reviews. The effects of product review dimensions are small compared to price elasticity; however, they significantly moderate price. A profit assessment highlights that different price changes can balance the impact that changes in valence exert on the corporate objectives of sales, revenue, and profit. In sum, Chapter 4 provides insights that highly recommend retailers including product review information in pricing decisions and actively managing product reviews.

The constellation of these three studies allows us to reach three overarching conclusions: first, regarding the profit impact of price decisions in an online environment; second, referring to the ubiquity of information in online retailing; and third, with respect to the moderation of price in online retailing.

First, this combination of three studies adds to the very limited knowledge on profit impact for retailers and it is the first to provide insights into the profit impact of price changes for online retailers. Foremost, managers must acknowledge that price reductions have opposing impacts on different corporate objectives. In particular, price reductions are detrimental to profit, while they drive sales and revenue. The profit the online retailers generate when they reduce prices across all three studies is lower than the profit generated at regular prices. Four aspects drive profit for the retailer: sales, price, costs, and manufacturer allowances. Since the estimated price elasticities are negative across all three studies, the quantity sold increases with decreasing prices. At constant costs, the resulting relation of price and profit describes an inverted u-shape: at low price levels, where sales are high, a price reduction leads to a profit decrease. With a price reduction, sales do not increase strongly enough to balance the loss in profit margin. At higher price levels with lower sales, a price reduction would increase profit. Given this inverted u-shaped relation between profit and price, the price level at the retailer, in general, might not be set to generate highest profit but be too low. As in all three studies a price reduction reduces profit, the retailer seems to be on the ascending part of the inverted u-shaped profit-price relation. Thus, if the retailer increases price, price reductions from higher price levels are more likely beneficial for the profit impact. Manufacturer allowances are another factor influencing profit. Manufacturer allowances are additional funds provided by manufacturers for promoting their specific brands. Hence, in order to counteract the lost profit based on price reductions, increasing margin by additional manufacturer allowances during the promotional period would counteract the lost profit. As practice shows that retailers frequently allow price reductions, retailers might have strong incentives to focus on sales and revenue rather than profit. We further find that the impact is brand-specific, meaning that brand criteria can guide promotion decisions. Furthermore, both advertised reference prices and product reviews offer promising avenues to decrease the loss in profit resulting from price reductions. Advertised reference prices have the potential to increase sales, although customers can easily search for alternative reference prices online. This, however, must be in line with legal regulations to avoid deception. Product reviews further provide a counteracting force, as they increase sales via different dimensions (valence, volume, variance). Hence, for an online retailer, steering promotions according to brand criteria, and providing advertised reverence prices and a product review platform for which they pursue an active review stimulation strategy can influence sales, revenue, and profit positively.

Second, the unique constellation of the three studies reveals a comprehensive picture of the role of information in online retailing. Although customers can easily search for the best price, price reductions move demand between brands in one category, i.e., they induce brand switching. This is of specific importance to retailers, which aim at the category's or shop's sales, revenue, and profit. Thus, despite the high probability that a competitive brand is on promotion in some other online shop, and that the information is available and accessible for the customer, the retailer can steer demand among brands in his or her category. Similarly, although other, maybe more relevant, reference price information is readily available online, advertised reference prices are still valuable to the retailer. Finally, retailers can use the impact of information by providing a platform for product reviews. Product reviews have a significant impact on sales via different dimensions. Hence, the customer's access to information online can even be guided by the retailer.

Third, price has a substantial impact on sales online, which is reflected in significant negative price elasticities across all three chapters. Furthermore, the impact of price is manageable. Both advertised reference prices and information conveyed via product reviews moderate the impact of price on sales. On the one hand, the actual selling price becomes a stronger signal the further away the manufacturer-suggested retail price is from the regular price, and vice versa. On the other hand, more information in the form of many, positive, agreeing product reviews can reduce the impact of price. Additionally, we find that retailers should not underestimate the role of the regular price.

The constellation of the three studies contributes to research on online pricing in retail environments and highlights the managerial importance of including the online environment in pricing decisions for practitioners.

5.2 Limitations and Future Research

As with any research, this dissertation has several limitations,[58] which offer opportunities for future research. We categorize these along the following four avenues.

First, our data was collected from one pure online retailer, which raises questions about the generalizability of our findings to other retailers or industries. Therefore, the first avenue for future research relates to the transfer to different settings. Future research could enhance the academic discourse by combining data from several retailers and combining household and retailer data.

The second avenue focuses on the impact of different cultures and categories to obtain a more granular understanding of the difference in online pricing across the retailer's assortment and branches. Our data set comprises a wide variety of goods sold by one retailer. While we account for product heterogeneity, we do not explore category differences. Hence, future research could extend our findings by category moderation, e.g., whether durables should be managed differently than non-durables. Similarly, we analyze data from multiple countries, while we do not dive deeper into the cultural differences between those countries. Future research could include the country as moderator of price elasticities, advertised reference prices, and product reviews. This might be a fruitful avenue for future research since the uncertainty perceived in purchasing situations might differ across cultures.

Third, although changing the price is a delicate topic for retailers, we were able to conduct a field experiment on advertised reference prices, which provided different insights into purchase processes than the analysis of laboratory and transaction data. Field experiments are time-consuming and require effort in their administration, as well as corporate partners; however, they have the potential to substantially enhance insights into price reductions and product reviews. Therefore, the third avenue for future research highlights the application of different approaches and thereby follows Gneezy (2017) in calling for more field experiment.

Our analyses offer results that could systematically differ between offline and online purchasing situations. Hence, we add evidence to the call by Bijmolt et al. (2005) for a meta-analysis that analyzes whether price elasticities online are systematically different. Thus, the fourth avenue underlines the need for a meta-analysis on online price elasticities.

[58] This chapter concentrates on limitations and suggestions with a broader perspective on the entire dissertation, whereas more specific limitations are presented in the specific paragraphs of Chapters 2 to 4.

Thus, although this dissertation addresses relevant gaps in the existing literature, a multitude of questions on pricing in online retailing still need to be answered by future research. For researchers and practitioners, understanding the impact of pricing on different corporate objectives in online retailing continues to be of critical importance.

6 Appendices

6.1 Appendix – Chapter 2

Note: Each panel represents one country-category combination, and each line represents one brand.

Figure 6.1: Heterogeneity Across Margins for Each Country-Category Combination

	Quantity	**Promo PI**	**Promo $PI_{t\text{-}IPF}$**	**Cross PI**	**Reg. Price**	**Cat. Quantity**
Quantity	1.0000	-0.0070	0.0171	0.0416	-0.2596	0.7049
Promo PI	-0.0070	1.0000	0.0016	0.0013	-0.0328	0.0195
Promo $PI_{t\text{-}IPF}$	0.0171	0.0016	1.0000	-0.0162	0.0121	0.0217
Cross PI	0.0416	0.0013	-0.0162	1.0000	0.0160	0.0464
Regular Price	-0.2596	-0.0328	0.0121	0.0160	1.0000	-0.1024
Category Quantity	0.7049	0.0195	0.0217	0.0464	-0.1024	1.0000

Table 6.1: Correlation Table: Demand Model[59]

	Quantity Impact	**Revenue Impact**	**Profit Impact**	**Brand Size**	**Line Length**	**Price Level**	**Private label**	**Price Range**	**Promo Frequency**	**Promo Intensity**
Quantity Impact	1.0000	0.9058	-0.2325	0.5515	0.2930	-0.3158	0.0438	-0.0018	0.1380	0.0774
Revenue Impact	0.9058	1.0000	-0.1208	0.4754	0.2586	-0.2057	0.0498	0.0059	0.1202	0.0824
Profit Impact	-0.2325	-0.1208	1.0000	-0.4341	-0.4614	-0.0999	0.2016	0.2806	-0.1408	0.0306
Brand Size	0.5515	0.4754	-0.4341	1.0000	0.4913	-0.2584	-0.0190	-0.1498	0.2405	0.0368
Line Length	0.2930	0.2586	-0.4614	0.4913	1.0000	0.0574	-0.0287	-0.2561	0.4122	0.0669
Price Level	-0.3158	-0.2057	-0.0999	-0.2584	0.0574	1.0000	-0.2933	-0.0392	-0.2218	-0.1343
Private label	0.0438	0.0498	0.2016	-0.0190	-0.0287	-0.2933	1.0000	0.1118	0.1785	0.1502
Price Range	-0.0018	0.0059	0.2806	-0.1498	-0.2561	-0.0392	0.1118	1.0000	-0.1974	-0.0504
Promo Frequency	0.1380	0.1202	-0.1408	0.2405	0.4122	-0.2218	0.1785	-0.1974	1.0000	0.3769
Promo Intensity	0.0774	0.0824	0.0306	0.0368	0.0669	-0.1343	0.1502	-0.0504	0.3769	1.0000

Table 6.2: Correlation Table: Correlates[60]

[59] PI = price index; all variables in logs.

[60] The correlation table displays the correlation of the standardized variables.

6.2 Appendix – Chapter 3

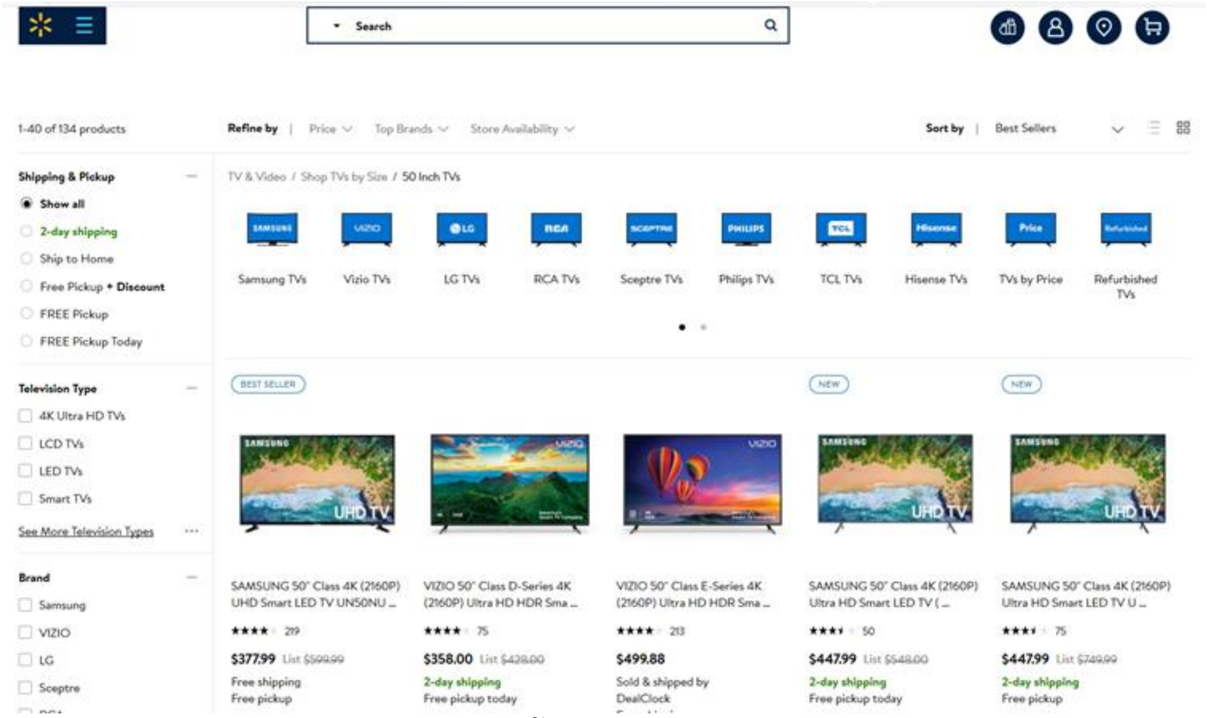


Figure 6.2: Walmart Advertised Reference Prices[61]

[61] Retrieved from: https://www.walmart.com/browse/electronics/50-inch-tvs/3944_1060825_2489948_5472490?povid=106 0825+%7C+2018-04-30+%7C+Popular%20Categories%2050%20Inch%20TVs, January 9, 2019.

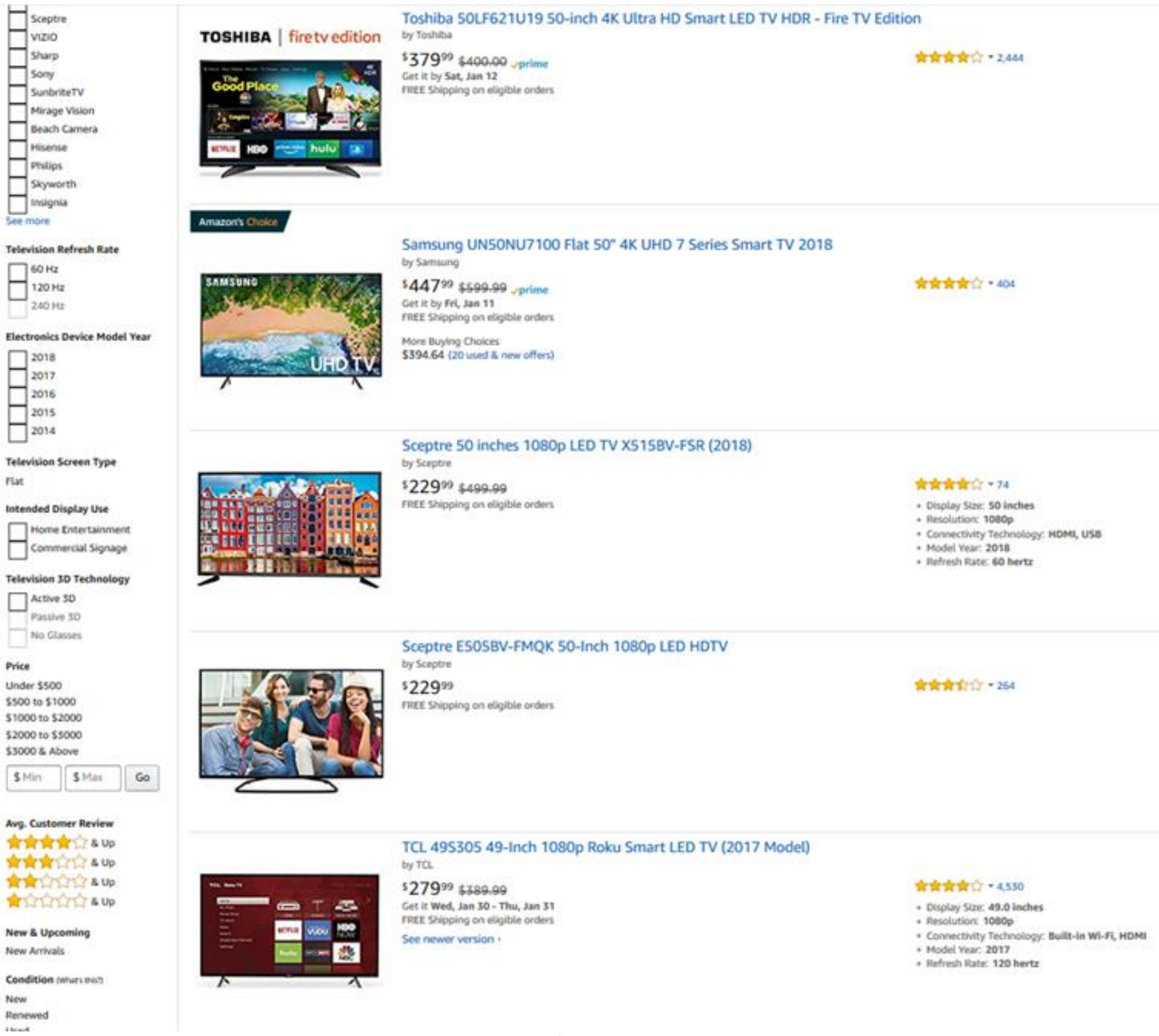


Figure 6.3: Amazon.com Advertised Reference Prices[62]

[62] Retrieved from: https://www.amazon.com/s/ref=nb_sb_noss?url=node%3D172659&field-keywords=50+inch &rh=n%3 A172659%2Ck%3A50+inch, January 9, 2019.

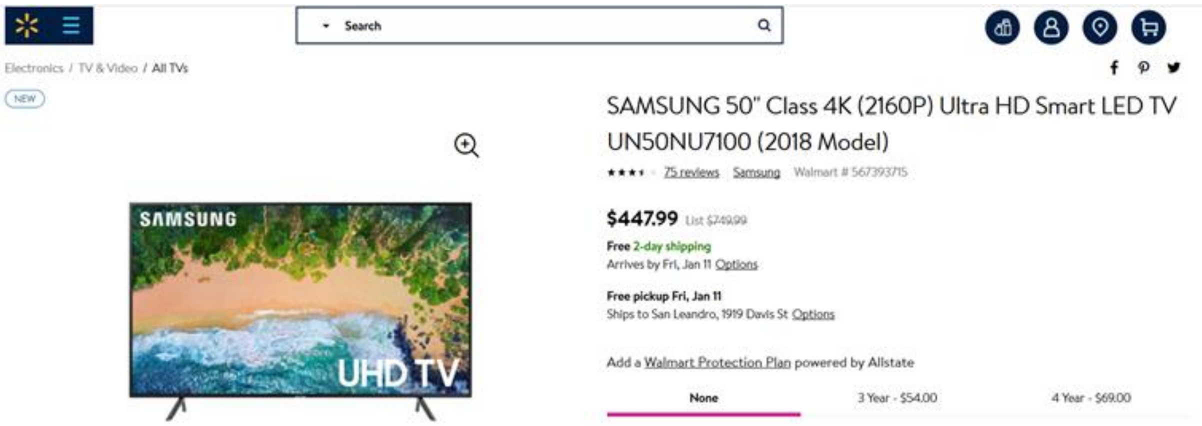


Figure 6.4: Walmart List Price for Samsung UN50NU7100FXZA in January, 2019[63]

Figure 6.5: Amazon.com List Price for Samsung UN50NU7100FXZA in January, 2019[64]

[63] Retrieved from: https://www.walmart.com/ip/SAMSUNG-50-Class-4K-2160P-Ultra-HD-Smart-LED-TV-UN50NU7100-2018-Model/938766895, January 9, 2019.

[64] Retrieved from: https://www.amazon.com/Samsung-50NU7100-Flat-Smart-2018/dp/B079NH7LJQ/ref=sr_1_5?s=tv&ie=UTF8&qid=1547043738&sr=1-5&keywords=50+inch, January 9, 2019.

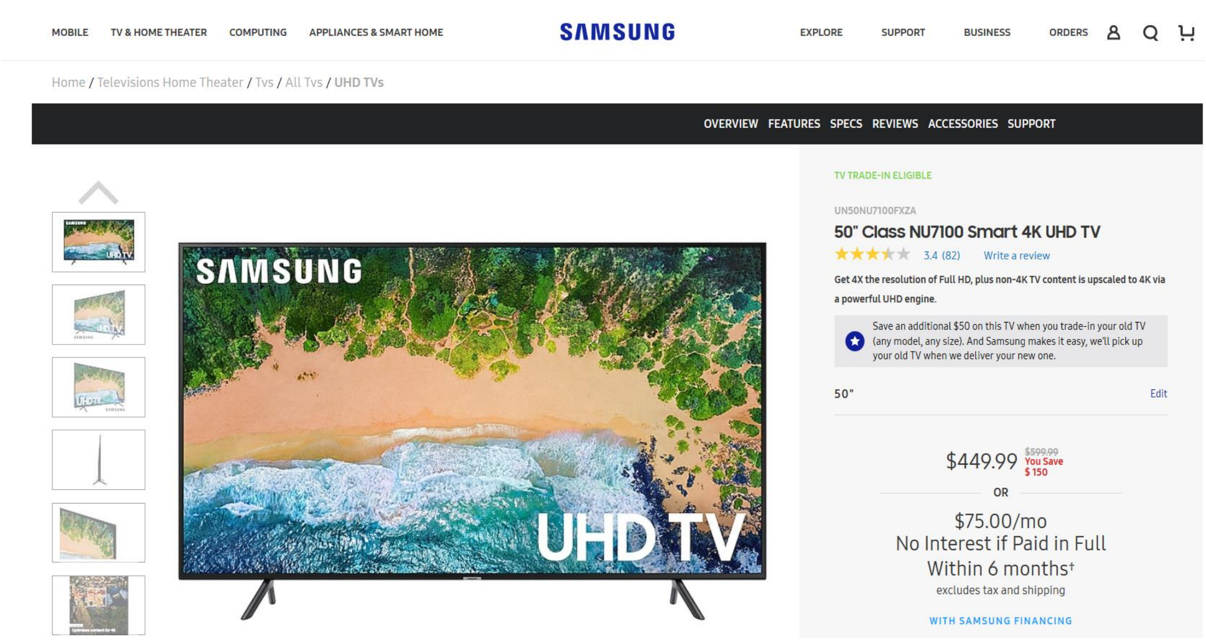


Figure 6.6: Samsung.com List Price for Samsung UN50NU7100FXZA in January, 2019[65]

[65] Retrieved from: https://www.samsung.com/us/televisions-home-theater/tvs/uhd-tvs/50--nu7100-smart-4k-uhd-tv-un50 nu7100fxza/, January 9, 2019.

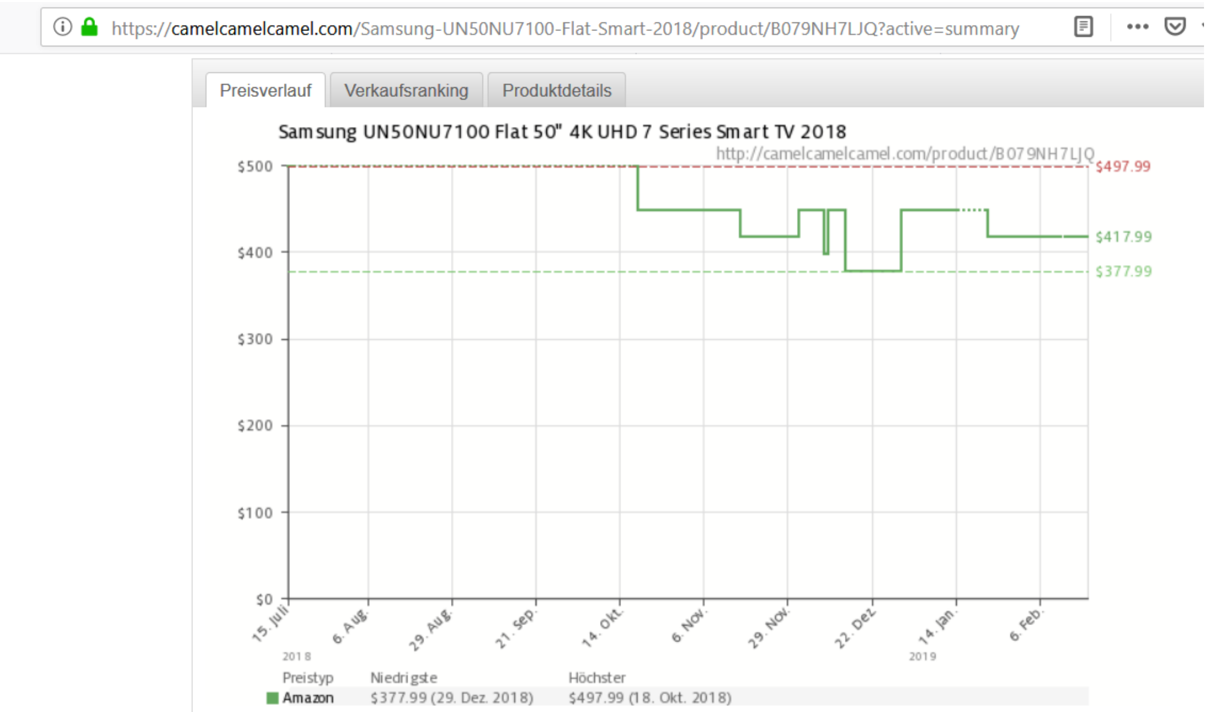


Figure 6.7: Historic Prices of Samsung UN50NU7100FXZA on Amazon.com[66]

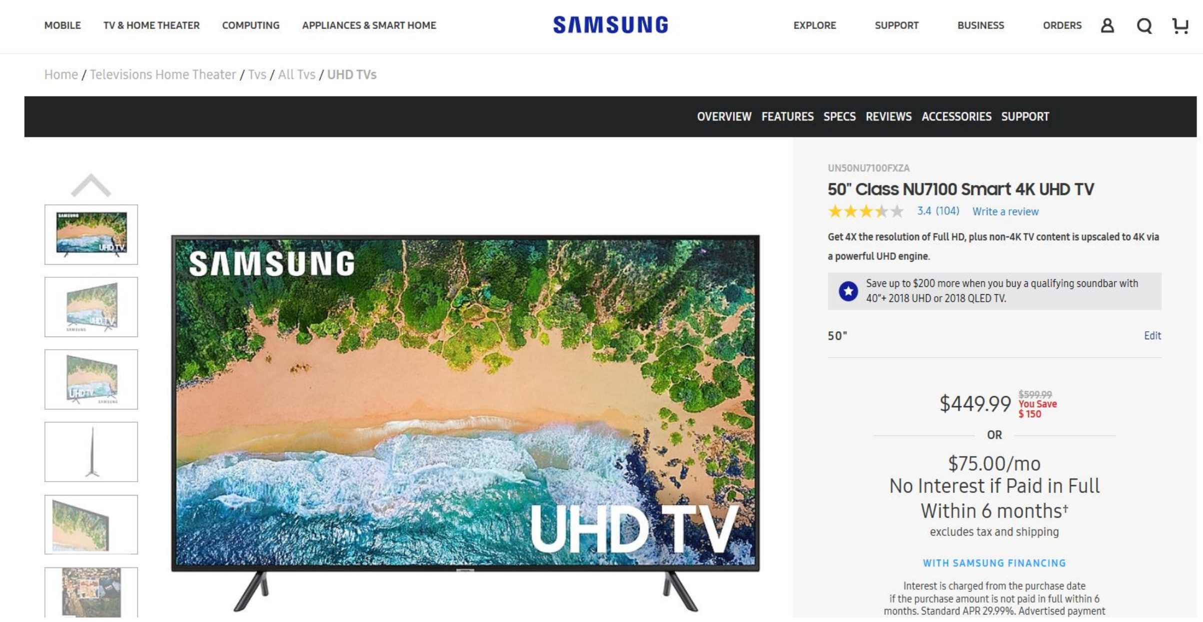


Figure 6.8: Samsung.com List Price for Samsung UN50NU7100FXZA in February, 2019[67]

66 Retrieved from: https://camelcamelcamel.com/Samsung-UN50NU7100-Flat-Smart-2018/product/B079NH7LJQ ?active=summary, February 18, 2019.

67 Retrieved from: https://www.samsung.com/us/televisions-home-theater/tvs/uhd-tvs/50--nu7100-smart-4k-uhd-tv-un50nu7100fxza/, February 18, 2019.

Figure 6.9: Walmart List Price for Samsung UN50NU7100FXZA in February, 2019[68]

[68] Retrieved from: https://www.walmart.com/ip/SAMSUNG-50-Class-4K-2160P-Ultra-HD-Smart-LED-TV-UN50NU7100-2018-Model/938766895, February 20, 2019.

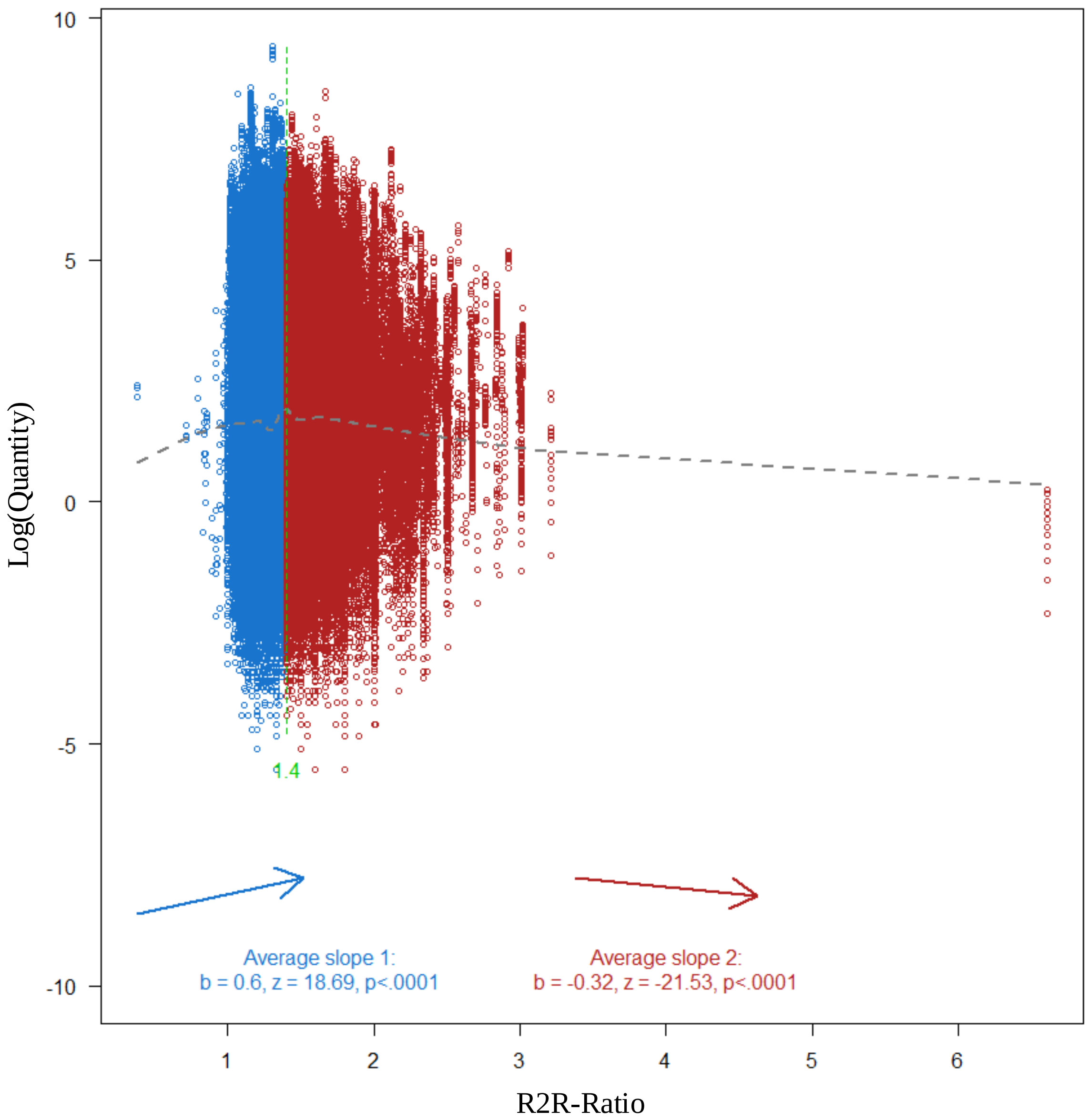


Figure 6.10: Model a1

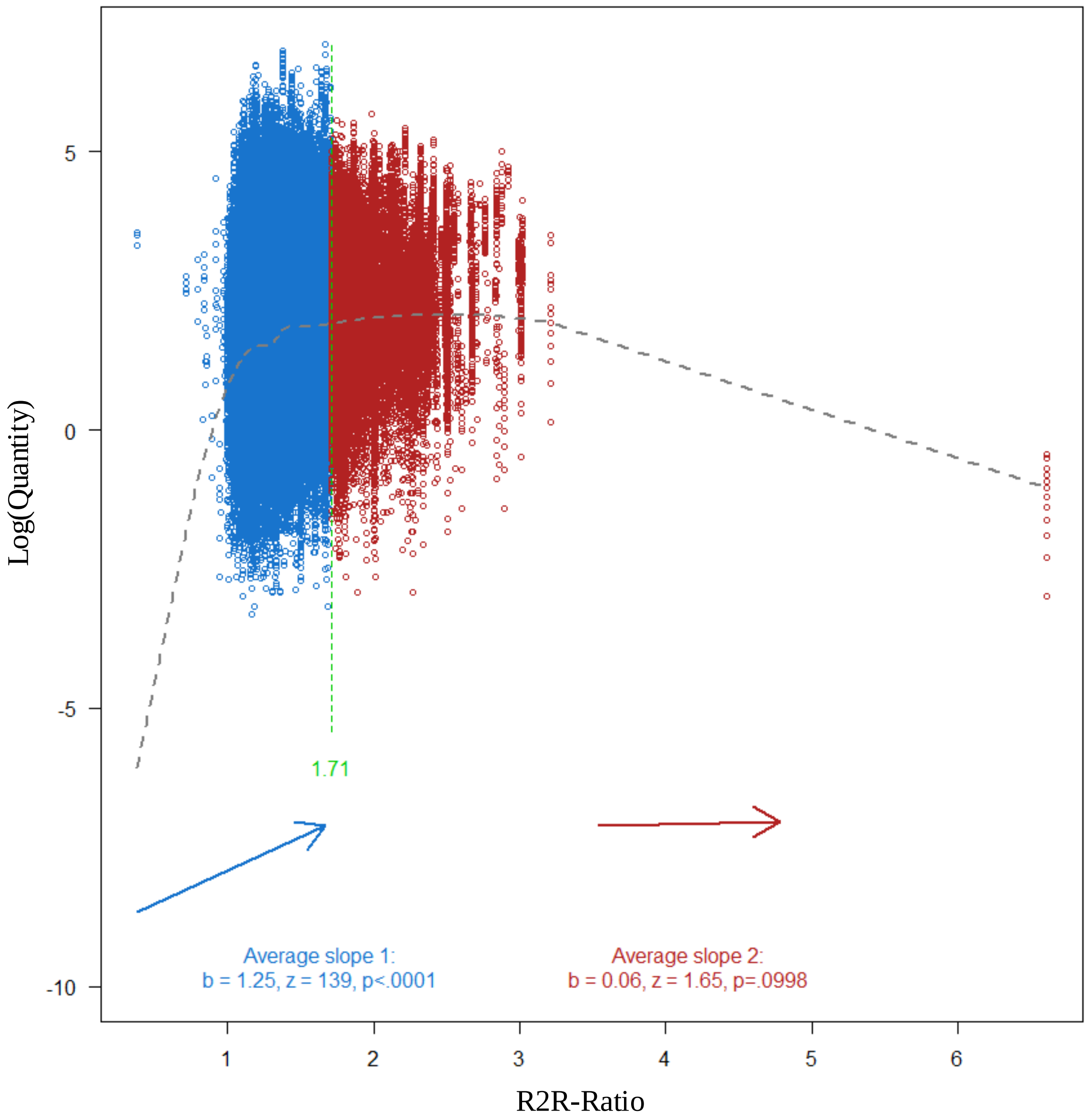


Figure 6.11: Model b1

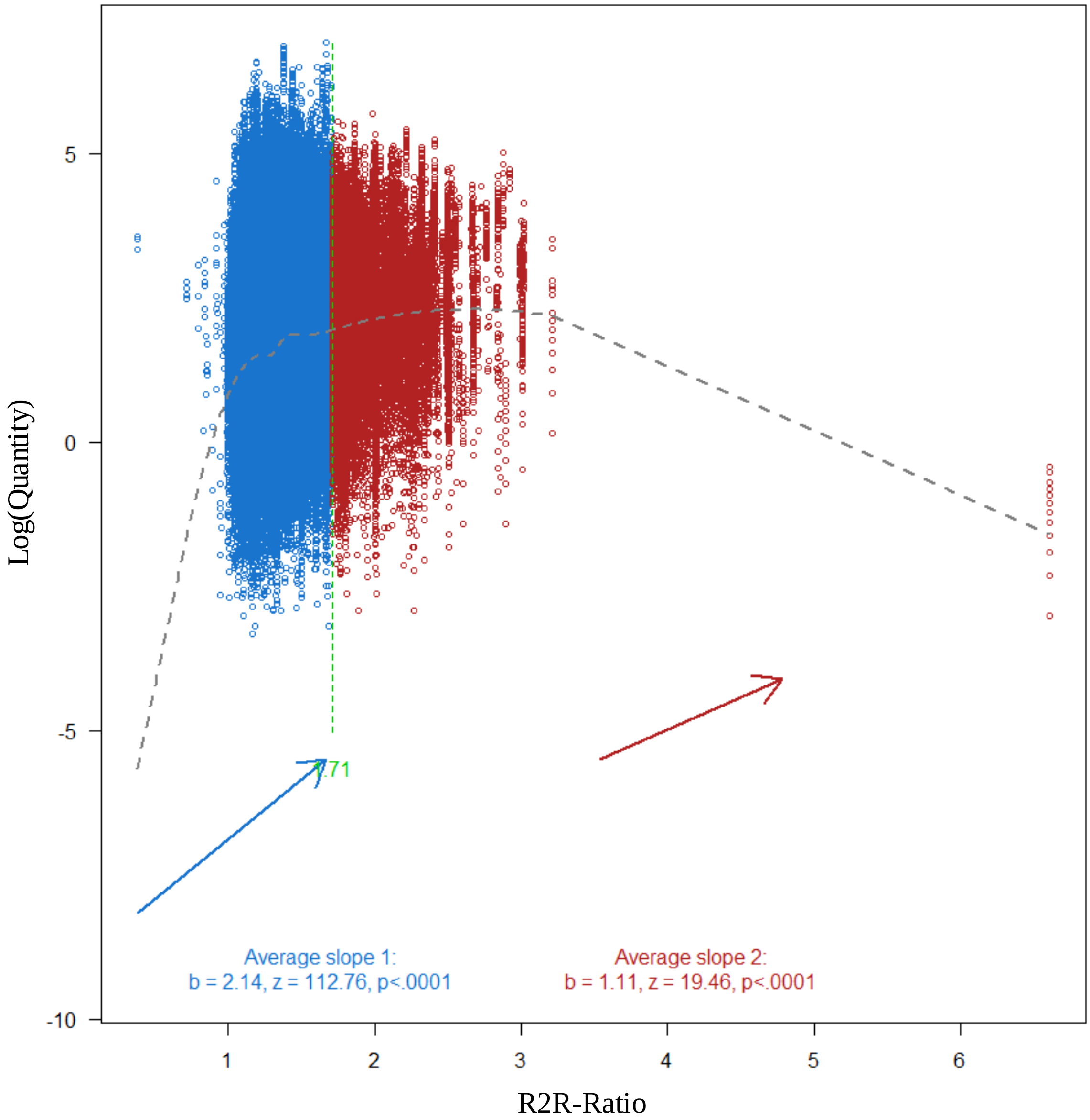


Figure 6.12: Model c1

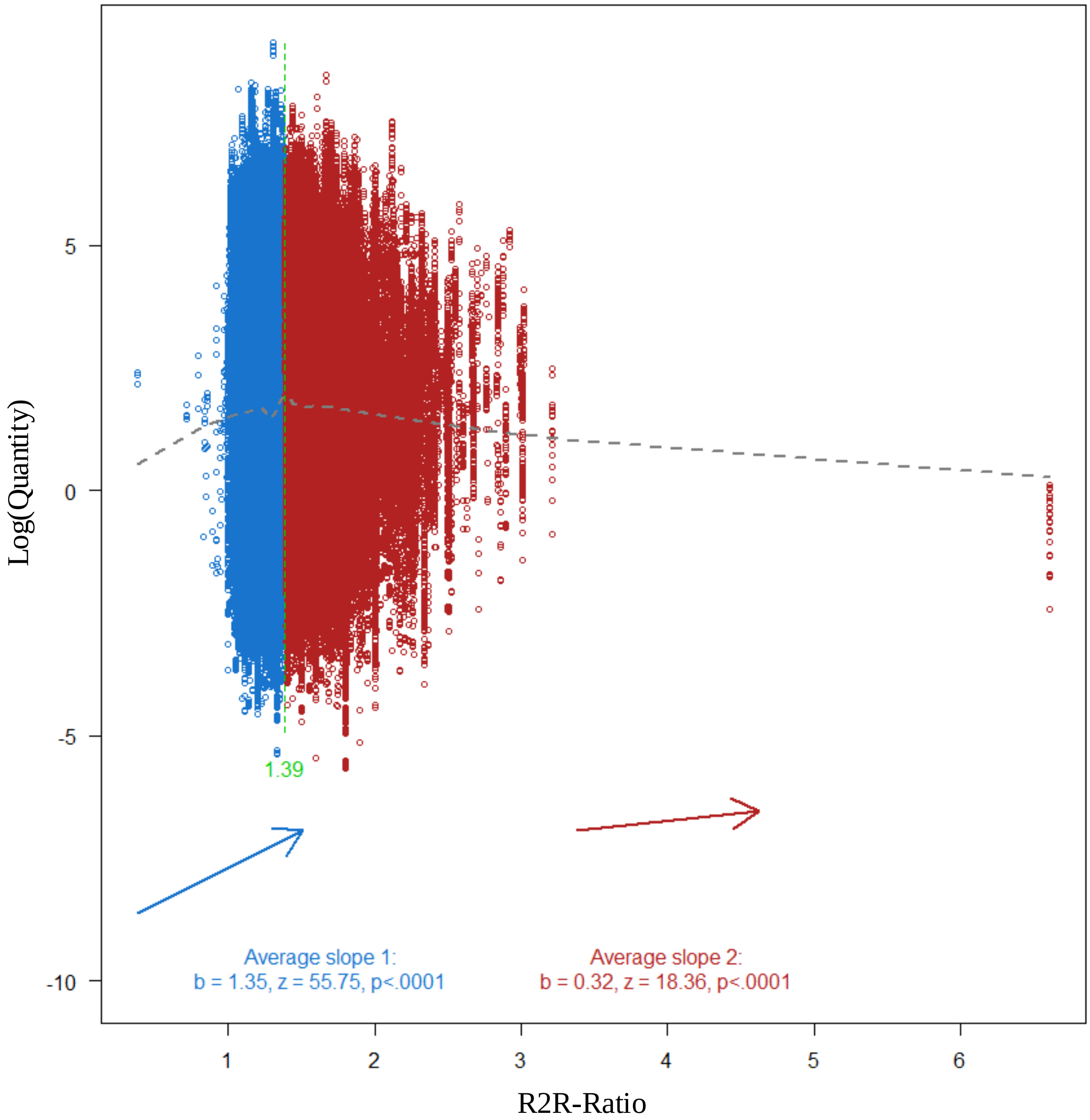


Figure 6.13: Model a2

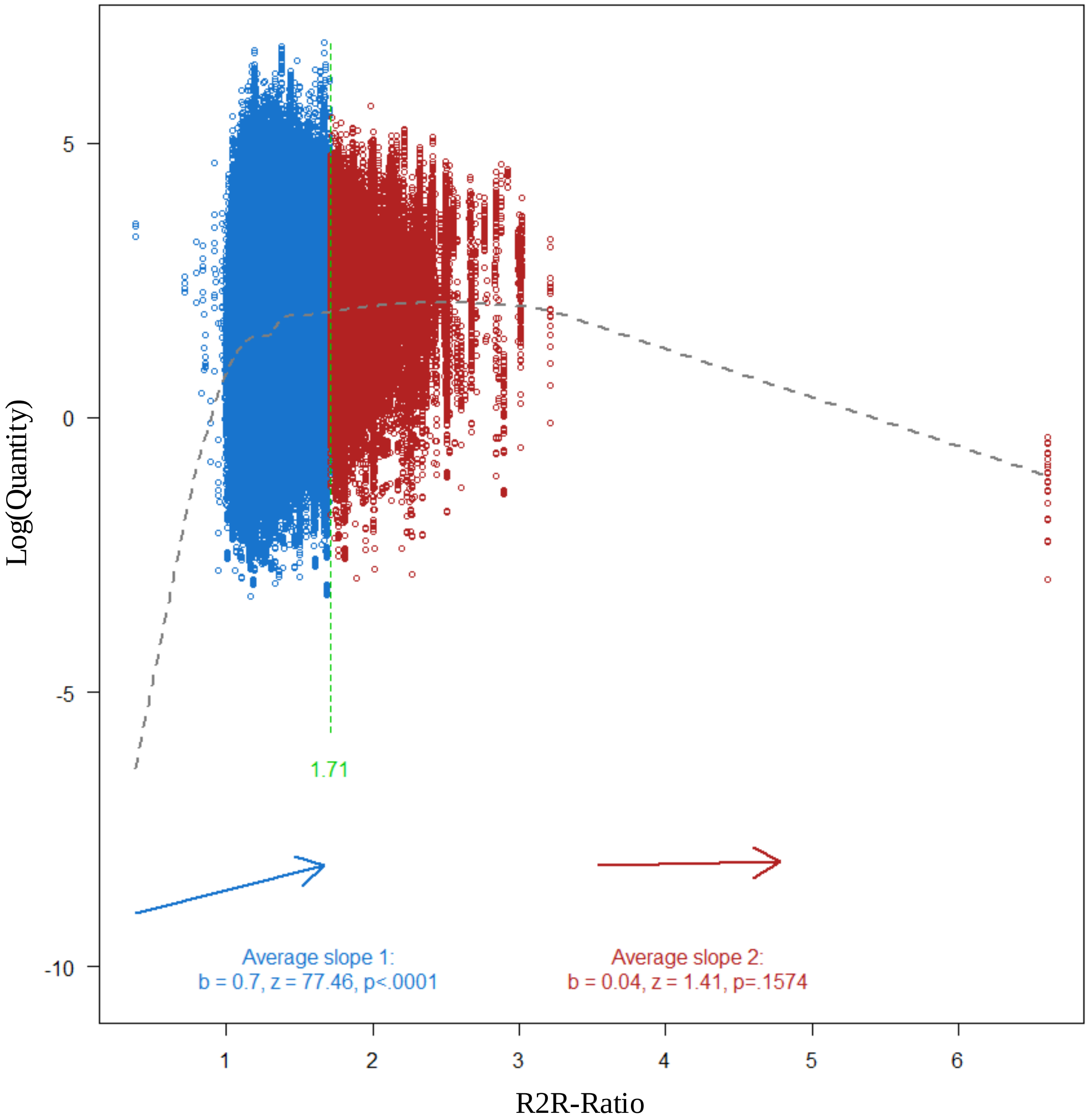


Figure 6.14: Model b2

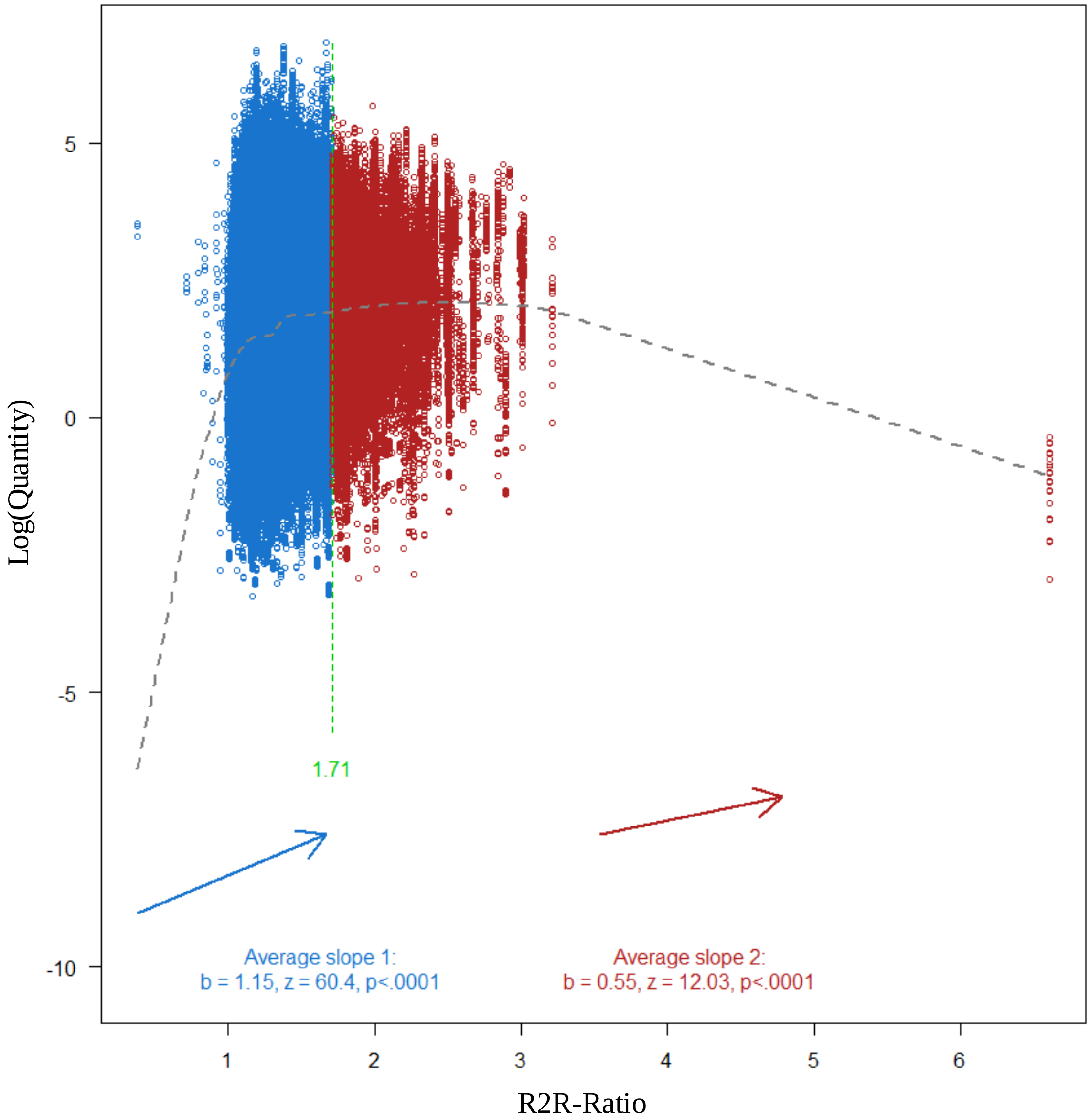


Figure 6.15: Model c2

6.3 Appendix – Chapter 4

Scenario	log(Price)	log(Volume)	Variance	Valence	log(Quantity)	Price Elasticity	Intercept
1	-1.24 low	-1.12 low	-0.59 low	1	4.1667	-1.7592	1.9772
2	0.00 mean	-1.12 low	-0.59 low	1	1.9772	-1.7592	1.9772
3	1.24 high	-1.12 low	-0.59 low	1	-0.2123	-1.7592	1.9772
4	-1.24 low	0.00 mean	-0.59 low	1	4.1297	-1.7982	1.8917
5	0.00 mean	0.00 mean	-0.59 low	1	1.8917	-1.7982	1.8917
6	1.24 high	0.00 mean	-0.59 low	1	-0.3462	-1.7982	1.8917
7	-1.24 low	1.12 high	-0.59 low	1	4.0927	-1.8371	1.8063
8	0.00 mean	1.12 high	-0.59 low	1	1.8063	-1.8371	1.8063
9	1.24 high	1.12 high	-0.59 low	1	-0.4802	-1.8371	1.8063
10	-1.24 low	-1.12 low	0.00 mean	1	3.8967	-1.5555	1.9608
11	0.00 mean	-1.12 low	0.00 mean	1	1.9608	-1.5555	1.9608
12	1.24 high	-1.12 low	0.00 mean	1	0.0248	-1.5555	1.9608
13	-1.24 low	0.00 mean	0.00 mean	1	3.8597	-1.5945	1.8753
14	0.00 mean	0.00 mean	0.00 mean	1	1.8753	-1.5945	1.8753
15	1.24 high	0.00 mean	0.00 mean	1	-0.1092	-1.5945	1.8753
16	-1.24 low	1.12 high	0.00 mean	1	3.8227	-1.6334	1.7898
17	0.00 mean	1.12 high	0.00 mean	1	1.7898	-1.6334	1.7898
18	1.24 high	1.12 high	0.00 mean	1	-0.2431	-1.6334	1.7898
19	-1.24 low	-1.12 low	0.59 high	1	3.6267	-1.3518	1.9443
20	0.00 mean	-1.12 low	0.59 high	1	1.9443	-1.3518	1.9443
21	1.24 high	-1.12 low	0.59 high	1	0.2618	-1.3518	1.9443
22	-1.24 low	0.00 mean	0.59 high	1	3.5897	-1.3908	1.8588
23	0.00 mean	0.00 mean	0.59 high	1	1.8588	-1.3908	1.8588
24	1.24 high	0.00 mean	0.59 high	1	0.1279	-1.3908	1.8588
25	-1.24 low	1.12 high	0.59 high	1	3.5527	-1.4297	1.7734
26	0.00 mean	1.12 high	0.59 high	1	1.7734	-1.4297	1.7734
27	1.24 high	1.12 high	0.59 high	1	-0.0060	-1.4297	1.7734
28	-1.24 low	-1.12 low	-0.59 low	2	4.1889	-1.7022	2.0704
47	0.00 mean	-1.12 low	0.59 high	2	2.0743	-1.7022	2.0743
30	1.24 high	-1.12 low	-0.59 low	2	-0.0481	-1.7022	2.0704
31	-1.24 low	0.00 mean	-0.59 low	2	4.1403	-1.6784	2.0514
38	0.00 mean	-1.12 low	0.00 mean	2	2.0724	-1.7022	2.0724
33	1.24 high	0.00 mean	-0.59 low	2	-0.0375	-1.6784	2.0514
34	-1.24 low	1.12 high	-0.59 low	2	4.0916	-1.6546	2.0324
29	0.00 mean	-1.12 low	-0.59 low	2	2.0704	-1.7022	2.0704
36	1.24 high	1.12 high	-0.59 low	2	-0.0269	-1.6546	2.0324
37	-1.24 low	-1.12 low	0.00 mean	2	4.1908	-1.7022	2.0724
50	0.00 mean	0.00 mean	0.59 high	2	2.0553	-1.6784	2.0553
39	1.24 high	-1.12 low	0.00 mean	2	-0.0461	-1.7022	2.0724
40	-1.24 low	0.00 mean	0.00 mean	2	4.1422	-1.6784	2.0533
41	0.00 mean	0.00 mean	0.00 mean	2	2.0533	-1.6784	2.0533
42	1.24 high	0.00 mean	0.00 mean	2	-0.0355	-1.6784	2.0533
43	-1.24 low	1.12 high	0.00 mean	2	4.0936	-1.6546	2.0343
32	0.00 mean	0.00 mean	-0.59 low	2	2.0514	-1.6784	2.0514
45	1.24 high	1.12 high	0.00 mean	2	-0.0249	-1.6546	2.0343
46	-1.24 low	-1.12 low	0.59 high	2	4.1928	-1.7022	2.0743
53	0.00 mean	1.12 high	0.59 high	2	2.0363	-1.6546	2.0363
48	1.24 high	-1.12 low	0.59 high	2	-0.0442	-1.7022	2.0743
49	-1.24 low	0.00 mean	0.59 high	2	4.1442	-1.6784	2.0553
44	0.00 mean	1.12 high	0.00 mean	2	2.0343	-1.6546	2.0343
51	1.24 high	0.00 mean	0.59 high	2	-0.0336	-1.6784	2.0553

Scenario	log(Price)	log(Volume)	Variance	Valence	log(Quantity)	Price Elasticity	Intercept
52	-1.24 low	1.12 high	0.59 high	2	4.0955	-1.6546	2.0363
35	0.00 mean	1.12 high	-0.59 low	2	2.0324	-1.6546	2.0324
54	1.24 high	1.12 high	0.59 high	2	-0.0230	-1.6546	2.0363
55	-1.24 low	-1.12 low	-0.59 low	3	4.2516	-1.7022	2.1332
56	0.00 mean	-1.12 low	-0.59 low	3	2.1332	-1.7022	2.1332
57	1.24 high	-1.12 low	-0.59 low	3	0.0147	-1.7022	2.1332
58	-1.24 low	0.00 mean	-0.59 low	3	4.2458	-1.6784	2.1569
59	0.00 mean	0.00 mean	-0.59 low	3	2.1569	-1.6784	2.1569
60	1.24 high	0.00 mean	-0.59 low	3	0.0681	-1.6784	2.1569
61	-1.24 low	1.12 high	-0.59 low	3	4.2400	-1.6546	2.1807
62	0.00 mean	1.12 high	-0.59 low	3	2.1807	-1.6546	2.1807
63	1.24 high	1.12 high	-0.59 low	3	0.1215	-1.6546	2.1807
64	-1.24 low	-1.12 low	0.00 mean	3	4.2352	-1.7022	2.1167
65	0.00 mean	-1.12 low	0.00 mean	3	2.1167	-1.7022	2.1167
66	1.24 high	-1.12 low	0.00 mean	3	-0.0018	-1.7022	2.1167
67	-1.24 low	0.00 mean	0.00 mean	3	4.2294	-1.6784	2.1405
68	0.00 mean	0.00 mean	0.00 mean	3	2.1405	-1.6784	2.1405
69	1.24 high	0.00 mean	0.00 mean	3	0.0516	-1.6784	2.1405
70	-1.24 low	1.12 high	0.00 mean	3	4.2235	-1.6546	2.1643
71	0.00 mean	1.12 high	0.00 mean	3	2.1643	-1.6546	2.1643
72	1.24 high	1.12 high	0.00 mean	3	0.1050	-1.6546	2.1643
73	-1.24 low	-1.12 low	0.59 high	3	4.2187	-1.7022	2.1002
74	0.00 mean	-1.12 low	0.59 high	3	2.1002	-1.7022	2.1002
75	1.24 high	-1.12 low	0.59 high	3	-0.0182	-1.7022	2.1002
76	-1.24 low	0.00 mean	0.59 high	3	4.2129	-1.6784	2.1240
77	0.00 mean	0.00 mean	0.59 high	3	2.1240	-1.6784	2.1240
78	1.24 high	0.00 mean	0.59 high	3	0.0352	-1.6784	2.1240
79	-1.24 low	1.12 high	0.59 high	3	4.2071	-1.6546	2.1478
80	0.00 mean	1.12 high	0.59 high	3	2.1478	-1.6546	2.1478
81	1.24 high	1.12 high	0.59 high	3	0.0885	-1.6546	2.1478
82	-1.24 low	-1.12 low	-0.59 low	4	4.3149	-1.7018	2.1969
83	0.00 mean	-1.12 low	-0.59 low	4	2.1969	-1.7018	2.1969
84	1.24 high	-1.12 low	-0.59 low	4	0.0788	-1.7018	2.1969
85	-1.24 low	0.00 mean	-0.59 low	4	4.3545	-1.6625	2.2854
86	0.00 mean	0.00 mean	-0.59 low	4	2.2854	-1.6625	2.2854
87	1.24 high	0.00 mean	-0.59 low	4	0.2163	-1.6625	2.2854
88	-1.24 low	1.12 high	-0.59 low	4	4.3940	-1.6231	2.3740
89	0.00 mean	1.12 high	-0.59 low	4	2.3740	-1.6231	2.3740
90	1.24 high	1.12 high	-0.59 low	4	0.3539	-1.6231	2.3740
91	-1.24 low	-1.12 low	0.00 mean	4	4.2856	-1.7072	2.1609
92	0.00 mean	-1.12 low	0.00 mean	4	2.1609	-1.7072	2.1609
93	1.24 high	-1.12 low	0.00 mean	4	0.0361	-1.7072	2.1609
94	-1.24 low	0.00 mean	0.00 mean	4	4.3251	-1.6678	2.2494
95	0.00 mean	0.00 mean	0.00 mean	4	2.2494	-1.6678	2.2494
96	1.24 high	0.00 mean	0.00 mean	4	0.1737	-1.6678	2.2494
97	-1.24 low	1.12 high	0.00 mean	4	4.3647	-1.6284	2.3380
98	0.00 mean	1.12 high	0.00 mean	4	2.3380	-1.6284	2.3380
99	1.24 high	1.12 high	0.00 mean	4	0.3112	-1.6284	2.3380
100	-1.24 low	-1.12 low	0.59 high	4	4.2562	-1.7125	2.1249
101	0.00 mean	-1.12 low	0.59 high	4	2.1249	-1.7125	2.1249
102	1.24 high	-1.12 low	0.59 high	4	-0.0065	-1.7125	2.1249
103	-1.24 low	0.00 mean	0.59 high	4	4.2958	-1.6731	2.2134

Scenario	log(Price)	log(Volume)	Variance	Valence	log(Quantity)	Price Elasticity	Intercept
104	0.00 mean	0.00 mean	0.59 high	4	2.2134	-1.6731	2.2134
105	1.24 high	0.00 mean	0.59 high	4	0.1310	-1.6731	2.2134
106	-1.24 low	1.12 high	0.59 high	4	4.3353	-1.6338	2.3019
107	0.00 mean	1.12 high	0.59 high	4	2.3019	-1.6338	2.3019
108	1.24 high	1.12 high	0.59 high	4	0.2686	-1.6338	2.3019
109	-1.24 low	-1.12 low	-0.59 low	5	4.2947	-1.6970	2.1827
110	0.00 mean	-1.12 low	-0.59 low	5	2.1827	-1.6970	2.1827
111	1.24 high	-1.12 low	-0.59 low	5	0.0707	-1.6970	2.1827
112	-1.24 low	0.00 mean	-0.59 low	5	4.3862	-1.6590	2.3214
113	0.00 mean	0.00 mean	-0.59 low	5	2.3214	-1.6590	2.3214
114	1.24 high	0.00 mean	-0.59 low	5	0.2566	-1.6590	2.3214
115	-1.24 low	1.12 high	-0.59 low	5	4.4777	-1.6211	2.4601
116	0.00 mean	1.12 high	-0.59 low	5	2.4601	-1.6211	2.4601
117	1.24 high	1.12 high	-0.59 low	5	0.4426	-1.6211	2.4601
118	-1.24 low	-1.12 low	0.00 mean	5	4.2647	-1.7025	2.1459
119	0.00 mean	-1.12 low	0.00 mean	5	2.1459	-1.7025	2.1459
120	1.24 high	-1.12 low	0.00 mean	5	0.0270	-1.7025	2.1459
121	-1.24 low	0.00 mean	0.00 mean	5	4.3563	-1.6646	2.2846
122	0.00 mean	0.00 mean	0.00 mean	5	2.2846	-1.6646	2.2846
123	1.24 high	0.00 mean	0.00 mean	5	0.2129	-1.6646	2.2846
124	-1.24 low	1.12 high	0.00 mean	5	4.4478	-1.6266	2.4233
125	0.00 mean	1.12 high	0.00 mean	5	2.4233	-1.6266	2.4233
126	1.24 high	1.12 high	0.00 mean	5	0.3989	-1.6266	2.4233
127	-1.24 low	-1.12 low	0.59 high	5	4.2348	-1.7080	2.1090
128	0.00 mean	-1.12 low	0.59 high	5	2.1090	-1.7080	2.1090
129	1.24 high	-1.12 low	0.59 high	5	-0.0167	-1.7080	2.1090
130	-1.24 low	0.00 mean	0.59 high	5	4.3263	-1.6701	2.2478
131	0.00 mean	0.00 mean	0.59 high	5	2.2478	-1.6701	2.2478
132	1.24 high	0.00 mean	0.59 high	5	0.1692	-1.6701	2.2478
133	-1.24 low	1.12 high	0.59 high	5	4.4178	-1.6321	2.3865
134	0.00 mean	1.12 high	0.59 high	5	2.3865	-1.6321	2.3865
135	1.24 high	1.12 high	0.59 high	5	0.3551	-1.6321	2.3865

Table 6.3: Scenarios for Visualization of Results

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