Essays on Price and Usage Effects

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1. Introduction

Publications in the area of pricing offer a wide range of both descriptive and predictive research to satisfy the growing awareness of the importance of developing sophisticated pricing strategies (e.g., Gijsbrechts 1993). Pricing strategies can have an influence on both, consumers' purchase decision and consumers' post-purchase behavior. E.g., a consumer's decision to switch brands can depend on own and competitor's pricing decisions (e.g., Sethuraman et al. 1999). Further, if consumers' post-purchase behavior – which can depend on price (e.g., Thaler 1980) – is related to future purchases, managers do not only have to account for price effects with respect to the focal product's demand plus competitive demand but have to specifically account for purchase and post-purchase effects when setting prices.

Managers are interested in consumers becoming loyal with a firm and repeatedly purchasing the firm's products. E.g., if the price that a consumer pays for a product is not independent from the consumer's post-purchase behavior (e.g., Thaler, 1980; Arkes and Blumer 1985), managers have to account for both effects – purchase and post-purchase effects – when developing pricing strategies. Consumers who purchase a product only because of a promotion generate short-term revenue to the firm. However, if the fact that the consumer purchases the product for a low price on promotion has a negative impact on e.g., how much the consumer uses the product (e.g., Arkes and Blumer 1985), the consumer may develop a lower brand attachment, brand attitude and customer loyalty (e.g., Park et al. 2010; Murray and Bellman 2011; Iyengar et al. 2007). This impact of marketing-mix instruments on purchase (e.g., brand switching from competitors) and post-purchase behavior could have an impact on future purchasing behavior e.g., cross-buying – purchase different products from the same firm – or repeat purchases. In that case it would be important for managers to not manage their products as silos – only accounting for a single product's demand effects – but to consider the effects of marketing-mix instruments on purchase and post-purchase behavior of the focal product and also on all other present and future products of the firm. Consequently, pricing decisions for a single product can have long-term effects that can reach beyond its demand effects. E.g., pricing decisions can impact consumers' usage behavior but do also have a strong interaction with the product's competition e.g., through brand switching.

To account for effects on consumers' purchasing behavior, it is crucial to understand factors that shape price sensitivity (e.g., Bijmolt et al. 2005). Further, to account for post-purchase effects, it is relevant to know how a product is used after purchase depending on price. Finally, to close the circle of purchase and post-purchase, it is essential to know the influence of a product's usage on subsequent purchases.

The relevant concepts in this dissertation that are utilized to analyze the circle of purchase behavior to post-purchase behavior to subsequent purchase behavior are (1) cross-price elasticities and (2) consumer's product usage.

(1) Cross-price elasticities, which are the key measure of competitive relationship, are defined as the percentage change in demand of a focal brand or product when a competing brand or product changes its price by one percent. Knowledge about cross-price elasticities leads to insights on market structure and price competition. These insights can guide managers in their decisions on pricing and promotions and how to respond to competitor's activities (e.g., Sethuraman and Srinivasan 2002).

(2) Consumer's product usage is defined as the accumulated time that a consumer makes use of a product after purchase. Knowledge about the effect on consumers' product usage enables firms to influence the later usage of their products, and information about the direction and strength of these effects opens doors to new possibilities for firms to foster customer satisfaction. Finally, knowledge about the effect of consumers' product usage on subsequent purchases opens new doors for e.g., consumer targeting.

In this dissertation, I analyze and combine two fields that are especially relevant for managers and researchers in the area of marketing: consumers' purchase and post-purchase behavior. More precisely, price effects in the field of purchase behavior and usage effects in the field of post-purchase behavior. In the field of consumers' purchase behavior, I analyze how consumers react to price changes of competing brands. Therefore, I conduct (1) a meta-analysis of cross-price elasticities to generate knowledge about an average effect size and determinants that shape the size of cross-price elasticities. In the field of post-purchase behavior, I analyze (2) how the price that a consumer pays for a product influences the consumer's usage and (3) how usage is related to future purchases. For the influence of price on usage, I analyze for a large set of consumers how the price that they pay for a digital good is related to their subsequent usage behavior. For the influence of usage on future purchases, I analyze how a consumer's decision to cross-buy is influenced by the consumer's usage of a previously purchased product of the firm.

This dissertation contributes to the literature by providing generalizing insights about cross-price elasticities (price effects), by providing insights of price on post-purchase behavior (price-usage effects) and by providing an understanding of the influence of post-purchase behavior on subsequent purchases (usage effects).

Managers and researchers are interested in understanding the full consequence of price changes. Therefore, they do not only have to be aware of a focal brand's own price elasticity, but they also need to know the respective cross-price effects. This knowledge on market structure and price competition can guide managers in their decisions on pricing and promotions and how to respond to competitor's activities (e.g., Sethuraman and Srinivasan 2002). Knowledge about size and determinants of cross-price effects support researchers in calibrating their research designs and to check the plausibility of their findings.

Farley et al. (1998) argue that in order to advance, theory needs to be confronted with data that is derived from accumulating knowledge across academic work. The importance of generalizing research in the field of marketing can be seen in a set of recent publications. Generalizing research in the field of marketing covers e.g., own price elasticities (e.g., Bijmolt et al. 2005), advertising elasticities (e.g., Sethuraman et al. 2011), personal selling elasticities (e.g., Albers et al. 2010), shelf space elasticities (e.g., Eisend 2014), online product reviews (e.g., Floyd et al. 2014) and electronic word-of-mouth elasticities (e.g., Ya et al. 2015). However, the literature lacks a recent generalization for cross-price elasticities. The most recent meta-analysis on cross-price effects considers research that was published until 1996 (Sethuraman et al. 1999).

After the year 1996 important changes in the market place have occurred (e.g., the surge in private labels) and many methodological advances were established in the literature (e.g., endogeneity). Consequently, it is warranted to update our knowledge on empirical generalizations on cross-price effects. Further, the literature lacks a generalizing publication on cross-price elasticities that analyzes a substantial set of determinants shaping the effect size.

Knowledge about the effect of price on usage enables managers to influence the later usage of their products, and information about the direction and strength of this effect opens doors to new possibilities for firms to foster customer satisfaction (e.g., Bolton and Lemon 1999). Consequently, knowledge about the influence of price on usage enables managers to account for post-purchase effects when setting prices. Neglecting these post-purchase effects can lead to negative customer-related long-term consequences for companies (e.g., through negative impact on future purchase behavior).

Previous research finds mixed results regarding the impact of a product's price on the product's usage. Research suggesting a positive relationship argues that the positive relationship between the price of a product and its usage is caused by sunk cost effects – consumers consider the money they spent on a product in their usage decisions – (e.g., Thaler

1980; Arkes and Blumer 1985). Other research suggests that the positive effect of price on usage is caused by screening effects and not sunk cost effects (e.g., Ashraf et al. 2010). Screening effects occur because customers with a high (low) expected usage have a high (low) willingness to pay. As a result, a higher (lower) price would be associated with higher (lower) usage rates even in the absence of any sunk-cost effect. However, as the results by Ashraf et al. (2010) are based on survey data and not actual usage, the literature lacks a publication that analyzes the effect of price on actual usage and additionally controls for screening effects. Further, consumers do not only self-select into specific prices leading to the described screening effect but they also self-select into whether or not to purchase the game at all. Neglecting the latter – selection effect – results in a sample selection bias due to non-randomly selected purchases and non-purchases (e.g., Heckman 1979). Existing research is not able to reach consensus about the distinction between the screening, selection and direct effect of price on usage due to a lack of information about the effect of price on purchase likelihood and actual behavior. I address this void in the literature by analyzing actual prices and actual usage behavior to assess the influence of price on usage above and beyond potential selection and screening effects

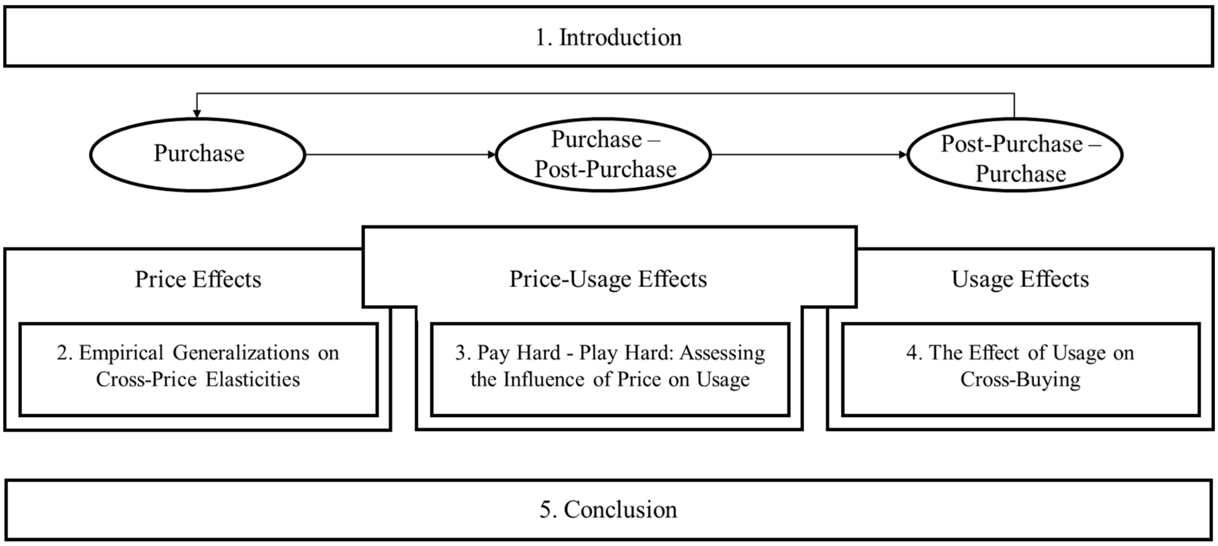
Companies can sell different products under the same brand in order to leverage a firm's brand value and to maximize revenues and profits (e.g., Kumar et al. 2008). Firms' focus has changed from solely keeping customers to the field of cross-selling additional services and products as a valuable field of customer relationship management (e.g., Verhoef et al. 2001). Consequently, it is important to understand the motivation of consumers to cross-buy and to identify drivers of cross-buying (e.g., Kumar et al. 2008).

Previous research covers a set of drivers that influence consumers' propensity to cross-buy (e.g., Verhoef et al. 2001; Ngobo 2004; Verhoef and Donkers 2005; Kumar et al. 2008). However, the literature lacks a publication that analyzes the impact of a product's actual usage on the purchase of future products. It is not clear if higher levels of consumers' usage with a firm's product boost the success of cross-buying and how this effect is heterogeneous for different consumer traits. The unique feature of this research is that we can link actual consumer and peer behavior to the propensity to cross-buy

Consequently, the literature lacks (1) a recent publication that generalizes knowledge about cross-price elasticities and analyzes the impact of determinants on the size of cross-price elasticities (2) a publication that analyzes the impact of price on usage based on actual usage and that controls for selection and screening effects (3) a publication that links the actual post-purchase behavior of consumers – in terms of usage – to the decision to purchase an additional product from the same company. Therefore, the results of this dissertation provide insights for managers and researchers in the fields of (1) purchase decision (2) post-purchase behavior (3) and a link of post-purchase behavior plus subsequent purchase decision.

I structure this dissertation as shown in Figure 1.1. After the introduction in Chapter 1, I analyze empirical generalizations on cross-price elasticities in Chapter 2. In Chapter 3, I analyze the impact of the price that a consumer pays on the consumer's post-purchase usage of that product. In Chapter 4, I analyze how a consumer's usage of a previously purchased product is related to the consumer's decision to purchase additional products from the same firm. Consequently, I analyze price effects (influence on purchase) in Chapter 2, I combine price and usage effects (influence of purchase on post-purchase) in Chapter 3 and I analyze usage effects (influence of post-purchase on purchase) in Chapter 4. Finally, I provide a conclusion in Chapter 5.

Figure 1.1: Dissertation Framework



In Chapter 2, joint work with Dominik Papies, we conduct a meta-analysis to derive empirical generalizations on cross-price elasticities. The domain of pricing has seen two important developments over the last years. Firms, in particular in the retail sector, are facing a changed competitive environment, in part fueled by the surge in popularity of private labels. In addition, research on pricing issues has benefitted from several important modelling advances (e.g., price endogeneity). Both developments, however, are not reflected in our knowledge about the key measure of price competition (i.e., the cross-price effect). Hence, it is not clear how cross-price effects have been shaped by these developments over the last years. To address this void, we provide empirical generalizations using a meta-analysis of prior econometric estimates of cross-price effects. As effect size, we use the cross-price elasticity, which is the percent change in demand of one product due to the percent change in price of a different product. This metric is easy to interpret and helps comparing findings from studies with different demand measures (e.g., market share, sales and choice share). Based on 7298 cross-price elasticities from 114 studies, we identify 6 new main empirical generalizations. (1) We find an overall cross-price elasticity of .26, which is half the effect size of the previous meta-analytic mean. The median cross-price elasticity is .10. (2) Cross-price elasticities have decreased over time. (3) Cross-price elasticities decrease over the product life cycle. (4) High-stockpiling groceries have the highest cross-price elasticities. (5) Long-term are larger than short-term cross-price elasticities. (6) The asymmetric share effect only holds in high-share tiers.

In Chapter 3, joint work with Dominik Papies, we analyze the impact of the price that a consumer pays on the consumer's post-purchase usage of that product. Although the strong impact of price promotions on demand is well documented in the literature, it is less clear how the price that consumers pay for a product is related to the way the product is used after purchase. However, this post-purchase usage is important, because it is potentially related to future purchase behavior. Usage is an antecedent of customer satisfaction and, therefore, managing customer usage levels is an important tool to sustain customer satisfaction and ensure long-term customer profitability. The conceptual challenges in this study are to control for (1) screening and (2) selection effects. Screening effects arise because consumers with a high expected utility are willing to pay more for a product compared to consumers with a low expected utility. Selection effects occur, because only consumers with a certain amount of expected utility purchase the product at all. We control for these effects by estimating two models: a selection and an outcome model. The selection model captures the propensity of a consumer to purchase the good. The outcome model captures the effect of price on usage. The goal of this study is to capture the direct effect of price on usage above and beyond potential selection and screening effects. This remaining effect of price on usage is attributed to sunk cost effects. Sunk cost effects arise, if past expenses are incorporated in the current decision processes. We show for a digital good, that above and beyond selection and screening effects, a positive sunk cost effect of price on usage exists. Based on 280,709 observations in our selection model and 55,622 observations in our outcome model, we find a price-usage elasticity of .09. This positive sunk cost effect increases for consumers with lower levels of experience in the marketplace.

In the single author paper in Chapter 4, I analyze the impact of consumers' product usage on the propensity to cross-buy – purchase another product from the same brand. Although previous research on cross-buying has identified a substantial set of drivers, the driver of consumer's usage of previous products from the brand is neglected. Cross-Buying is important for firms to leverage a firm's brand value and to maximize revenues and profits. To sell different products under the same brand can extent the brand and transfer associations of the brand to new products (e.g., Kim and Sullivan 1998). Further, this transfer reduces risk and increases success chances of new products (e.g., Swaminathan 2003).

I contribute to the literature by introducing a new driver of cross-buying: consumers' usage behavior. A beneficial aspect of my research is that I observe the actual usage of each purchased product for a huge set of consumers. Further, as I have information about the usage behavior of a consumer's friends, I am able to analyze a consumer's usage and purchase behavior in the context of her/his social group. Based on a panel dataset of 793 consumers, I find for a digital good that higher product usage leads to a higher propensity to purchase an additional product. For consumers who use the product heavily, the predicted probability of purchasing another product from the same firm is twice as high compared to users with a low level of usage. Further, the positive effect of the base product's usage increases for consumers with low levels of category experience.

In Chapter 5, I come to a conclusion by summarizing the results from previous chapters and by providing implications for managers and researchers.

2. Empirical Generalizations on Cross-Price Elasticities

Chapter 2 is a slightly modified version of the working paper "Empirical Generalizations on Cross-Price Elasticities" by Johannes Auer and Dominik Papies. The contributions of the respective coauthors were as follows: Johannes Auer conducted the data collection, data management, all analyses, and the first draft of the working paper. Dominik Papies contributed to the analyses, gave feedback and revised the draft of the working paper.

Abstract

In the last decades, the competitive landscape in many markets (e.g., retailing) and the way in which researcher analyze data from these markets have heavily changed. This resulted in updates of empirical generalizations in many areas. For cross-price elasticities, which is the key measure of competitive relationship, this update is pending, and we do not know how these changes have affected cross-price elasticities. To address this void, we provide empirical generalizations using a meta-analysis of prior econometric estimates. Based on 7,298 cross-price elasticities from 114 studies, we identify 6 new main empirical generalizations. (1) We find an overall cross-price elasticity of .26, which is half the effect size of the previous meta-analytic mean. The median cross-price elasticity is .10. (2) Cross-price elasticities have decreased over time. (3) Cross-price elasticities decrease over the product life cycle. (4) High-stockpiling groceries have the highest cross-price elasticities. (5) Long-term are larger than short-term cross-price elasticities. (6) The asymmetric share effect only holds in high-share tiers. These findings support researchers in calibrating their research designs and to check the plausibility of their findings.

Keywords: Cross-Price Elasticity; Meta-Analysis; Cross-Price Effect, Pricing

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2.1 Introduction

To understand the full consequence of price changes, researchers and managers alike not only have to be aware of a focal brand's own price elasticity, but they also need to know the respective cross-price effects. This knowledge on market structure and price competition can guide managers in their decisions on pricing and promotions and how to respond to competitor's activities (e.g., Sethuraman and Srinivasan 2002). Consequently, a large number of papers studying cross-price effects have been published in the last decades, and the seminal work on cross-price effects (e.g., Sethuraman 1995; Sethuraman et al. 1999; Sethuraman and Srinivasan 2002) have accumulated a large number of citations. Against this background, it is surprising to find that the literature lacks empirical generalizations on cross-price effects. The most recent publications that summarize research on cross-price effects considers research that was published until 1996 (e.g., Sethuraman and Srinivasan 2002). With important changes in the market place having occurred in the years after 1996 (e.g., the surge in private labels, the rise of the Internet as a distribution channel) and many methodological advances being established in the literature (e.g., endogeneity, heterogeneity, dynamics), it is warranted to update our knowledge on empirical generalizations on cross-price effects.

What do we know so far? Sethuraman (1995) and Sethuraman et al. (1999) provided first generalizations for cross-price effects and report a mean cross-price elasticity of .52. Further, Sethuraman et al. (1999) analyzed two asymmetric effects that arise in the context of cross-price effects. The *asymmetric price effect* states that cross-price elasticities are larger if the price changing brand has a higher price compared to the demand changing brand. For the *neighborhood price effect,* cross-price elasticities are larger the closer two competing brands are in price. In addition, Sethuraman and Srinivasan (2002) provide evidence for an *asymmetric share effect*, i.e., cross-price elasticities are larger if the price changing brand has a larger market share compared to the demand changing brand.

The most recent meta-analysis uses 1,060 cross-price elasticity estimates from 15 studies that were published before 1996 (Sethuraman et al. 1999). We build on their work and contribute to the literature in the following three aspects. (1) We update our knowledge on the mean cross-price elasticities and provide new empirical generalizations across 7,298 elasticities from 114 publications. (2) Previous meta-analyses have not assessed a comprehensive set of determinants that shape cross-price elasticities. To assess the heterogeneity in cross-price elasticities, we therefore investigate a large set of determinants that impact the magnitude of cross-price effects. (3) A unique aspect of analyzing cross-elasticities (in contrast to, say, marketing-mix elasticities) is that each observation is a cross-effect within a pair of two competing brands or products. This implies that heterogeneity arises because of the different characteristics of the two brands involved in this competitive relationship. These characteristics are important because, e.g., consumers may be more willing to switch from a low quality, low price brand to a high quality, high price brand when the latter is on promotion (e.g., Allenby and Rossi 1991; Bronnenberg and Wathieu 1996; Sivakumar and Raj 1997). Further, promotions of high share brands may have stronger impact on smaller brands than vice versa due to a stronger clout of high share brands (e.g., Kamakura and Russel 1989). We therefore contribute to the literature by updating previous findings and by providing new empirical generalizations on these asymmetric effects.

To achieve our research goals, we compile a large set of 7,298 brand and product level cross-price elasticities covering the period from 1960 to 2015. This is the full set of cross-price elasticities that we could identify from previous research. We form three groups of determinants, i.e., (1) those that relate to market characteristics (year of data collection, stage of product life cycle, category price elasticity, type of parent brand, country, household disposable income, inflation rate), (2) those that pertain to research methodology (price definition, duration of the effect, endogeneity of own price effect, heterogeneity of price sensitivity, inclusion of other variables, temporal aggregation, and item definition), and (3) those that capture the asymmetries between the competing brands (brand ownership, share asymmetries, market share tier, price asymmetries, price tier). We provide a comparison of the determinants of this study and the determinants of previous meta-analyses in Table 2.1.

Based on 7,298 elasticities from 114 studies, we add several new insights to the literature. (1) We find an overall mean cross-price elasticity of .26, which is about half the magnitude identified in the previous meta-analysis (Sethuraman et al. 1999). 70% of all observations are below the mean, and the median is .10. (2) Cross-price elasticities have significantly decreased in magnitude over the past four decades. This finding also allows us to trace back the difference between Sethuraman et al. (1999) and this study. (3) Cross-price elasticities decrease over the product life cycle. (4) High-stockpiling groceries have the highest cross-price elasticities. (5) Cross-price elasticities based on models that measure long-term effects are substantially stronger than short-term elasticities. (6) The asymmetric share effect is not universal. Rather, this effect only holds for brands located in a high market share tier. In addition, we find that cross-price elasticities are overestimated if other marketing variables such as advertising are omitted and if endogeneity of the own price effect is not accounted for.

Table 2.1: Comparison of Current Study with Previous Meta-Analyses

	Determinant	**Sethuraman (1995)**	**Sethuraman et al. (1999)**	**Sethuraman and Srinivasan (2002)**	**This Paper**
Market Characteristics	Year of data collection				x
	Brand ownership	x	x		x
	Stage of product life cycle				x
	Product category		x	x	x
	Country				x
	Number of products in category		x	x	x
	Household disposable income				x
	Inflation rate				x
	Category price elasticity				x
	Parent brand				x
	Complement				x
Research Methodology	Temporal aggregation				x
	Item definition				x
	Criterion variable		x	x	x
	Functional form	x	x	x	x
	Duration of effect				x
	Price definition				x
	Endogeneity of price effect				x
	Inclusion of other variables (advertising, sales promotion, quality)				Advertising, sales promotion, quality
	Heterogeneity in price sensitivity				x
Asymmetric Effects	Prices/Price-ranks		Prices / Price-ranks		Prices
	Market share	x		x	x

In the next section we will describe our method, including data collection, coding, theoretical expectations, and model. We then present our findings for the average effect of cross-price elasticities and the impact of determinants. Afterwards, we discuss the implications of the findings.

2.2 Data Collection

2.2.1 Cross-Price Elasticities

In order to identify all relevant studies published between 1960 and 2015 that report cross-price elasticities, we apply a multi-pronged search strategy. The first part of our search strategy includes an examination of citations based on the Social Sciences Citation databases. We inspect all papers that were cited by previous work on cross-price effects (Sethuraman 1995;

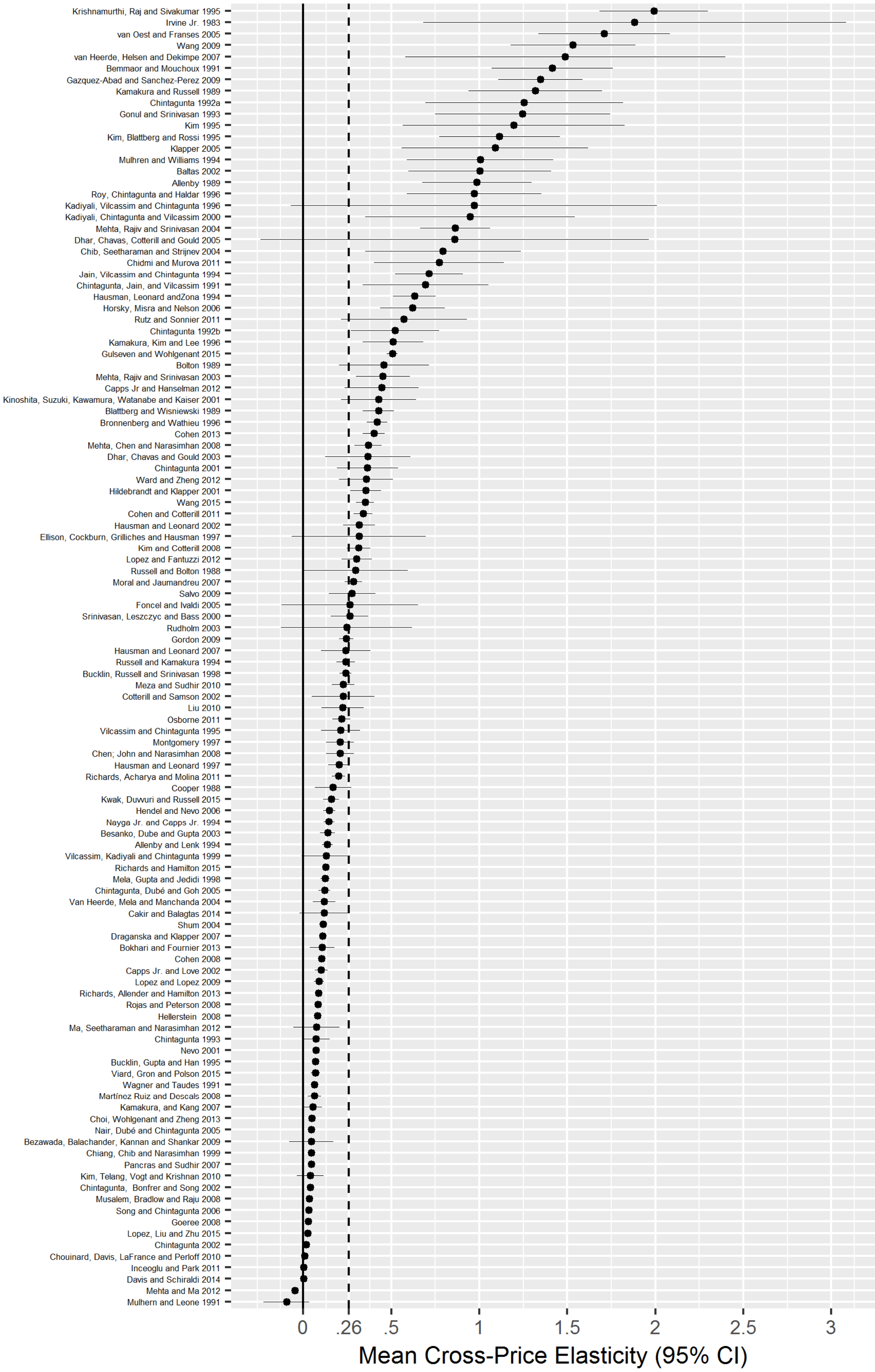
Sethuraman et al. 1999; Sethuraman and Srinivasan 2002) or cite one of these studies. Second, we perform a multiple keyword search in the EBSCO Business Source Premier database. In a third step, we check the references of publications we had already obtained. Fourth, we examine all papers that cite one of the publications that we had already obtained. We repeat the third and fourth step until we cannot identify any more new publications. Figure 2.1 shows the mean cross-price elasticity and the respective confidence interval of effects for each publication. The distribution of mean cross-price elasticities ranges between -.1 and 2.0.

We included all cross-price elasticities if they fulfilled the following criteria (Sethuraman et al. 1999; Bijmolt et al. 2005). First, we consider brand- and SKU-level elasticities[1]. Second, we only use those observations that report data based on actual purchases and not e.g., simulations or lab studies. Third, we exclude observation for which no information about the product category are provided. Fourth, in the case of multiple model estimates for the same dataset, we include only the authors' recommended model if model differences are not captured by our determinants. In contrast to Sethuraman et al. (1999), we also include those observations that do not report prices and market shares as we are interested in a complete set of cross-price elasticities. However, the analysis of asymmetric price and share effects is based on the subset that reports prices and market shares.

This data collection results in a set of 114 publications reporting 7,298 cross-price elasticities. Consistent with previous meta-analyses for marketing-mix instruments, we include both, significant and insignificant observations in the analysis (e.g., Sethuraman et al. 2011). We drop 50 (.7%) outliers outside the interval of the mean plus minus five times the standard deviations (e.g., Bijmolt et al. 2005).

[1] We analyze both cross-price elasticities between different brands and elasticities between SKUs of the same brand. As the majority of our elasticities is derived from competition between brands, we subsequently use the term brand elasticity.

Figure 2.1: Overview of Studies Included in the Analysis



Note: each dot represents the mean per study. The horizontal bar denote the 95% CI across the estimates reported in a given study.

2.2.2 Control Variables

To ensure that the findings from this analysis are comparable with existing research, we code and analyze all of the determinants used in the publications by Sethuraman (1995), Sethuraman et al. (1999), Sethuraman and Srinivasan (2002) and Bijmolt et al. (2005). Two independent judges (one is not an author of this study) coded the respective determinants for all cross-price elasticities. Agreement between judges was 84 percent and inconsistencies were resolved by discussion. For 22 publications, the year of data collection is not given. We follow the approach by Bijmolt et al. (2005) and impute the missing value as the year of publication minus 9, which is the average difference between year of data collection and publication for all other studies. Observations for year of data collection range from 1975 to 2010.

We obtain the growth rates of disposable household income from the OECD, Worldbank and tradingeconomies.com. Values for countries with missing values are imputed as the average over all countries in this year. Values for the growth rate of disposable household income range from -.41 to 17.23 with a mean of 3.38. The Worldbank provides information on the inflation rate, which ranges from -1.27 to 13.96 with a mean of 2.90.

2.2.3 Data Collection and Coding for Absolute Cross-Price Effects

For the analysis of asymmetric effects, we require information about prices and market shares of all elasticity estimates. In total, 63 papers report prices and market shares in addition to the cross-price elasticities, which results in a set of 3444 cross-price elasticities. In this set, the average number of cross-price elasticities reported by a publication is 54.7 with a minimum of 2 and a maximum of 420. For the analysis of asymmetric effects, we will work with this reduced data set.

2.3 Theoretical Expectations

2.3.1 Market Characteristics

Year of data collection. The literature reports a shift of marketing expenditures from advertising to promotions (e.g., Mela et al. 1998) and a focus on price promotions as reaction to competitive attacks (e.g., Steenkamp et al. 2005). This development should lead to higher cross-price elasticities because more promotions increase price sensitivity and encourage brand switching (e.g., Mela et al. 1997). Then again, brands have grown to be one of firms' most valuable intangible asset and a top management priority (e.g., Keller and Lehmann 2006). Growing emphasis on branding leads to stronger brand differentiation, which should reduce cross-price elasticities because it becomes more difficult for consumers to substitute one brand by another. These opposing predictions from previous research imply that we do not have a clear priori expectation.

Brand ownership. One recurring theme in the literature in the past years is the surge in private label sales. Traditionally, national brands have been characterized by higher prices, higher quality perception compared to private labels (e.g., Steenkamp et al. 2010), by a higher brand strength (e.g., Bijmolt et al. 2005) and lower price-sensitivity of consumers (e.g., Danaher and Brodie 2000). Although private labels may have made some inroads in terms of quality perception, we expect that private labels suffer more from price changes of national brands as consumers can purchase brands with a higher perceived quality for a closer price to private labels. This implies that we expect that price changes of national brands have a stronger effect compared to price changes of private labels because price reductions of national brands draw sales from both national brands and private labels whereas price reductions of private labels tend to not affect demand of national brands (e.g., Aggarwal and Cha 1998). Therefore, price changes of private labels should lead to smaller cross-price elasticities compared to price changes of national brands.

Stage of product life cycle. Demand for brands at the beginning of the lifecycle should react stronger to price changes of competing brands because of high purchase risks and low level of repeat purchases (e.g., Parker and Neelamegham 1997), and hence less established purchase patterns. We therefore expect that cross-price elasticities will be lower when the demand changing brand is in a mature stage of the product life cycle.

Product category. Previous research suggests that product categories differ in terms of price sensitivity (e.g., Simon 1979). The reason is that category characteristics like the ability to stockpile or the product lifetime affect purchase acceleration in response to a price change and therefore elasticities (e.g., Narasimhan et al. 1996). Accordingly, we distinguish between durables on the one hand and groceries with either low or high stockpiling ability on the other hand. Products that can be stockpiled enable the consumer to act on a promotion and switch brands, and hence, consumers are more likely to purchase competing brands with reduced prices (e.g., Narasimhan et al. 1996). We therefore expect larger cross-price elasticities for products with a high stockpiling ability compared to products with a low stockpiling ability. For durables, we argue that the longer product life entails a higher purchase risk, and consumers may be more reluctant to switch brands in response to price changes. Hence, we expect that durables have smaller cross-price elasticities than groceries.

Country. Prior research has found differences in buying behavior across different countries and cultures (e.g., Kacen and Lee 2002). However, when aggregated across studies, Bijmolt et al. (2005) find that price sensitivity does not differ across countries. While we do not have clear expectations regarding the direction of the effect, we include the country as a control variable.

Number of products in category. With an increasing number of products in a category, consumers can choose from a larger set of alternatives, which may intensify competition, leading to more brand switching and higher cross-price elasticities (e.g., Narasimhan et al. 1996). However, when one brand in a category with many competitors cuts prices, it will draw demand not only from one competitor, but a small share from a larger number of competitors, i.e., the demand it draws will be distributed across many brands. Further, more products in a category implies higher degree of differentiation between products (e.g., Barena and Sánchez 2009) and as a result, price may not be the only decision criterion. This will lead to lower cross-price elasticities (e.g., Sethuraman et al. 1999).

Household disposable income. With increasing income, consumers are less likely to have a high level of price knowledge and show a smaller price sensitivity (e.g., Estelami et al. 2001). As a result, we expect smaller cross-price elasticities in countries and years with higher disposable income.

Inflation rate. The literature is inconclusive regarding the effect of inflation rate on price sensitivity. On the one hand, a higher degree of price variation in times of inflation reduces the information content of prices and consumer price knowledge will be lower (e.g., Estelami et al. 2001). On the other hand, consumers may pay more attention to prices in times of high inflation because of the awareness that the money's value is declining. This is in line with the meta-analysis by Bijmolt et al. (2005) who find that price sensitivity increases with an increasing inflation rate. Accordingly, we expect higher cross-price elasticities for higher levels of inflation.

Category price elasticity. To avoid that the general price responsiveness in a given study is picked up by other covariates, we control for the mean category price responsiveness because we expect that in categories in which consumers strongly react to prices, more brand switching will occur. To this end, we calculate the category mean own price elasticity as the mean of all own price elasticities for a category within one publication[2]. We expect a negative relationship between this category price elasticity and cross-price elasticities, i.e., if the category mean own

[2] Constrained elasticities derived from e.g., multinomial logit models are by construction not independent from each other. Therefore, we assess the effect of the *category* mean own price elasticity and not the effect of the focal brand's own price elasticity.

price elasticity is more negative (higher magnitude), cross-price elasticities are more positive (higher magnitude) because more brand switching will occur.

Parent brand. On the one hand, for products with the same parent brand, consumers do not have to take the risk of adopting a new brand when changing from one product to another. This suggests a higher degree of substitutability and, hence, cross-price elasticities may be higher. On the other hand, it is likely that the parent brand will seek to differentiate its sub-brands from one another, which would lead to lower cross-price elasticities. We leave this as an empirical question.

Table 2.2: Summary of Determinants and Theoretical Expectations

Determinant	Levels	Definition	Theoretical Expectation for Effect on CPE	Number of Observations	Mean CPE
Year of data collection	Continuous	Time trend for year of data collection	+/-	7,248	cont.
Brand ownership	P_NB vs D_NB	Price changing brand is national brand; demand changing brand is national brand	Base category	6,235	.25
	P_NB vs D_PL	Price changing brand is national brand; demand changing brand is private label	+	459	.28
	P_PL vs D_PL	Price changing brand is private label; demand changing brand is private label	+/-	71	.28
	P_PL vs D_NB	Price changing brand is private label; demand changing brand is national brand	-	483	.22
Stage of product life cycle	Introduction or growth	Demand changing brand is in introduction or growth stage	Base category	294	.33
	Mature or Decline	Demand changing brand is in mature or decline stage	-	6,954	.24
Product category	Durables	Brand pair is from durable category	-	2,047	.21
	Groceries, high stockpiling	Brand pair is from grocery category with high stockpiling ability	Base category	3,018	.28
	Groceries, low stockpiling	Brand pair is from grocery category with low stockpiling ability	-	1,832	.24
	Intangibles	Brand pair is from intangible category (e.g. services)	+/-	6	.25
	Pharmaceutics	Brand pair is from pharmaceutics category	+/-	345	.13
Country	Asia	Asia	+/-	36	.40
	Europe	Europe	+/-	613	.38
	US	US	Base category	6,508	.23
	Other	Pooling Brazil and Australia	+/-	91	.54
Number of products in category	Continuous	Number of analyzed competing products in study	+/-	7,248	cont.
Household disposable income	Continuous	Household disposable income growth rate for year and country of data collection	-	7,248	cont.
Inflation rate	Continuous	Inflation rate for year and country of data collection	+	7,248	cont.
Category price elasticity	Continuous	Mean own price elasticity of all observed brands in the sub-category	-	7,009	cont.
Parent brand	Different	Brand pair has the same parent brand	Base category	6,700	0.25
	Same	Brand pair has different parent brand	+	548	0.18
Complement	Complement	Defined by the authors based on product characteristics and not the sign of their cross-price elasticity	Base category	343	-.05
	Substitute		+	6,905	.26

Table 2.2 (continued)

Determinant	Levels	Definition	Theoretical Expectation for Effect on CPE	Number of Observations	Mean CPE
Temporal aggregation	Daily/weekly	Data is aggregated on a daily or weekly base	+	4,713	.28
	Longer weekly	Data is aggregated on a longer weekly base	Base category	2,535	.19
Item definition	SKU	Data is collected from SKU data	-	1,664	.25
	Brand	Data is collected from or aggregated to brand data	Base category	5,584	.25
Criterion variable	Absolute	Absolute demand measures	Base category	2,186	.19
	Relative	Relative demand measures (market share, choice share)	-	5,062	.27
Functional form	Additive	Linear models	+/-	201	.31
	Attraction	Attraction and choice models	Base category	4,268	.27
	Multiplicative or Exponential	Multiplicative and exponential models (including log-models)	+/-	2,779	.21
Duration of effect	Short term		-	5,814	.22
	Long term	Model includes aspect that consider past periods (e.g., lagged or loyalty variables)	Base category	1,434	.36
Price definition	Actual price	Price that the consumer pays at checkout	Base category	5,461	.27
	Regular price	Representing the price in regular conditions like non-promotional weeks	-	1,130	.14
	Promotional price	Prices for promotional weeks or a price index	+	657	.26
Endogeneity of price effect	Not accounted for		+/-	3,279	.34
	Accounted for	Model accounts for endogeneity (e.g., instrumental variable approach)	Base category	3,969	.17
Inclusion of other variables	Advertising omitted		+	3,626	.21
	Advertising included	Inclusion of advertising (e.g., newspaper, feature, display)	Base category	3,622	.28
	Sales promotion omitted		+	4,551	.21
	Sales promotion included	Inclusion of sales promotion variable (e.g., couponing, deal promotions)	Base category	2,697	.31
	Quality omitted		+/-	6,327	.24
	Quality included	Inclusion of quality variable	Base category	921	.32
Heterogeneity in price sensitivity	Not accounted for		+/-	1,892	.32
	Accounted for	Model accounts for heterogeneity (e.g., random consumer intercepts, demographics)	Base category	5,356	.22

Complements. Complements are usually defined as brand pairs with negative cross-price elasticities (e.g., Shocker et al. 2004). We control for whether authors of a given study explicitly label the relation between brand pairs as either complements or substitutes and expect negative (positive) cross-price elasticities for complements (substitutes).

2.3.2 Research Methodology

Temporal aggregation. Aggregating sales and price data over time, e.g., by using average prices or average demand, reduces the variance of these variables (e.g., Bijmolt et al. 2005). On top of that, aggregated data may not fully capture dynamic consumer reactions to promotions, e.g., purchase acceleration and a post-promotion dip (e.g., van Heerde et al. 2000). Therefore, we expect that cross-price elasticities will be lower for data aggregated to a monthly/yearly base compared to a daily/weekly aggregation.

Item definition. If a SKU of brand i raises its price, demand can move to several other SKUs of e.g., one competing brand j. Consequently, the demand change will be split across several of brand j's SKUs. For measurements on a brand level, the entire demand change for all SKUs that belong to brand j is aggregated. As a result, we expect that cross-price elasticities measured on a brand level will be larger because they aggregate all demand changes of SKUs within the same brand j.

Criterion variable. When price changes only lead to brand switching but do not stimulate primary demand, absolute elasticities (i.e., sales volume is the criterion variable) and relative elasticities (i.e., market share or choice share is the criterion variable) are equal. However, primary demand effects (category expansion) caused by price changes are not captured by a relative criterion variable because the market shares of the competing brands do not change. Hence, it is relevant to control for the definition of the criterion variable (e.g., Bijmolt et al. 2005). Because absolute elasticities contain both the brand switching and general category expansion effects, we expect that absolute cross-price elasticities are stronger compared to relative cross-price elasticities.

Functional form. Previous meta-analyses for (cross-)price elasticities (e.g., Sethuraman 1995; Bijmolt et al. 2005) do not find evidence for a major effect of functional form. Nevertheless, we control for this potentially relevant variable, although we have no theoretical expectations regarding the direction of the effect.

Duration of effect. Demand models can be either short-term models that consider only contemporaneous demand changes, or long-term models, which account for intertemporal effects through carry-over coefficients or loyalty variables. A price promotion can result in a sales increase in the present period due to e.g., brand switching and a sales dip in following periods due to e.g., stockpiling and purchase acceleration (e.g., Blattberg et al. 1995). Further, demand changes from e.g., brand switching can last longer than one period as consumers may continue to purchase the competing brand. These effects are not captured by a short-term model. As a result, we expect that cross-price elasticities derived from long-term models will be higher than cross-price elasticities derived from short-term models.

Price definition. Prior research suggests that different definitions of price lead to different price sensitivities (e.g., Srinivasan et al. 2000). We therefore distinguish between the actual price, representing the price that the consumer pays at checkout, the regular price, representing the price in regular conditions like non-promotional weeks, and the promotional price, which is the price during promotional weeks or a price index (e.g., Bijmolt et al. 2005). We expect that cross-price elasticities for promotional prices will be higher compared to those of regular prices because brand switching and stockpiling in case of a promotion is more likely because the deal is not permanently available (e.g., Narasimhan et al. 1996). As the actual price contains both regular and temporary price changes, we expect that the cross-price elasticities will be higher than for regular prices, but lower than for promotional prices (e.g., Bijmolt et al. 2005).

Endogeneity of own price effect. Ignoring potential own price endogeneity in a model will likely lead to inconsistent price response parameters (e.g., Villas-Boas and Winer 1999). For instance, managers may set higher prices in response to a positive demand shock that is unobserved to the model. This results in a positive relationship between the error term and price and in a smaller absolute magnitude of own price-elasticities (e.g., Bijmolt et al. 2005). For cross-price elasticities, we expect that same effects. If unobserved demand shocks are correlated with price changes of competitors, the demand changes will be erroneously attributed to competitor prices.

Omitted variables. Previous meta-analyses find significant effects of omitted variables in the research design. An omission of advertising and sales promotions may bias price effects as demand changes are attributed to price reactions whereas they occur due to changes in advertising or sales promotions (e.g., Bijmolt et al. 2005). For an omission of quality, the direction of the effect is not clear. While own price elasticities are biased when quality is omitted (e.g., Tellis 1988), the effect on cross-price elasticities is unclear.

Heterogeneity of price effect. Consumer heterogeneity can have an effect on their price sensitivity. Bijmolt et al. (2005) argue that the majority of research finds a stronger magnitude of own price elasticity when heterogeneity is accounted for. Other studies find that price and promotion elasticities are mostly independent from allowing for heterogeneity in the model (e.g., Ailawadi et al. 1999). Hence, we do not have clear expectations for cross-price elasticities.

We provide a summary of theoretical expectations for each determinant in Table 2.2.[3]

[3] In addition, we collect information on distribution, data source, and estimation method. These variables, however, show insufficient variance and cause collinearity problems in the estimation. We therefore omit these variables from further consideration.

2.3.3 Asymmetric Effects

The literature provides ample evidence for the presence of asymmetric effects (e.g., Blattberg and Wisniewski 1989; Allenby and Rossi 1991; Bronnenberg and Wathieu 1996; Sethuraman et al. 1999; Sethuraman and Srinivasan 2002; Horváth and Fok 2013). Asymmetric effects occur for instance due to differences in prices or market shares of competing brands. In addition to the analysis of asymmetries regarding national brands and private labels, we will analyze three additional types of asymmetric effects, i.e., the asymmetric price effect, asymmetric share effect, and the neighborhood price effect (Sethuraman et al. 1999; Sethuraman and Srinivasan 2002).

We follow previous research and extend the analysis such that we do not only analyze asymmetric effects regarding cross-price elasticities, but also with regard to *absolute cross price effects*. The reason is that otherwise scaling effects may bias cross-price elasticities towards asymmetry[4]. We calculate the absolute cross price effect as follows (Sethuraman et al. 1999):

$$ACPE_{i,j} = CPE_{i,j} * .01\, price_c * \frac{marketshare_j}{price_i} \tag{1}$$

The absolute cross-price effect (ACPE) is defined as the percentage change in demand of a target brand j when the price of brand i is changed by one percent of the price of category c. In comparison to the cross-price elasticity (CPE), the absolute cross-price effect has a percentage-unit-change interpretation rather than a percentage-percentage-change. In a category with a mean price of 20$, the absolute cross-price effect measures the change in demand for brand j in response to a change in price of brand i, where the price is changed by 1% of the mean category price (i.e., .2$). This implies that a 1% change of the price of the category is the same unit price change for all brands in the category, no matter how high the price is. Hence, the absolute cross-price effect is not subject to scaling effects. In contrast, for the cross-price *elasticity*, the demand change in percentage is referring to a price change of 1% of brand i's price.

In the analysis of absolute cross-price effects, we control for the same set of determinants as in the analysis above.

[4] A 1% price change of a brand in a high price tier is larger in terms of dollars compared to a 1% change in a low price tier. This difference in dollars itself can lead to higher cross-price effects (Sethuraman et al. 1999).

Asymmetric Effects for Market Shares. In addition to the regressors we discuss above, we rely on two additional variables plus their interaction. First, following Sethuraman and Srinivasan (2002), we use a dummy variable that indicates if the share of the price changing brand is higher or lower compared to the demand changing brand (*asymmetric share*). Based on the results by Sethuraman and Srinivasan (2002), we expect that *absolute cross-price effects* (ACPE) are smaller if the price changing brand has a higher market share. For cross-price *elasticities*, Kamakura and Russell (1989) argue that larger brands have a greater impact on the demand of low share brands and in reverse are less vulnerable to price changes of smaller brands. Therefore, we expect that cross-price elasticities are larger if the price changing brand has a higher market share. Second, because this variable captures only relative differences between two brands but not the general market share level, we extend Sethuraman and Srinivasan (2002) and add a dummy variable that indicates if the market share of the price changing brand is above or below the category mean market share (*market share tier*). As brands with a high market share have a high visibility (e.g., Buzzel et al. 1975), more consumers are aware of price changes of high share brands compared to brands in a low market share tier. Therefore, we expect that price changes of brands with a market share above the category mean have a stronger impact on cross-price elasticities and absolute cross-price effects. Additionally, we use an interaction effect of both dummy variables, which allows us to assess whether the asymmetric share effect holds regardless of whether the brands are located in high or low share tiers.

Table 2.3: Summary of Asymmetric Effects and Theoretical Expectations

	Determinant	**Definition**	**Theoretical Expectation for Effect on CPE**	**Theoretical Expectation for Effect on ACPE**	**Number of Observations**	**Mean CPE**	**Mean ACPE**
Share Effects	Asymmetric Share	Price changing brand has lower market share	Base	Base	1,738	.20	.05
		Price changing brand has higher market share	+	-	1,706	.29	.03
	Market Share Tier	Price changing brand in low share tier	Base	Base	2,096	.19	.04
		Price changing brand in high share tier	+	+	1,348	.33	.04
	Asymmetric Share X Market Share Tier	Price changing brand has higher market share; Price changing brand in high share tier	+	-	3,444	Interaction	
Price Effects	Neighborhood Price Effect	Linear effect	-	-	3,444	cont.	cont.
	Relative Price X Neighborhood Price Effect	Price changing brand has higher price; Linear effect	+	+/-	3,444	Interaction	
	Price Tier	Price changing brand in low price tier	Base	Base	1,695	.24	.05
		Price changing brand in high price tier	+	+	1,749	.25	.03

Asymmetric Effects for Prices. For the analysis of asymmetric effects for prices, we utilize three variables. First, for measuring the neighborhood price effect and asymmetric price effect, we utilize the methodology by Sethuraman et al. (1999). To this end, we use a continuous variable (neighborhood price; NP), indicating the price relation between the lower and higher priced brand, hence measuring how far the prices are apart. The effect of this variable is the neighborhood price effect. The variable is bound between 0 and 1. The closer two brands are in price, the smaller is the variable NP. We expect that cross-price elasticities and absolute cross-price effects are larger, the closer two brands are in price.

$$NP = 1 - \left(\frac{price\ of\ lower\ priced\ product}{price\ of\ higher\ priced\ product}\right) \tag{2}$$

Second, we use a dummy variable Relative Price, which indicates if the price of the price changing brand is higher or lower compared to the demand changing brand[5]. As the variable neighborhood price does not differentiate between price changing brand being the higher priced brand or the reverse, we follow the approach by Sethuraman et al. (1999) and interact NP and Relative Price to capture the asymmetric price effect. In contrast to the asymmetric share effect that captures if cross-price elasticities or absolute cross-price effects are larger if the price or demand changing brand has the higher market share, the asymmetric price effect looks at an moderating effect. The asymmetric price effect captures if the neighborhood price effect is larger when the price or demand changing brand has the higher price. We expect that for cross-price elasticities the neighborhood price effect is larger if the price changing brand has the higher price. For absolute cross-price effects we expect that this effect diminishes (Sethuraman et al. 1999).

Third, we extend previous research by studying also the price position of the brand relative to all other brands. The rationale is that brands in high price tiers can draw demand from both other high price tier brands and low price tier brands whereas low price tier brands draw only demand from other low tier brands (e.g., Blattberg and Wisniewski 1989). Therefore, we expect that cross-price elasticities and absolute cross-price effects are larger if the price changing brand is in the high price tier. To assess this question, we include a dummy variable "price tier" that indicates if the price of the price changing brand is above or below the category

[5] We analyze the variable Relative Price only as a moderating and not as a direct effect to make the results comparable to the findings by Sethuraman et al. (1999).

price mean. We provide a summary of theoretical expectations for each asymmetric effect in Table 2.3.

2.4 Models

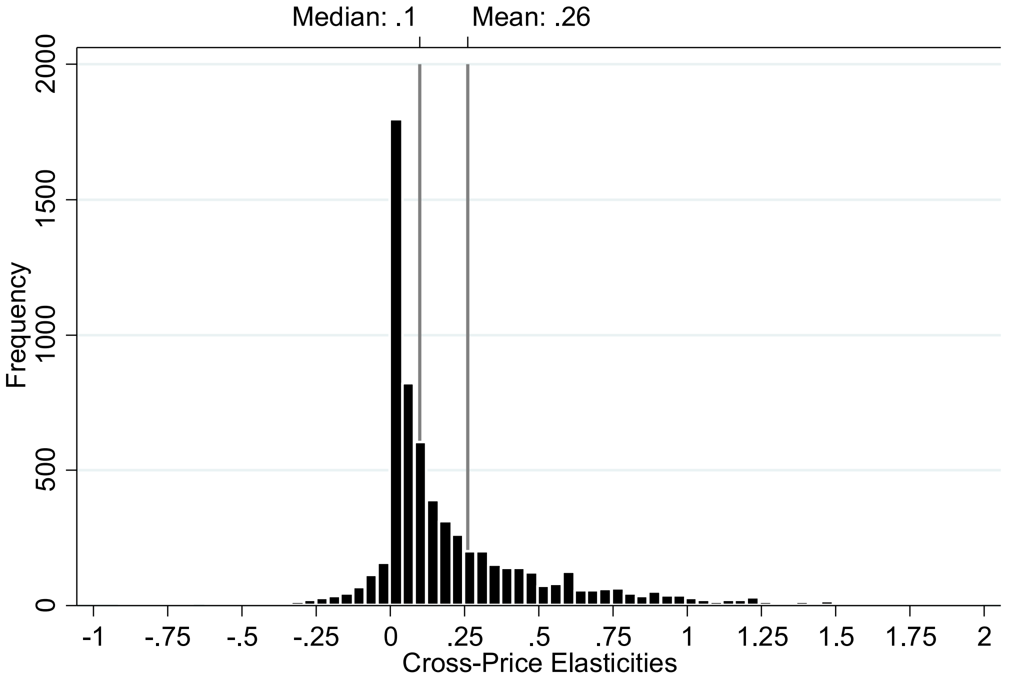
We rely on three models to assess (1) the impact of determinants on cross-price elasticities (2) the impact of asymmetries on cross-price *elasticities* and (3) the impact of asymmetries on *absolute cross-price effects*. We use hierarchical linear models to account for within-study error correlation between cross-price effects, which is in line with other meta-analyses (e.g., Bijmolt and Pieters 2001; Bijmolt et al. 2005). More specifically, to allow for publication-specific intercepts, we apply a linear mixed-effects model estimated with hierarchical Bayes (Stan Development Team 2016). This approach accounts for the fact that multiple observations (i.e., elasticities) originating from one study may share common, unobserved characteristics. We use normal(0,1) priors and run four chains with 50,000 draws for warmup and 4*50,000 draws for inference. The sampling approach uses Markov Chain Monte Carlo, in particular Hamiltonian Monte Carlo. The results are robust against different prior selections, and all chains are well converged and mixed with a potential scale reduction factor ($\hat{R}$) of 1. For (1) the effective sample size is 200,000 for all coefficients. For (2) and (3) the effective sample size is over 160,000 for all coefficients.

2.5 Results

2.5.1 The Overall Magnitude of Cross-Price Effects

The first key results of this study is the mean cross-price elasticity across all 6,905 observations (which were defined as substitutes), which is .26 (SD =.52, median =.10). We provide a histogram of all cross-price elasticities in Figure 2.2. This mean cross-price elasticity of .26 is considerably lower compared to the result by Sethuraman et al. (1999), who find a mean of .52, and the result by Sethuraman (1995), who reports a mean of .54. Although the mean of .26 is already a substantial deviation from previous meta-analyses, we note that the distribution is not symmetric (Figure 2.2). Rather, 70% of all observations are below the mean, and the median is .10. Further, 9% of the observation are below zero, which mirrors the results by Sethuraman et al. (1999).

Figure 2.2: Frequency Distribution of Cross-Price Elasticities for Substitutes



For the analysis of the asymmetric effects, we compute the mean absolute cross-price effect. Across all observations that report the required information (N = 3,444), we find a mean absolute cross-price effect of .04 (SD = .16). Again, this is roughly half of the estimate reported by Sethuraman et al. (1999) who find an estimate of .08 (SD = .16). This is expected because absolute cross-price effects are linked to cross-price elasticities.

2.5.2 Effects of Determinants

Table 2.4 reports the results of the analysis of the drivers of cross-price elasticities. We will first discuss estimates for the effect of market characteristics, followed by the research methodology. We will discuss the asymmetric effects in a separate analysis because of the reduced sample that is available for that analysis. Throughout the text, we refer to coefficients for which the 95% posterior interval excludes zero as "significant", and these coefficients are printed in bold in Table 2.4.

2.5.2.1 Market Characteristics

Year of data collection. We find a negative effect (β = -.01) for the time trend, which suggests a decrease of cross-price elasticities over the observation period. While we did not have strong a priori expectations regarding the direction of the effect, this negative trend reconciles the difference between the mean cross-price elasticity in this study and the mean reported by Sethuraman et al. (1999) of .52. Using the estimates from our model to compute the predicted cross-price elasticity for the mean year of data collection of Sethuraman et al. (1999), we arrive at a prediction (.42) for substitutes in that period, which is similar to their result.[6]

Brand ownership. When national brands change their prices, demand of competing brands is strongly affected, be it other national brands (with an estimated cross-price elasticity of .26) or private labels (.23). Conversely, if private labels change their prices, demand of other private labels or national brands is less affected, with estimated cross-price elasticities of .14 and .18, respectively. These finding support the results by Sethuraman et al. (1999) and Horváth and Fok (2013). All in all, these results seem to suggest that the strongest degree of price-induced substitution is occurring between national brands. The weakest effect occurs between private labels, and price changes of national brands have stronger effects on the demand of private labels than the reverse.

Stage of product life cycle. We find lower cross-price elasticities for the mature and decline stage compared to the introduction and growth stage (β = -.20). This finding is consistent with the results for own price-elasticities by Bijmolt et al. (2005), i.e., that price reactions are stronger for the introduction and growth stage.

Product category. As expected, low-stockpiling groceries have lower cross-price elasticities (β = -.15) compared to the base category high stockpiling groceries. As groceries with a low ability to stockpile have high storage cost, brand switching and stockpiling in response to a price change is less attractive (e.g., Narasimhan et al. 1996).

As expected, we find that durables have lower cross-price elasticities (β = -.15) compared to high stockpiling groceries. However, this effect is associated with uncertainty as the 95% posterior interval includes zero and only the 90% posterior interval excludes zero. In sum, we find that predicted values for durables and groceries with a low stockpiling ability are similar, while high stockpiling goods have higher cross-price elasticities. These results are not in line with Sethuraman et al. (1999). They find that cross-price elasticities for nonfood products are higher compared to food products, and our updated empirical generalizations suggest that grocery items with high stockpiling ability exhibit the strongest brand switching in response to price changes, whereas brand switching is less prevalent for durables and low stockpiling groceries.

[6] We cannot exactly replicate their results because their analysis does not only rely on other published studies but also includes additional, non-public data.

Number of products in category. We find a negative effect of an increasing number of products (β = -.02) on cross-price elasticities. The 95% posterior interval, however, includes zero, reflecting the uncertainty around this estimate. As most of the posterior parameter distribution is negative, we tentatively conclude that the direction of this effect is consistent with the results by Sethuraman et al. (1999). This may suggest that competitors in categories with many brands are more strongly differentiated, which inhibits substitution.

Category price elasticity. As expected, we find a significant negative relationship (β = -.02) between the mean category price elasticity and cross-price elasticities. This implies that categories with price responsive consumers are associated with consumers who are willing to switch brands.

Complement. As expected and well established in the literature, we find higher cross-price elasticities for brands that were labeled as substitutes (β = .16) compared to complements.

Other determinants. The theoretical expectations suggest that high disposable income is associated with smaller cross-price elasticities. We find some support for this expectation, but the effect is not significant. Further, the results neither provide evidence for differences between countries, nor for a measurable effect of inflation rate on cross-price elasticities, nor for differences regarding whether product pairs have the same or a different parent brand.

2.5.2.2 Research Methodology

Against our expectations, we neither find significant differences between cross-price elasticities based on data aggregated on a monthly/yearly vs. weekly level, nor between cross-price elasticities measured at the brand level compared to those measured at the SKU level, nor for different criterion variables, nor for different functional forms.

Duration of effect. We find significant differences (β = -.22) between cross-price elasticities based on short vs. long-term models, i.e., cross-price elasticities based on models that measure short-term effects are substantially weaker compared to models that measure long-term effects.

Price definition. Promotions can accelerate the purchase behavior of consumers, which results in stockpiling. The motivation to stockpile regular priced brands is lower due to the permanent availability of this deal (e.g., Bijmolt et al. 2005). We therefore expect that cross-price elasticities for promotional prices are higher compared to regular prices in the short term. The results support this expectation; cross-price elasticities for promotional prices (β = .28) are higher compared to regular prices. As expected, the effect of actual prices (β = .26) lies between the effects of regular and promotional prices. Both effects are associated with uncertainty as only the 90% posterior interval excludes zero.[7] The predicted cross-price elasticity for regular price changes is very close to zero (.03), which suggests that regular price changes lead only to very little brand switching.

Endogeneity of own price effect. We find stronger cross-price elasticities for models that do not account for endogeneity of own price effects (β = .20). However, only the 90% posterior interval excludes zero. This again highlights that accounting for endogeneity can have a substantial influence on results of market response models.

Omitted variables. Previous meta-analyses have found significant effects of omitted variables in the research design due to an omitted variable bias, and this analysis is no exception. We find that an omission of advertising has a significant positive effect on cross-price elasticities (β = .26). Larger cross-price elasticities occur as demand changes are attributed to price reactions whereas they occur due to changes in advertising. If sales promotions (e.g., couponing) are ignored, we find a positive but insignificant effect on cross-price elasticities. For an omission of quality, the effect is close to zero and not significant.

Heterogeneity of price effect. Not accounting for heterogeneity tends to inflate cross-price elasticities, although the effect is not significant. This result is consistent with the findings by Bijmolt et al. (2005) and Ailawadi et al. (1999) who find that elasticities are in most instances independent from accounting for heterogeneity.

2.5.3 Asymmetric Effects for Market Shares

In contrast to previous research, we find that the *asymmetric share* effect on cross-price elasticities does not hold across all levels of market shares. For brands in the low market share tier, we do not find evidence for the asymmetric share effect, i.e., the difference depending on whether the price changing brand has a higher or lower market share than the demand changing brand is not significant (β = -.01, lines 1&2 in Table 2.5).[8]

[7] We also tested for an interaction between duration and price definition, which was not significant

[8] The "direct effect" in lines 1&2 of Table 2.5 is – because of the presence of the interaction – the effect of the base level of the market share tier, which is the low market share tier.

Table 2.4: Effects of Determinants on Cross-Price Elasticity

	Determinant	Levels	Median	95% Posterior Interval		Predicted Value
				2.50%	97.50%	
Market characteristics	Constant		.50	-.17	1.17	
	Year of data collection	Linear effect	**-.01**	-.03	.00	cont.
	Brand ownership	P_NB vs D_NB	Base			.26
		P_NB vs D_PL	-.03	-.07	.02	.23
		P_PL vs D_PL	**-.12**	-.23	-.01	.14
		P_PL vs D_NB	**-.08**	-.13	-.04	.18
	Stage of product life cycle	Introduction or growth	Base			.44
		Mature or decline	**-.20**	-.27	-.13	.24
	Product category	Durables	-.15	-.31	.00	.19
		Groceries, high stockpiling	Base			.34
		Groceries, low stockpiling	**-.15**	-.28	-.02	.19
		Intangibles	.14	-1.02	1.30	.48
		Pharmaceutics	-.21	-.62	.20	.13
	Country	Asia	-.02	-.73	.69	.22
		Europe	.05	-.22	.33	.29
		Other	.38	-.26	1.02	.62
		US	Base			.24
	Number of products in category	Linear effect	-.02	-.04	.00	cont.
	Household disposable income	Linear effect	-.02	-.08	.03	cont.
	Inflation rate	Linear effect	.03	-.02	.08	cont.
	Category price elasticity	Linear effect	**-.02**	-.04	-.01	cont.
	Parent brand	Different	Base			.25
		Same	-.01	-.05	.03	.24
	Complement	Complements	Base			.10
		Substitutes	**.16**	.09	.22	.26
Research Methodology	Temporal aggregation	Longer Weekly	Base			.27
		Weekly	-.02	-.23	.19	.24
	Item definition	Brand	Base			.27
		SKU	-.10	-.31	.11	.17
	Criterion variable	Absolute	Base			.26
		Relative	-.02	-.15	.12	.25
	Functional form	Additive	.09	-.26	.45	.38
		Attraction	Base			.29
		Multiplicative or Exponential	-.10	-.30	.11	.19
	Duration of effect	Long-Term	Base			.43
		Short-Term	**-.22**	-.40	-.05	.21
	Price definition	Actual	.26	-.03	.55	.29
		Promotional (price index)	.28	-.04	.61	.31
		Regular	Base			.03
	Endogeneity of own price effect	Accounted for	Base			.16
		Not accounted for	.20	.00	.39	.36
	Advertising effect	Included	Base			.12
		Not included	**.26**	.08	.44	.38
	Sales promotion effect	Included	Base			.21
		Not included	.07	-.10	.24	.28
	Quality effect	Included	Base			.24
		Not included	.02	-.27	.30	.25
	Heterogeneity in price effects	Accounted for	Base			.21
		Not accounted for	.14	-.07	.35	.35

In bold are the parameters whose 95% posterior interval excludes zero.

P_ (D_) refers to the price (demand) changing brand.

Number of observations reduces from 7,248 to 7,009 as not all papers report own price-elasticities.

However, the picture is different for brands in the high market share tier. The interaction between the asymmetric share and the market share tier is positive and significant, which means that cross-price elasticities are larger if the price changing brand has the higher market share and is in the high share tier (β = .07; line 5 in Table 2.5). This implies that the asymmetric share effects only holds for brands in the high market share tier.[9] This result expands the findings by Sethuraman and Srinivasan (2002), who find a general positive effect if the price changing brand has a higher market share. In addition, we find that brands have higher cross-price elasticities when they are in the high market share tier (β = .10, lines 3&4, Table 2.5), and, as discussed, the interaction suggests (β = .07; line 5 in Table 2.5) that this effect becomes even stronger if the price changing brand has a higher market share.

In line with previous research, we identify differences in the *asymmetric share effect* between absolute cross-price effects as compared to elasticities. Irrespective of the market share tier, the absolute cross-price effects are smaller if the price changing brand has the higher market share (β = -.03, lines 1&2, right panel of Table 2.5). Further, we find that absolute cross-price effects are stronger for brands in a high *market share tier* (β = .03 lines 3&4, right panel of Table 2.5). The interaction between both variables is insignificant in the case of absolute cross-price effects.

In sum, for cross-price *elasticities* (Table 2.6a) we conclude that for small brands, it does not matter whether the price changing brand is larger or smaller than the demand changing brand. In the high share tier, however, it does matter. For *absolute cross-price effects* (Table 2.6b) we conclude that both, market share tier and asymmetric share effect, are of similar importance.

Asymmetric effects for prices. The results support the *neighborhood price effect* (line 6 in Table 2.5) and findings by Sethuraman et al. (1999), i.e., the further two brands are apart in prices, the smaller are the corresponding cross-price elasticities (β = -.34). Because the model contains the interaction, this effect denotes the impact if the price changing brand has the lower price. Unlike previous research, however, we do not find a significant neighborhood price effect for absolute cross-price effects (β = -.02, line 6, right panel of Table 2.5).

The *asymmetric price effect* is the interaction between relative price and the neighborhood price effect (line 7 in Table 2.5). We again find similar results as Sethuraman et al. 1999), i.e., the asymmetric price effect holds for cross-price *elasticities* but tends to reverse

[9] If we change the base of the interaction, the "direct effect" of Asymmetric Share (in high market share tier) is significant.

for absolute cross-price *effects*. More specifically, the effect of the neighborhood price effect on cross-price elasticities is higher (β = .14, line 7, left panel of Table 2.5) if the price changing brand has a higher price compared to the demand changing brand. In the case of absolute cross-price effects, the neighborhood price effect is insignificant but tends to be smaller (β = -.02, line 7, right panel of Table 2.5) if the price changing brand has a higher price compared to the demand changing brand.

The effect of the price tier is quite close to zero, both in the case of cross-price elasticities as well as absolute cross-price effects. This suggests that the degree of between brand substitution and price competition does not depend on the brands' price level (lines 8&9, Table 2.5).

2.6 Discussion

More than 20 years have passed since an empirical study was published that found its way into a meta-analysis on cross-price elasticities. In these 20 years, important developments took place that shaped the marketplace and the understanding of it, e.g., the retail landscape saw a surge in private labels, a strong commitment of firms to branding (e.g., Keller and Lehmann 2006), and the advent of online retailing. At the same time, several methodological advances were established in the literature (e.g., treatment of endogeneity and heterogeneity). So far, these developments were not reflected in the knowledge about cross-price elasticities. We therefore contribute to the literature by conducting a meta-analysis that is broader in scope (114 studies vs. 15 studies in previous meta-analyses) and deeper (a much larger number of determinants that affect the magnitude of cross-price elasticity) than previous meta-analyses. Through this analysis, our research contributes to the literature by updating and extending the knowledge on the mean cross-price elasticity and by providing new insights and new empirical generalizations.

Table 2.5: Effects of Asymmetries on Cross-Price Effects

	Determinant	Levels	Cross-Price Elasticities: Median	95% Posterior Interval 2.5%	97.5%	Predicted Value	Absolute Cross-Price Effects: Median	95% Posterior Interval 2.5%	97.5%	Predicted Value
Share Effects	Asymmetric Share	Price changing brand has lower market share	Base			.23	Base			.05
		Price changing brand has higher market share	-.01	-.05	.03	.22	**-.03**	-.04	-.02	.01
	Market Share Tier	Price changing brand in low share tier	Base			.18	Base			.02
		Price changing brand in high share tier	**.10**	.04	.16	.28	**.03**	.02	.05	.05
	Asymmetric Share X Market Share Tier	Price changing brand has higher market share; Price changing brand in high share tier	**.07**	.00	.15	(see Table 2.6a)	-.02	-.04	.00	(see Table 2.6b)
Price Effects	Neighborhood Price Effect	Linear effect	**-.34**	-.46	-.22	cont.	-.02	-.05	.01	cont.
	Relative Price X Neighborhood Price Effect	Price changing brand has higher price; Linear effect	**.14**	.01	.26	cont.	-.02	-.06	.01	cont.
	Price Tier	Price changing brand in low price tier	Base			.24	Base			.03
		Price changing brand in high price tier	-.03	-.07	.01	.21	-.01	-.02	.00	.03
	Controlling for other determinants	21 other determinants	yes				yes			

In bold are the parameters whose 95% posterior interval excludes zero.

Table 2.6a: Predicted Values for Market Share Interaction (Cross-Price Elasticities)

Cross-Price Elasticities		
Price changing brand…	… has lower market share	… has higher market share
… in low share tier	.17	.15
… in high share tier	.26	.33

Table 2.6b: Predicted Values for Market Share Interaction (Absolute Cross-Price Effects)

Absolute Cross-Price Effects		
Price changing brand…	… has lower market share	… has higher market share
… in low share tier	.04	.01
… in high share tier	.07	.02

What are the main findings and key new insights?

(1) New empirical generalization identifies .26 as mean cross-price elasticity. Across 7,298 elasticities from 114 publications, we find a mean cross-price elasticity of .26 for substitutes, which is about half the effect size of the previous meta-analysis of .52 (Sethuraman et al. 1999). This implies that markets are characterized much less by brand-switching in response to price changes than previously thought. Researcher should therefore adjust their expectations of what constitutes a normal cross-price elasticity, and this downward adjustment is substantial. What's more, the bulk of all observations (70%) is much closer to zero than .26, as evidenced by the median of .10. In other words, researchers should not be concerned if their cross-price elasticities are just barely above zero, in fact, most other researchers' cross-price elasticities are.

(2) Cross-price elasticities have decreased over time. The results clearly indicate that cross-price elasticities have substantially decreased in magnitude over the past four decades. In fact, if we use the estimates to predict the mean cross-price elasticity for the mean of the data collection period of the last meta-analysis (1983), we find a mean elasticity of .42. One reason for this development could be that branding has grown in relevance for many firms over the past years (e.g., Keller and Lehmann 2006). This growing emphasis on branding may have led to a stronger brand differentiation, which in turn inhibits substitutability of brands and thus reduces cross-price elasticities. As we outlined in the theoretical expectations, there are theoretical arguments that would suggest increasing cross-price elasticities over time because one could argue that competition has intensified over the last years, e.g., fueled by the surge in private labels or the advent of online shopping. The latter in particular should make markets more transparent, which should lead to more price competition. Our results, however, do not

support this notion, and the conclusion is that brands appear to become differentiated and less easy to substitute.

On top of that, we derive additional new insights from the large set of determinants that have not been studied in previous meta-analyses on cross-price elasticities.

(3) Cross-price elasticities decrease over the product life cycle. The results suggest that cross-price elasticities are higher in the introduction or growth stage compared to later stages. One interpretation of this effect is that consumers are more willing to try new brands in early stages of the product life cycle, whereas in later stages, consumers have stronger, well established brand preferences that cannot be easily overturned by price changes. On top of that, brands may be more differentiated in later stages of the product life cycle (e.g., Simon 1979), which makes it more difficult for consumers to switch brands.

(4) High-stockpiling groceries have the highest cross-price elasticities. In contrast to previous research we find that cross-price elasticities for groceries with a high ability to stockpile are stronger compared to groceries with low stockpiling ability or durables. This finding deserves attention because of two reasons. First, it is not in line with Sethuraman et al. (1999) who find that cross-price elasticities for durables are the highest. Second, one might be tempted to assume that settings in which the own price elasticity is high, the cross-price elasticity will also be high, and indeed, this is also confirmed in our analysis as we find a negative relationship between the mean category own price elasticity and cross-price elasticities. This principle, however, does not universally apply because Bijmolt et al. (2005) find the highest own price elasticities for durables, whereas we find that high-stockpiling groceries are those with the highest cross-price elasticity. This suggests that price changes for durables lead only to little brand switching compared to high-stockpiling goods. One explanation is that brands may not be as easy to substitute in the case of durables, which means that it is more likely that consumers who observe a price increase for their preferred brand postpone the purchase, rather than switch brands. For high-stockpiling groceries, the situation is different. Here, stockpiling is attractive, and hence, more brand switching occurs.

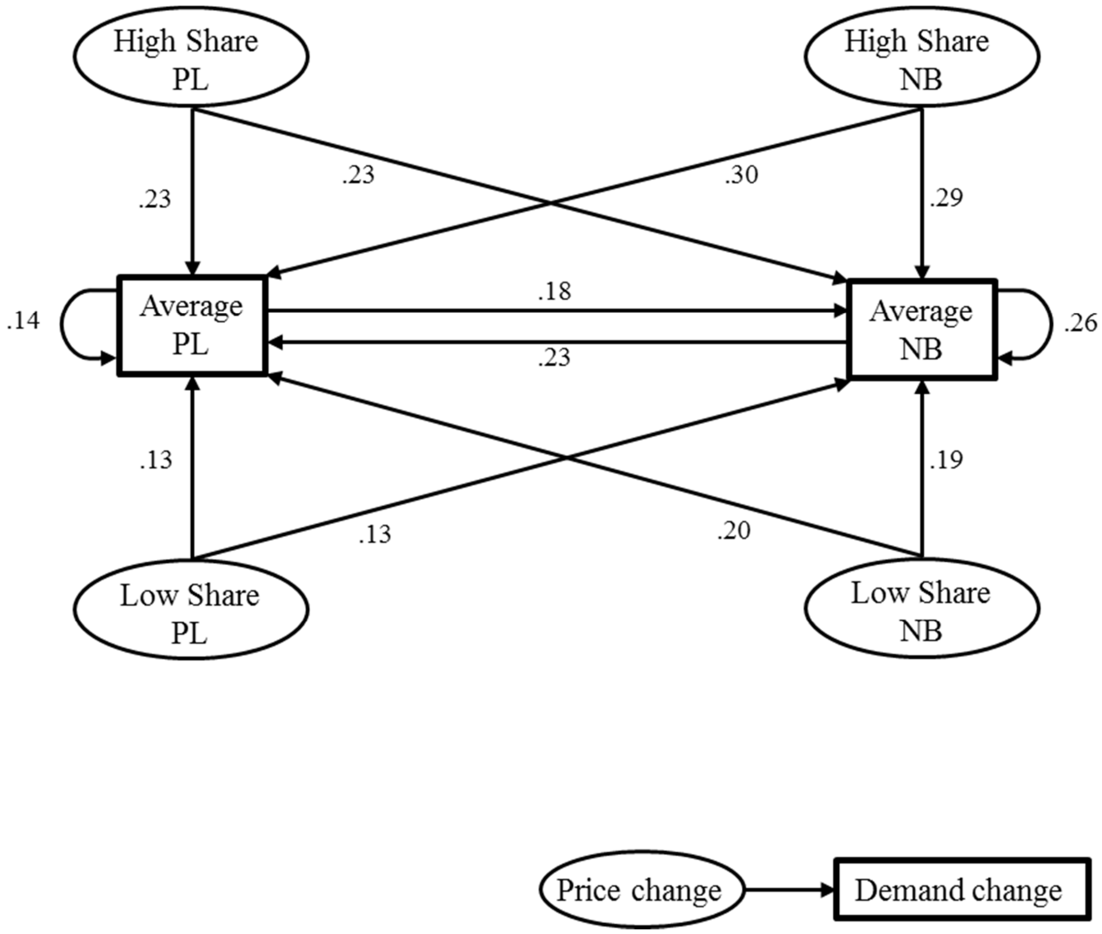
(5) Long-term cross-price elasticities are larger than short-term cross-price elasticities. Cross-price elasticities differ depending on whether they are considered as a short- or long-term effect. In line with our theoretical expectations, we find higher cross-price elasticities for long-term effects. This implies that the brand switching due to price changes leads consumers to a new preferred brand that consumers continue to buy in future periods and not only the period of the price change.

(6) The asymmetric share effect only holds in high-share tiers. We expand existing research (Sethuraman and Srinivasan 2002; Horvath and Fok 2013) and show that the asymmetric share effect does not hold across all levels of market shares. Rather, it only holds for brands in the high share tier. In contrast, for brands in the low market share tier, it is not important whether the price- or demand changing brand has the higher market share. Further, cross-price elasticities are larger if the price changing product is located in the high market share tier. These results imply that in particular price changes of the largest brands matter, such that smaller competitors are affected, but in particular brands from the low share tier.

Findings for the asymmetric price support previous research, i.e., the asymmetric price effect holds for cross-price *elasticities* but tends to reverse for absolute cross-price *effects.* Again in line with prior research we find that the neighborhood price effect is present when using elasticities, but not when we consider cross-price effects. The neighborhood price effect in the context of cross-price elasticities implies that primarily brands with similar prices compete against one another.

We utilize our findings to gauge the extent to which an average private label and an average national brand will be affected by competitors' price changes. This assessment combines the brand ownership information with the asymmetric effects, and we summarize the results in Figure 2.3. To this end, we use the mean price and the mean market share of all private labels (national brands) from our sample of studies to predict cross-price elasticities if different archetypes of competitors change their prices. The average national brand and the average private label experience the strongest changes in demand when a high-share national brand changes its prices, with predicted cross-price elasticities of .30 and .29, respectively. This implies that managers of (average) brands must have large national brands on the top of their watch list. This also holds true for other average national brands, whose price changes exert substantial influence on average private labels and national brands. On top of that, the average national brand must pay more attention to price changes of large private labels (.23) than small national brands (.19). The important take away from this is that brand size matters, and it matters more than ownership of small brands.

Figure 2.3: Effects on Average Private Labels and Average National Brands



We suggest that managers can use these strategic conclusions to assess which competing brands to monitor most closely and which brands are less relevant.

One additional observation deserves attention. Surprisingly, the magnitude of the cross-price elasticities that researchers have estimated seems to be largely independent of the research design that the researchers chose. Most of the factors that we study and that pertain to research methodology only have small and insignificant effects on the cross-price elasticity (e.g., degree of temporal aggregation, item definition, criterion variable, functional form, accounting for heterogeneity). The only factors that are strong and where the posterior interval excludes zero are the duration of the effect and the omission of advertising.

To summarize how this research updates and extends the literature about cross-price elasticity, we combine the most important findings and extended generalizations in Table 2.7.

Table 2.7: Overview of Updated and Extended Generalizations

		Sethuraman (1995)	Sethuraman et al. (1999)	Sethuraman and Srinivasan (2002)	This Paper
	Mean cross-price elasticity	.54	.52	.52	.26
	Observation period	1991 - 1993	1970 - 1996	1970 - 1996	1960 - 2015
	Number of observations	261	1,060	1,060	7,298
Market Characteristics	Year of data collection				Negative effect
Market Characteristics	Brand ownership	NB > PL	NB > PL		NB > PL
Market Characteristics	Stage of product life cycle				Introduction/growth > mature/decline
Market Characteristics	Product category		Nonfood > food products	Controlled	Highest for groceries (high stockpiling)
Market Characteristics	Number of products in category		Negative effect	Controlled	No significant effect
Market Characteristics	Category price elasticity				Negative effect
Market Characteristics	Complement				Negative effect
Research Methodology	Criterion variable		Controlled	Controlled	No significant difference
Research Methodology	Functional form	No significant difference	Controlled	Controlled	No significant difference
Research Methodology	Duration of effect				Short-term < long-term
Research Methodology	Price definition				Promotional > actual > regular
Research Methodology	Endogeneity of price effect				Ignoring leads to overestimation
Research Methodology	Inclusion of other variables (advertising, sales promotion, quality)				Omitting advertising leads to overestimation
Asymmetric effects	Asymmetric price effect		CPE: Price changing brand has higher price: positive effect ACPE: no significant effect		CPE: Price changing brand has higher price: positive effect ACPE: no significant effect
Asymmetric effects	Neighborhood price effect		CPE: negative effect ACPE: negative effect		CPE: negative effect ACPE: no significant effect
Asymmetric effects	Asymmetric share effect			CPE: Price changing brand has higher share: positive effect ACPE: Price changing brand has higher share: negative effect	CPE: Price changing brand has higher share: positive effect only in high share tier ACPE: Price changing brand has higher share: negative effect
Asymmetric effects	Market share tier				Price changing brand in high share tier: positive effect

Note: Controlled denotes that the authors include the variable as control but do not report coefficients.

These findings support researchers in calibrating their research designs and to check the plausibility of their findings. This means in particular that researchers must expect cross-price elasticities to be lower than the literature previously assumed. Most likely, researchers will find price elasticities that are below .26. Researchers have to be aware that cross-price elasticities differ depending on the decision to model them as short- or long-term effect. Models that capture only short-term effects potentially miss demand changes that occur in future periods because of a price change in a previous period. Further, although this has been mentioned in previous meta-analyses, we highlight the relevance of including all potentially relevant control variables, in particular other marketing instruments such as advertising. The results suggest that failure to do so can result in severe overestimation of the cross-price elasticity.

Limitations and future research. One major change in the retailing landscape of the last two decades is the advent of online retailing. It is striking to see that in our data base of cross-price elasticities, we observe no cross-price elasticities from the online domain. This is similar to the situation noted in Bijmolt et al. (2005). We speculate that an inclusion of a larger number of online cross-price elasticities may change our results such that it increases the mean cross-price elasticity because price competition is likely to be higher online. However, this is speculation, and we believe this would be a fruitful avenue for future research.

In addition, the data provides no information about asymmetric effects that can occur because consumers may respond differently to price increases vs. decreases. Further research has to distinguish between cross-price effects derived from each price change.

Finally, the dataset is derived from countries with a rather high degree of economic development. Future studies have to assess whether the generalizations derived from this study hold globally.

Appendix:

Table 2.8: Publications Included in the Meta-Analysis on Cross-Price Effects

Authors	Year	Publication	Volume (Issue), Pages	Number of Cross-Price Elasticities	Average
Allenby	1989	Marketing Science	8 (3), 265-281	30	.99
Allenby and Lenk	1994	Journal of the American Statistical Association	89 (428), 1218-1231	12	.14
Baltas	2002	Applied Economics	34 (9), 1171-1175	6	1.00
Bemmaor and Mouchoux	1991	Journal of Marketing Research	28 (2), 202-214	12	-1.41
Besanko, Dube and Gupta	2003	Management Science	49 (9), 1121-1138	12	.14
Bezawada, Balachander, Kannan and Shankar	2009	Journal of Marketing	73 (3), 99-117	56	.05
Blattberg and Wisniewski	1989	Marketing Science	8 (4), 291-310	156	.43
Bokhari and Fournier	2013	Journal of Industrial Economics	61 (2), 339-392	272	.11
Bolton	1989	Journal of Retailing	65 (2), 193-219	19	.46
Bronnenberg and Wathieu	1996	Marketing Science	15 (4), 379-395	60	.42
Bucklin, Gupta and Han	1995	Journal of Marketing Research	32 (1), 66-74	12	.07
Bucklin, Russell and Srinivasan	1998	Journal of Marketing Research	35 (1), 99-113	72	.24
Cakir and Balagtas	2014	Journal of Retailing	90 (1), 1-12	12	.12
Capps Jr and Hanselman	2012	Journal of Food and Distribution Research	43 (3), 15-29	12	.45
Capps Jr. and Love	2002	American Journal of Agricultural Economics	84 (3), 807-816	110	.10
Chen; John and Narasimhan	2008	Marketing Science	27 (3), 398-416	30	.21
Chiang, Chib and Narasimhan	1999	Journal of Econometrics	89 (1/2), 223-248	12	.05
Chib, Seetharaman and Strijnev	2004	Journal of Marketing Research	41 (2), 184-196	12	.79
Chidmi and Murova	2011	Agribusiness	27 (4), 435-449	12	.77
Chintagunta	2002	Journal of Marketing Research	39 (2), 141-154	20	.02
Chintagunta	1992	Marketing Science	11 (4), 386-408	30	.52
Chintagunta	1993	Marketing Science	12 (2), 184-208	12	.07
Chintagunta	2001	Marketing Science	20 (4), 442-457	6	.37
Chintagunta	1992	International Journal of Research in Marketing	9 (2), 161-175	12	1.26
Chintagunta, Bonfrer and Song	2002	Management Science	48 (10), 1242-1267	20	.04
Chintagunta, Dubé and Goh	2005	Management Science	51 (5), 832-849	12	.12
Chintagunta, Jain, and Vilcassim	1991	Journal of Marketing Research	28 (4), 417-428	12	.69
Choi, Wohlgenant and Zheng	2013	American Journal of Agricultural Economics	95 (4), 1009-1028	56	.05
Chouinard, Davis, LaFrance and Perloff	2010	Applied Economic Perspectives and Policy	32 (1), 59-76	169	.01
Cohen	2013	Journal of Economics and Management Strategy	22 (1), 101-124	132	.40
Cohen	2008	International Journal of Industrial Organization	26 (2), 502-516	210	.10
Cohen and Cotterill	2011	Journal of Industrial Economics	59 (3), 372-395	132	.34
Cooper	1988	Management Science	34 (6), 707-723	132	.17
Cotterill and Samson	2002	American Journal of Agricultural Economics	84 (3), 817-823	20	.23
Davis and Schiraldi	2014	RAND Journal of Economics	45 (1), 32-63	56	.00
Dhar, Chavas and Gould	2003	American Journal of Agricultural Economics	85 (3), 605-617	71	.44
Dhar, Chavas, Cotterill and Gould	2005	Journal of Economics and Management Strategy	14 (4), 905-931	12	.86

Table 2.8 (continued)

Authors	Year	Publication	Volume (Issue), Pages	Number of Cross-Price Elasticities	Average
Draganska and Klapper	2007	Journal of Retailing	83 (2), 183-198	42	.11
Ellison, Cockburn, Grilliches and Hausman	1997	RAND Journal of Economics	28 (3), 426-446	41	.20
Foncel and Ivaldi	2005	Journal of Industrial Economics	53 (2), 265-297	20	.27
Gazquez-Abad and Sanchez-Perez	2009	Agribusiness	25 (1), 36-55	81	1.85
Goeree	2008	Econometrica	76 (5), 1017-1074	72	.03
Gonul and Srinivasan	1993	Marketing Science	12 (3), 213-230	6	1.25
Gordon	2009	Marketing Science	28 (5), 846-867	12	.24
Gulseven and Wohlgenant	2015	Quality and Quantity	49 (5), 2077-2096	272	.51
Hausman and Leonard	2002	Journal of Industrial Economics	50 (3), 237-263	42	.32
Hausman and Leonard	2007	Journal of Econometrics	139 (2), 242-258	12	.24
Hausman and Leonard	1997	George Mason Law Review	5, 321-346	56	.20
Hausman, Leonard andZona	1994	Annales d'Économie et de Statistique	34, 159-180	20	.63
Hellerstein	2008	Journal of International Economics	76 (1), 14-32	42	.08
Hendel and Nevo	2006	Econometrica	74 (6), 1637-1673	162	.15
Hildebrandt and Klapper	2001	International Journal of Research in Marketing	18 (1/2), 139-159	72	.36
Horsky, Misra and Nelson	2006	Marketing Science	25 (4), 322-335	42	.62
Inceoglu and Park	2011	Applied Economics	43 (30), 4803-4815	6	.00
Irvine Jr.	1983	Southern Economic Journal	49 (3), 764-782	8	3.69
Jain, Vilcassim and Chintagunta	1994	Journal of Business and Economic Statistics	12 (3), 317-328	36	.71
Kadiyali, Chintagunta and Vilcassim	2000	Marketing Science	19 (2), 127-148	12	.95
Kadiyali, Vilcassim and Chintagunta	1996	Journal of Business	69 (4), 459-487	11	2.22
Kamakura and Russell	1989	Journal of Marketing Research	26 (4), 379-390	12	1.32
Kamakura, and Kang	2007	Journal of Retailing	83 (2), 159-170	271	.06
Kamakura, Kim and Lee	1996	Marketing Science	15 (2), 152-173	49	1.16
Kim	1995	Marketing Letters	6 (2), 159-169	4	2.76
Kim and Cotterill	2008	Journal of Industrial Economics	56 (1), 32-48	90	.31
Kim, Blattberg and Rossi	1995	Journal of Business and Economic Statistics	13 (3), 291-303	20	1.11
Kim, Telang, Vogt and Krishnan	2010	Management Science	56 (2), 234-252	2	.04
Kinoshita, Suzuki, Kawamura, Watanabe and Kaiser	2001	Agribusiness	17 (4), 515-525	30	.43
Klapper	2005	OR Spectrum	27 (4), 583-601	2	1.09
Krishnamurthi, Raj and Sivakumar	1995	Journal of Business Research	34 (1), 47-56	40	2.18
Kwak, Duvvuri and Russell	2015	Journal of Retailing	91 (1), 19-33	132	.16
Liu	2010	Journal of Marketing Research	47 (3), 428-443	2	.22
Lopez and Fantuzzi	2012	Applied Economics	44 (22), 2859-2865	132	.30
Lopez and Lopez	2009	Agribusiness	25 (4), 453-465	56	.09
Lopez, Liu and Zhu	2015	Applied Economics	47 (25), 2563-2576	56	.03
Ma, Seetharaman and Narasimhan	2012	Journal of Retailing	88 (1), 47-62	55	.15
Martínez Ruiz and Descals	2008	International Journal of Retail and Distribution Management	36 (6), 495-517	90	.51
Mehta and Ma	2012	Journal of Marketing Research	49 (4), 435-451	40	-.05
Mehta, Chen and Narasimhan	2008	Marketing Science	27 (3), 334-355	20	.37

Table 2.8 (continued)

Authors	**Year**	**Publication**	**Volume (Issue), Pages**	**Number of Cross-Price Elasticities**	**Average**
Mehta, Rajiv and Srinivasan	2003	Marketing Science	22 (1), 58-84	12	.45
Mehta, Rajiv and Srinivasan	2004	Quantitative Marketing and Economics	2 (2), 107-140	12	.86
Mela, Gupta and Jedidi	1998	International Journal of Research in Marketing	15 (2), 89-107	72	.13
Meza and Sudhir	2010	Quantitative Marketing and Economics	8 (3), 333-363	132	.23
Montgomery	1997	Marketing Science	16 (4), 315-328	110	.21
Moral and Jaumandreu	2007	Span Econ Rev	9 (3), 193-218	210	.29
Mulhern and Leone	1991	Journal of Marketing	55 (4), 63-76	56	-.10
Mulhren and Williams	1994	Journal of Retailing	70 (3), 231-251	20	1.01
Musalem, Bradlow and Raju	2008	Journal of Marketing Research	45 (6), 715-730	56	.03
Nair, Dubé and Chintagunta	2005	Marketing Science	24 (3), 444-460	83	.05
Nayga Jr. and Capps Jr.	1994	American Journal of Agricultural Economics	76 (4), 800-808	420	.15
Nevo	2001	Econometrica	69 (2), 307-342	249	.07
Osborne	2011	Quantitative Marketing and Economics	9 (1), 25-70	17	.22
Pancras and Sudhir	2007	Journal of Marketing Research	44 (4), 560-578	12	.05
Richards and Hamilton	2015	Review of Economics and Statistics	97 (1), 166-179	90	.13
Richards, Acharya and Molina	2011	Agribusiness	27 (1), 62-81	132	.20
Richards, Allender and Hamilton	2013	American Journal of Agricultural Economics	95 (3), 650-668	90	.09
Rojas and Peterson	2008	International Journal of Industrial Organization	26 (1), 288-307	272	.08
Roy, Chintagunta and Haldar	1996	Marketing Science	15 (3), 280-299	12	.97
Rudholm	2003	Applied Economics	35 (14), 1609-1617	12	.25
Russell and Bolton	1988	Journal of Marketing Research	25 (3), 229-241	33	.44
Russell and Kamakura	1994	Journal of Marketing Research	31 (2), 289-303	90	.24
Rutz and Sonnier	2011	Marketing Science	30 (2), 274-289	12	.57
Salvo	2009	Journal of Industrial Economics	57 (4), 677-711	72	.28
Shum	2004	Quantitative Marketing and Economics	13 (2), 241-272	156	.11
Song and Chintagunta	2006	Management Science	52 (10), 1594-1609	240	.03
Srinivasan, Leszczyc and Bass	2000	International Journal of Research in Marketing	17 (4), 281-305	32	.26
van Heerde, Helsen and Dekimpe	2007	Marketing Science	26 (2), 230-245	8	1.49
van Heerde, Mela and Manchanda	2004	Journal of Marketing Research	41 (2), 166-183	42	.12
van Oest and Franses	2005	Quantitative Marketing and Economics	3 (3), 281-304	24	1.71
Viard, Gron and Polson	2015	Applied Stochastic Models in Business and Industry	31 (4), 435-456	72	.07
Vilcassim and Chintagunta	1995	Journal of Retailing	71 (2), 103-128	12	.21
Vilcassim, Kadiyali and Chintagunta	1999	Management Science	45 (4), 499-518	6	.13
Wagner and Taudes	1991	International Journal of Research in Marketing	8 (3), 223-249	30	.07
Wang	2009	Australian Journal of Agricultural and Resource Economics	53 (4), 467-483	11	3.11
Wang	2015	RAND Journal of Economics	46 (2), 409-441	132	.35
Ward and Zheng	2012	Telecommunications Policy	36 (4), 301-310	4	.36

3. Pay Hard - Play Hard: Assessing the Influence of Price on Usage

Chapter 3 is a slightly modified version of the working paper "Pay Hard - Play Hard: Assessing the Influence of Price on Usage" by Johannes Auer and Dominik Papies. The contributions of the respective coauthors were as follows: Johannes Auer conducted the data collection, data management, all analyses, and the first draft of the working paper. Dominik Papies contributed to the analyses, gave feedback and revised the draft of the working paper.

Abstract

It is not clear how the price that consumers pay for a product is related to the way the product is used after purchase and how this effect is influenced by screening and selection effects. Screening effects arise because consumers who plan to use a product heavily are willing to pay more for a product. Selection effects occur because only consumers who plan to use the product for an adequate amount purchase the product at all. The goal of this study is to assess the direct effect of price on usage above and beyond potential selection and screening effects. We attribute the remaining effect of price on usage to sunk cost. We show for a digital good that positive sunk cost effects of price on usage exist above and beyond selection and screening effects such that a 1% increase in price increases the usage of those consumers who purchase by .09%. This positive sunk cost effect is higher for consumers with lower levels of experience in the marketplace.

Keywords: Usage; Pricing; Post-Purchase Behavior

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3.1 Introduction

Companies often stimulate demand through sales promotions, and their strong impact on demand is well documented in the literature (e.g., Blattberg et al. 1995). It is, however, less clear how the price that consumers pay for a product is related to the way the product is used after purchase (e.g., Gourville and Soman 2002). Evidence from previous literature suggests that consumers' post-purchase behavior is often not independent of price. Thaler (1980) illustrates this relation with the example of a consumer who pays $300 for a yearly tennis club membership but develops a tennis elbow after two weeks. As he does not want to "waste" the sunk cost of 300$, he continues to play (in pain). In contrast, a consumer who pays only 10$ for the same membership would likely stop playing. This stylized example implies that the higher the price for a product is, the higher should be the post-purchase usage behavior.

Previous research suggests a positive relationship between the price of a product and its usage because consumers consider the money they spent on a product (henceforth referred to as sunk costs) in their usage decisions (e.g., Arkes and Blumer 1985). Thaler (1980) argues that if consumers have to pay for the right to use a good or service, the rate at which the good will be utilized will increase. Empirical studies find support for this sunk-cost effect (e.g., Arkes and Blumer 1985). However, more recent studies question the strength of this effect as screening effects and not sunk cost effects may drive usage. E.g., if we assume in the example of Thaler (1980) that the height of the tennis membership fee is randomly set for each consumer, consumers who plan to spend every weekend on the court will be willing to accept higher fees compared to consumers who plan to play only occasionally. On an individual level, screening effects occur because customers with a high (low) expected utility have a high (low) willingness to pay. As a result, a higher (lower) price would be associated with higher (lower) usage even in the absence of any sunk-cost effect. On an aggregated level, Ashraf et al. (2010) define screening effects as a change in the mix of consumers as a result of a price change. On top of that, consumers do not only self-select into specific prices leading to the screening effect that we describe above, but they also self-select into whether or not to purchase the game at all. Neglecting the latter effect results in a sample selection bias due to non-randomly selected purchases and non-purchases (e.g., Heckman 1979). We henceforth refer to the latter effect as selection effect. Further, previous literature suggests that, with a higher level of training and experience, consumers improve their decision making (e.g., Fennema and Perkins 2008). Consequently, consumer with a high level of experience have undergone the process of purchase and resulting post-purchase behavior more often and should be better aware of biases in their decision making. Therefore, the size of the sunk cost effect could be heterogeneous for consumers with different levels of experience in the marketplace.

The post-purchase behavior that we analyze in this study is a consumer’s usage of a product. Usage is likely to be important because it will be related to future purchase behavior, e.g., via brand attachment, brand attitude and customer loyalty (e.g., Park et al. 2010; Murray and Bellman 2011; Iyengar et al. 2007). Knowledge about this price-usage effect enables firms to influence the later usage of their products, and information about the direction and strength of this effect opens doors to new possibilities for firms to foster customer satisfaction. Bolton and Lemon (1999) argue that usage is an antecedent of customer satisfaction and, therefore, managing customer usage levels might be an important tool to sustain customer satisfaction and ensure long-term customer profitability. Consequently, knowledge about the influence of price on usage enables managers to account for purchase and post-purchase effects when setting prices.

We test our research questions in the context of the video game industry as the analysis of video games provides the benefit that usage is easily observable and that a broad range of control variables is available. Managers in the video games industry are interested in the influences on usage as the usage of prequel games potentially influences the purchase probability of sequel games. Further, a high usage provides more opportunity for additional revenue streams like e.g., in-game purchases or up- and cross-selling. Finally, consumers with a high usage have a more positive attitude towards the game (e.g., Holbrook et al. 1984) which possibly results in e.g., more positive word of mouth.

The main research questions are the following: (1) How strong is the price-usage elasticity (sunk cost effect) after controlling for selection and screening effects. (2) How is the price-usage elasticity moderated by the experience of the consumer in the marketplace? We contribute to the literature by providing evidence for a positive effect of price on usage based on observational and not lab or survey data.

Our data consists of a panel of 3,161 consumers whose purchasing behavior on one of the leading online distributors of video games is observed in 15 countries over a time period of 18 months. The distribution platform fulfills two functions for users: (1) users obtain access to games in the shop and (2) the platform is a community in which users can join groups and communicate or play with friends. Consequently, the dataset includes a set of consumer and game variables. Further, we are able to track not only an individual’s behavior but also the behavior of his/her friends within the community. The video games in our data are purchased through a one-time payment. Consumers acquire the game for a specific price and are able to play as much as they like. As the distribution platform frequently changes prices and runs price promotions, we observe for different purchases different prices for the same game.

On the basis of our data, we estimate two econometric models that assess (1) the propensity of a consumer to purchase a specific game and (2) the influence of price on usage. By calculating the propensity to purchase a game in step (1), we are able to control for the selection effect in step (2). We estimate the inverse mills ratios in step (1) and include them as control variable in step (2). Further, we address the screening effect in step (2) by controlling for unobserved game and consumer heterogeneity and by introducing a set of control variables. In a subsequent robustness check, we additionally estimate the price as a function of instrumental variables. These models allows us to assess the direct effect of price on usage above and beyond potential selection and screening effects.

The results show a positive sunk cost effect that increases for consumers with lower levels of experience in the marketplace. Not accounting for the selection effect leads to an overestimation of the influence of price on usage. Further, we find that screening effects occur for specific games and specific consumers but seem to be less prominent when we look at game-consumer combinations. There are (1) consumers who are in general willing to pay more for games and (2) games for which consumers are in general willing to pay more. After controlling for (1) and (2), we only find weak evidence for a remaining screening effect on a game-consumer level which could occur because a specific consumer is willing to pay more for one specific game. Our findings allow us to draw new implications as price changes and associated sunk cost do not only effect demand but also post-purchase behavior – even after controlling for screening and selection effects.

3.2 Contribution to the Literature

3.2.1 Literature on the Influence of Price on Usage

Classic economic theory would suggest that prices should not have an influence on the post-purchase behavior of consumers because decisions should be affected only by benefits and incremental costs (e.g., Thaler 1980). Consequently, consumers' usage of products should be independent of the price a consumer paid for the product. Nevertheless, a stream of literature on the post-purchase behavior of consumers exists.

We identify three important streams of research on the influence of price on usage. The first stream of price-usage literature is mainly focused on fast moving consumer goods and the impact of price promotions on accelerated usage and the reduction of stockpiled goods (e.g., Ailawadi and Neslin 1998). Here, lower prices induce a higher consumption rate, which is a key component of purchase acceleration.

This notion is also reflected in the second stream of price-usage literature: the research on tariff structures. Iyengar et al. (2011) find support for a different usage for different tariff structures. Higher usage occurs for pay-per-use pricing compared to two-part tariffs. Consistent with prospect theory and mental accounting, the authors argue that consumers derive lower utility in two-part tariff conditions because multiple prices are perceived as more negative compared to a single constant price (e.g., Kahneman and Tversky 1979). In addition, Ascarza et al. (2012) find that consumers adapt their usage behavior based on the tariff pricing scheme, and that consumers increase their usage when they switch from two-part tariffs to three-part tariffs. The reason is that the free component in a three-part tariff leads to an increase in valuation and a more positive affective response. Bolton and Lemon (1999) analyze the relationship between payment equity – the perceived fairness consumers derive from usage benefits compared to economic costs – and usage behavior. They find that if payment equity is achieved, overall satisfaction is positively affected, which leads to stronger future usage of a service. Finally, consumption rates differ depending on the payment plan a consumer chooses. The highest usage occurs for monthly payments in contrast to e.g., quarterly or annual payments (e.g., Gourville and Soman 2002). A potential explanation is that, in contrast to yearly payments, where consumers experience one strong sunk cost effect at the beginning, monthly payments lead to recurring sunk cost effects which induce higher usage.

The third stream of price-usage literature is focused on the isolated effect of prices on usage. Arkes and Blumer (1985) analyze the direct effect by experimentally manipulating prices customers had to pay for a subscription to a theater series. They find that customers who had to pay the regular price attended more plays than those who were randomly assigned to a price promotion. The authors explain this behavior by sunk-cost effects or the sunk cost fallacy. Generally, the term sunk cost fallacy describes the behavior of decision-makers who deviate from axioms of classic economic theory and incorporate past expenses – sunk costs – in their current decision processes. It is against classic economic theory because only present and future costs should affect one's decision making (e.g., Thaler 1985). Sunk cost can have a utilization or progress character. A utilization character is the influence of sunk cost on the decision whether or not to consume a product. A progress character is the influence of sunk cost on the decision how much to further invest into a product (e.g., Moon 2001).

In a recent meta-analysis, Roth et al. (2015) find empirical evidence for sunk cost effects. However, the literature does not consistently agree on the effect of sunk-cost. Ashraf et al. (2010) separates sunk-cost effects from screening effects. The latter arises if the mix of buyers changes as a result of price changes, i.e., if the price is higher, people who intend to use the product less would be also less likely to buy it a priori. Consequently, a higher price would be associated with higher usage even in the absence of any sunk-cost effects. Ashraf et al. (2010) find strong evidence for screening effects but no evidence for sunk-cost effects. However, Ashraf et al. (2010) do not trace actual total usage behavior but survey whether or not a product is used. Research by Nunes (2000) supports the notion of consumers being well aware of their expected usage when making a purchase decision. It is often a necessary decision of a consumer to invest time in a good before the consumer decides to purchases it (e.g., Luo et al. 2013). Therefore, customers anticipate their utility and adjust their willingness to pay before the purchase which leads to higher prices for consumers with a high expected usage (e.g., Hamilton et al. 2011; Tanner and Carlson 2009). Additionally, consumers can use the price as a commitment device. DellaVigna and Malmendier (2006) find that consumers of a health club are willing to pay for more expensive flat-fee memberships because they try to self-condition themselves towards attendance. Finally, Just and Wansink (2011) develop a theoretical model for the consumption under flat rate (or fixed) pricing. In the context of all-you-can-eat restaurants, they argue that consumers do not consume until a marginal utility of zero is reached but consume until they “get their money’s worth”.

Finally, we find literature on the effect of prices on customer perception. Typically, higher prices are associated with higher perceived product quality (e.g., Gerstner 1985; Rao and Monroe 1989). Discounted products are associated with inferior product quality and consumers derive a smaller benefit from consuming the product. This effect is explained with a placebo effect of price on perceived and actual quality (e.g., Shiv et al. 2005).

We are not aware of any study that is able to reach consensus about the distinction between the screening, selection and direct effect of price on usage due to a lack of information about the effect of price on purchase likelihood and actual behavior. We address this void in the literature by analyzing actual prices and actual usage behavior. As a result, this study contributes to the literature by assessing the influence of the price of a product on its subsequent usage above and beyond potential selection and screening effects.

3.2.2 Literature on Video Games

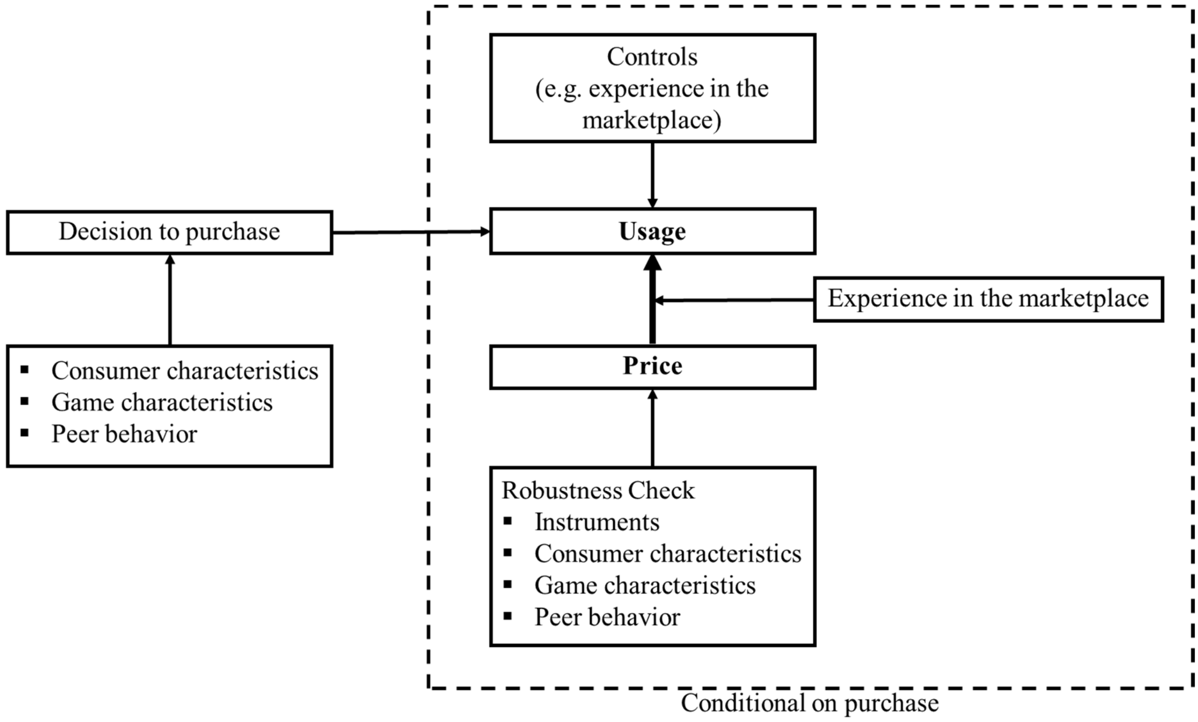
Video games have shifted from a niche to a blockbuster industry (e.g., Marchand and Hennig-Thurau 2013) and are the object of extensive research in a broad range of marketing topics (e.g., Cox 2014; Binken and Stremersch 2009). Further, several studies access the effect of consumer characteristics on game usage. E.g., Holbrook et al. (1984) find that consumers increase positive emotions such as a game's liking with rising mastery of the game. Additionally, for hedonic experiences, consumers are more interested in practicing in order to increase their derived value within a given period in contrast to minimizing the utilitarian amount of time spent on a task (e.g., Murray and Bellman 2011). Further, studies by Lee and Larose (2007) analyze the effect of flow experience on usage. Flow experiences are enjoyable experiences that are products from deeply engaging in everyday activities. The authors find that the extent of a flow experience has no influence on the total usage of a game but only on the length of the single play session. Consequently, with respect to flow experiences, total video game usage is no automatism but consumers decide actively after each play session whether or not to continue playing the game. Finally, Hartmann et al. (2012) find evidence for the impact of habit and less of addictive tendencies on video game usage especially, when consumers showed a high intention to play the game in advance.

However, these studies do not analyze the influence of prices but game and consumer characteristics on usage. In this study, we link the literature on pricing research with the literature on video game usage and try to identify the direct effect of price on usage above and beyond potential selection and screening effects.

3.3 Conceptual Framework and Research Questions

In order to identify the direct effect of price on usage, we use the framework shown in Figure 3.1. The focal outcome variable in our framework is the usage of a consumer for a specific game. We model the decision to purchase (step 1) as a function of consumer characteristics, game characteristics and friends' behavior. The estimation of the decision to purchase allows us to control for the selection effect. We model usage (step 2) as a function of price and control variables. As we expect a screening effect to occur, we control for unobserved heterogeneity across consumers and games. This controls for (1) consumers who are in general willing to pay more for games based on their expected utility and (2) games for which consumers are in general willing to pay more. As there may be a remaining screening effect on a game-consumer level – a specific consumer's willingness to pay for a specific game based on his/her expected utility –, in a subsequent robustness check, we model price as an endogenous variable in step 2 and estimate it with instruments. We expect the effect of price on usage to be moderated by the experience of a consumer in the marketplace.

Figure 3.1: Conceptual Framework



This allows us to analyze the direct effect of price on usage after controlling for selection (step 1) and screening effects (step 2). We model the price-usage relation as an elasticity, which is the percent change in usage of a game by a consumer due to the percent change in the price for that game. We henceforth refer to it as price-usage elasticity. This metric is easy to interpret and helps comparing price changes of games with different usage and price levels. Further, we attribute the remaining effect after controlling for selection and screening effects to sunk costs.

3.3.1 Effect of Price on Usage Above and Beyond Potential Selection and Screening Effects

Although economic theory would suggest that prices should not have an influence on the post-purchase behavior of consumers because decisions should be affected only by benefits and incremental costs (e.g., Thaler 1980), evidence for an effect of sunk costs on consumers' post-purchase behavior exists (e.g., Roth et al. 2015). Experiencing sunk cost can lead to a sunk cost fallacy – decision-makers deviate from microeconomic theory and incorporate past expenses, sunk costs, in their current decision processes – (e.g., Arkes and Blumer 1985). Sunk cost effects occur because of a mixture of prospect theory (Kahneman and Tversky 1979) and mental accounting (Thaler 1985). Consumers use mental accounts to organize and evaluate e.g., their financial activities. The purchase of a game opens a mental account with a negative balance that depends on the price that the consumer pays for the game. This negative account balance is perceived as a loss to consumers unless the consumer can compensate it with an exchange value – e.g., usage. As consumers strive for avoiding losses (e.g., Kahneman and Tversky 1979), consumers try to balance the account. Further, the progress character of sunk cost has an encouraging influence on the decision how much to further invest into a product (e.g., Moon 2001) and consumers do not consume until a marginal utility of zero is reached but consume until they "get their money's worth" (e.g., Just and Wansink 2011). Consequently, based on previous findings, we expect the sunk cost effect on usage to be positive (e.g., Arkes and Blumer 1985). However, we expect the effect to be closer to zero compared to a raw estimate in which we do not control for screening effects.

3.3.2 Selection Effects

Consumers self-select into whether or not to purchase the game at all within our dataset. Due to consumer preferences and game characteristics, some games provide no utility to some consumers in the non-purchase group. However, for other consumers in the non-purchase group, the game would provide utility but even the lowest observed price is too high of a sacrifice to balance the derived utility. Consequently, two consumer groups exist: a purchase group and a non-purchase group. By controlling for the selection effect, we control for the possibility that the selection into purchase and non-purchase group is non-random.

Technically, as we have no information about purchases at a lower price than the lowest observed price, this leads to a truncation of our data. Neglecting this effect results in a sample selection bias due to non-randomly selected purchases and non-purchases (e.g., Heckman 1979). We assume that the mechanism of selecting into observed and unobserved data is not random. As we have no information about the characteristics of the unobserved data, we refrain from providing an expectation about the direction of this effect.

3.3.3 Screening Effects

Conditional on purchase, if consumers select into different prices based on their expected usage, we should find a positive price-usage elasticity even in the absence of any sunk-cost effect (e.g., Ashraf et al. 2010). In that case consumers with a high expected usage are willing to pay higher prices compared to consumers with a lower expected usage. We provide a numerical example of this screening effect in Table 3.1. Here, we have a world with only one video game and four consumers, and the distribution platform offers two prices to consumers, i.e., initially, in t = 1, a price of 60$ and at a later point in time t = 2 a price of 20$ is offered.

Each consumer purchases the video game once. The consumers in our example have a different expected usage in mind before making the purchase. Based on this expected usage, the consumers set their willingness to pay (WTP). Naturally, a higher expected usage is associated with a higher WTP because consumers anticipate their utility and adjust their WTP (e.g., Hamilton et al. 2011; Tanner and Carlson 2009). At the first offered price of 60$, consumers A and B make a purchase as the price does not exceed their WTP. After the price is reduced to 20$, consumers C and D make a purchase. Even in the absence of any sunk-cost effect, we observe higher usage with higher prices. In our example, the mean usage of all consumers who made a purchase at 60$ is 45h. For consumers who made a purchase at 20$ the mean usage is 25h. As we expect that consumers can make reasonable predictions of their expected usage, we would find a positive effect of price on usage that is mainly driven by consumers setting their WTP based on their expected usage.

After controlling for the screening effect, e.g., consumer's expected usage, which is otherwise reflected in the WTP, the remaining effect of price on usage should be less positive. In that case only sunk cost effects and not a mixture of screening and sunk cost effects should shape the size of the price-usage elasticity.

Table 3.1: Numerical Example for Screening Effect

Consumer Characteristics for one Game:

Consumers	**Expected Usage**	**WTP**	**t = 1 p = 60**	**t = 2 p = 20**	**Mean Expected Usage for Prices**	**Observed Usage**
A	50h	70$	60$		45h	50h
B	40h	60$				40h
C	30h	30$		20$	25h	30h
D	20h	20$				20h

3.3.4 The Raw Effect of Price on Usage

For the raw price-usage elasticity without controlling for selection and screening effects, we expect a positive effect. The notion that (1) consumers with high expected usage are more likely to purchase the game and (2) that consumers with higher expected usage are willing to pay more for the game should lead to a positive price-usage elasticity (e.g., Arkes and Blumer 1985). We therefore expect that higher prices are associated with higher usage.

3.3.5 Experience in the Marketplace

One research question of this study is how the price-usage elasticity is moderated by the experience of the consumer in the marketplace. An indicator of the experience of a consumer with purchase and post-purchase behavior is the number of games in possession at the time of purchase. With a higher level of training and experience, consumers improve their decision making (e.g., Fennema and Perkins 2008). Further, previous research suggests that especially inexperienced and untrained consumers use mental budgeting (e.g., Heath 1995). This increases the sunk cost effect for inexperienced consumers. Consequently, consumer with a high level of experience have undergone the process of purchase and resulting post-purchase behavior more often and should be better aware of biases in their decision making. We therefore expect for consumers with a low level of experience in the marketplace an increase of the sunk cost effect.

3.4 Data and Measures

3.4.1 Sample

We test our framework (Figure 3.1) in the context of the video game industry. With revenues of $23.5 billion in 2016 (ESA 2016), it is one of the most important industries in the entertainment sector.

The specific object of our study are computer games purchased through an online distribution platform. With more than 125 million accounts, the platform is one of the leading online distributors of video games. For a sample of 3,161 consumers, we obtain daily usage and purchase behavior. Users who are active on this platform must install a software on consumers' devices that automatically registers the games consumers purchase as well as the usage behavior and updates the user's profile webpage. Hence, the distribution platform fulfills two functions for users: (1) users obtain access to games in the shop and (2) the platform is a community in which users can join groups and communicate or play with friends.

Our dataset consists of two intertwined subsets: For our first dataset, we randomly select 5,000 users with publicly available profiles from 15 countries. We clean our sample based on three criteria: (1) the user was active within the last 30 days; (2) the user is connected within the network which means that s/he has at least one "friend" or has joined at least one "group"; (3) the user has made at least two purchases within our observation period. This results in a core dataset of 3,161 consumers.

For our second dataset, we collect information about all "friends" of the 3,161 focal customers. This leads to an additional 63,821 friends, whose purchase and usage behavior we observe daily. While the main object of our analysis is the core dataset of 3,161 consumers, we use the information about the behavior of all friends to explain the behavior of the 3,161 customers in our core dataset. We collect our data for the period February 2015-July 2016. As some games cannot only be bought directly on the distribution platform but on a third party website via redeemable keys, we have no information about the price that consumers pay for these keys that are redeemed on the distribution platform. Therefore, we decide to drop these games from our dataset. After data cleaning, we observe 55,622 purchases made by the 3,161 focal customers. An observation in our data is always a consumer-game combination: a game that is purchased by a consumer. Therefore, we observe for one consumer multiple purchases of different games and for one game multiple purchases by different consumers. The video games in our sample are from a broad range of genres. We provide information about the distribution of games and observations across genres in Table 3.2.

Table 3.2: Distribution of Games

Genre	**Number of Observations**	**Number of Games**
Action	19,680	805
Adventure	7,033	450
Indie	6,205	562
Strategy	8,031	471
RPG	7,721	356
Simulation	3,927	208
Racing	1,518	94
Casual	1,176	149
Sports	331	34
Total	55,622	3,129

3.4.2 Dependent Variables

Usage. As central dependent variable and as usage measurement, we utilize the cumulated usage (in minutes) for a consumer-game combination. We have information about the daily consumer level usage for each game in a consumer’s possession. To avoid a censoring of the dependent variable that may occur if the observation period restricts the number of days that we can observe usage for this consumer who has bought a game later than other consumers, we measure usage as the cumulated usage of each consumer-game combination within the first

30 days of possession[10]. We include in our analysis only consumer-game combinations that we observe for at least 30 days.

Purchase. As second dependent variable we analyze the binary outcome whether or not a consumer has purchased a specific game within our full observation period. This variable is observed for each possible consumer-game combination. This leaves us with a set of 10,000,000 single observations. As we are faced with a sample that is characterized by rare events (not every consumer purchases each game), we randomly select for each game non-buying consumers to make computation more feasible as proposed by King and Zeng (2001). The remaining dataset consists of 55,622 purchases and 225,087 randomly per game selected non-purchases.

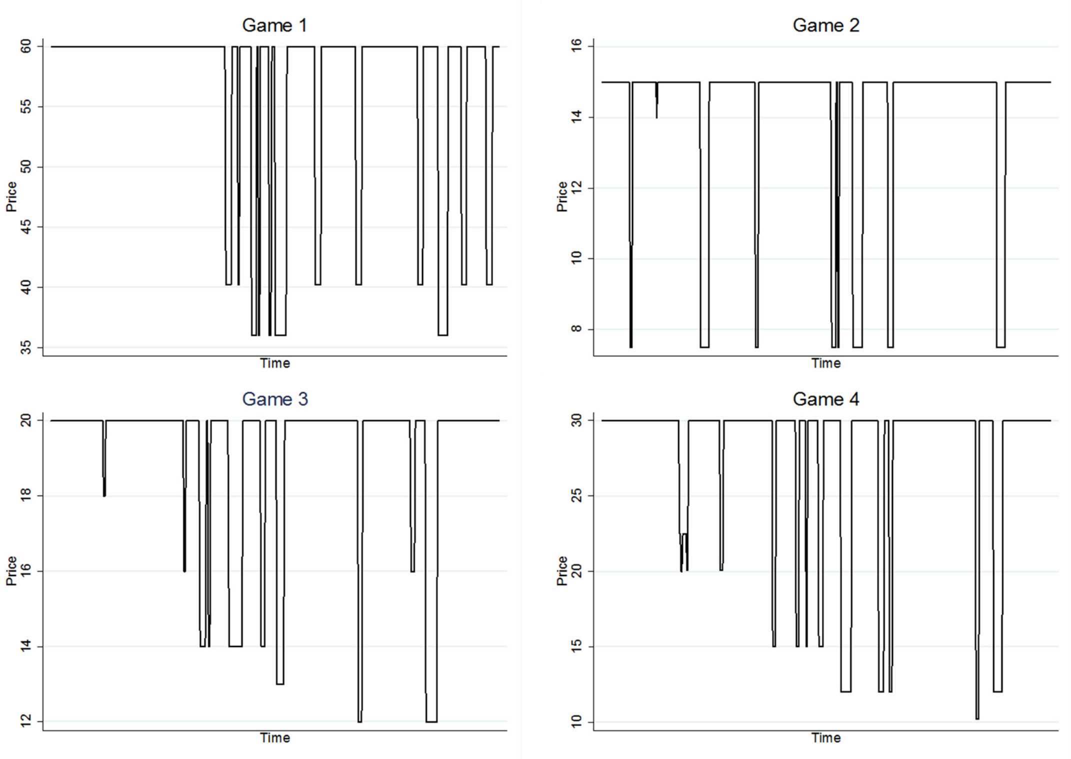
3.4.3 Independent Variables

3.4.3.1 Game Specific Variables

Price. We obtain daily price information from the online distributor's shop and match them with the time of purchase for each consumer's purchase. In our data, price variation for a game comes from two sources: (1) regular price changes (2) price promotions. We provide an example of the price developments of four games in Figure 3.2. Consequently, we observe different prices for the same game depending on when the consumer makes the purchase. As we observe consumers in different countries with different currencies, we decide to use a price index as price variable. The price index measures for each country the relation of the price to the highest observed price in our observation period. Consequently, our price variable is bound between 0 (low prices) and 1 (highest price). This price index allows us to compare the effect of prices across several currencies.

[10] In 73% of observations usage in first 30 days = usage at the end of our observation period. If we calculate the ration of usage in first 30 days and usage at the end of our observation period, we capture 86% with usage in first 30 days.

Figure 3.2: Price Developments



MeanPrice. In our first step, we analyze the propensity to buy a game. In that course, we compare consumers who have purchased the game to consumers who did not. As we have only price information for consumers who purchased the game but not for consumers who did not, we are not able to include a purchase-dependent price variable in step 1. Further, our level of observation are consumer-game combinations. As we observe a game-purchase by a consumer only once, we are not able to estimate a consumer-game panel with varying prices over time. As alternative, we include the game-specific mean price over our observation period in the model in order to capture price differences between different games.

ReviewScore. To have a proxy for game quality, we use the review score that a consumer observes in the shop of the online distributor before making the purchase (e.g., Zhu and Zhang 2010). The review score is created by other consumers who up vote or down vote the game after purchase. We match each game purchase with the day-specific review score for that game. The review score is calculated by taking the relation of up votes to total votes. For our outcome model, we use the review score that a consumer observes at the time of purchase. For our selection model, comparable to the variable MeanPrice, we replace all values with the game specific mean review score.

3.4.3.2 Consumer Related Variables

Level. The level that a consumer earned across all games is an indicator of how active the consumer is on the distribution platform, the affiliated community and within the games s/he plays.

Groups and *Friends*. Within the community of the distribution platform, consumers can join groups that match their field of interest. Consequently, a high number of group memberships is an indicator of a high activity within the community. Consumers add friends to their network for two purposes: to communicate with them within the community and to play games with multiplayer features together. Contrary to the variable Groups, the variable Friends is not only an indicator of how active a consumer is within the community, but it indicates also her/his peer activities within games. Further, as consumers are susceptible to interpersonal influence (e.g., Bearden et al. 1989), we add the number of group memberships and the number of friends as control variables.

Country. We have information about consumers from the following countries: United States (38.7%), Russia (10.7%), UK (8.1%), Germany (7.7%), Canada (6.2%), Australia (5.2%), Brazil (4.8%), France (4.6%), Spain (2.9%), Poland (2.7%), Netherlands (2.4%), Sweden (2.4%), South Korea (1.9%), Ukraine (1.1%), Turkey (.8%).

We observe the variables Level, Groups, Friends and Country once at the beginning of our observation period.

NumberofGames. The variable NumberofGames captures how many games a consumer has in possession at the time of purchase. A higher number of games can be an indicator for a consumer who derives a lot of utility from video games. This can result in a high usage of all games that the consumer purchases. It can also be an indicator of cannibalization effects. With a growing number of games, consumers have to divide their available time between more games. This can lead to a lower usage for the single game. Further, the number of games is an indicator for a consumer's experience in the marketplace. The more games a consumer has in possession, the more often has the consumer made the experience of a purchase process and the involved consequences.

3.4.3.3 Usage Related Variables

SimilarUsage. The variable SimilarUsage captures the cumulated usage of the five most similar games to the purchased game for each consumer. For each game that is sold on the distribution platform, the focal game's shop site offers information about the five most similar games that are sold on the distribution platform. We adopt this definition and measure for each game of a consumer how much s/he has played the five most similar games until the purchase of the focal game. Two possible effects of a high usage of similar games are possible. First, consumers have a general liking of certain types of games that they will play consistently to a high extend. Second, variety seeking effects which lead to higher usage for low levels of similar usage.

Table 3.3: Observed Variables for Selection Model (Equation 2)

Variable	Description	Mean	SD	Min	Max
$Purchase_{i,p}$	Consumer i purchases game p	.21	.41	.00	1.00
$Level_{i}$	Level of consumer i across all games	6.53	7.30	.00	110.00
$Groups_{i}$	Number of group memberships of consumer i	4.91	10.61	.00	213.00
$Friends_{i}$	Number of friends of consumer i	26.59	41.34	.00	793.00
$Country_{i}$	Country of consumer i				
$SimilarUsage_{i,p}$	Total usage (minutes) of similar games to game p for consumer i at time of purchase	1217.93	9091.23	.00	501120.00
$UsageFriends_{i,p}$	Total usage (minutes) of game p for all friends of consumer i at time of purchase	446.09	10693.18	.00	3147360.00
$ReviewScore_{i,p}$	Review score of game p at purchase by consumer i	77.03	18.16	.00	100.00
$NumberofGames_{i,p}$	Number of games in possession of consumer i at purchase of game p	96.08	153.65	1.00	2078.00
$Gini_{i,p}$	Gini coefficient of the usage distribution of all games in possession for consumer i at purchase of game p	.72	.17	.00	.96
$TotalUsage_{i,p}$	Total usage (hours) of all games for consumer i at purchase of game p	1570.80	1544.70	.10	14895.50
$MeanPrice_{p}$*	Mean price of game p	.88	.13	.07	1.00

*As we have no information in our selection model about prices of consumers who have not purchased game p, we replace all prices with the mean price of game p.

UsageFriends and *UsageFriends30*. One advantage of our dataset is that we are not only able to observe a consumer's behavior but that we also observe the behavior of his/her friends. The variable UsageFriends provides information about the total usage of all friends for a specific game at the time of purchase. The variable UsageFriends30 provides information about the total usage of all friends for a specific game within the first 30 days of possession.

TotalUsage. This variable captures the total past usage of all games in possession for a consumer at each purchase. Two possible effects of a high total usage of games in possession are possible. First, consumers get bored by video games and turn to other activities. Second, a high total usage of games in possession is an indicator of a tendency to play heavily in the future.

Table 3.4: Observed Variables for Outcome Model (Equation 3)

Variable	**Description**	**Mean**	**SD**	**Min**	**Max**
$Usage_{i,p}$	Total usage (minutes) of consumer i for game p in the first month of possession	358.63	1084.20	.00	24660.00
$Price_{i,p}$*	Price index of consumer i for game p	.61	.36	.01	1.00
$TotalUsage_{i,p}$	Total usage (hours) of all games for consumer i at purchase of game p	1639.37	1398.44	.10	13810.40
$UsageFriends30_{i,p}$	Total usage (minutes) of game p for all friends of consumer i at the end of the first month of possession	1880.92	15153.35	.00	1358604.00
$NumberofGames_{i,p}$	Number of games in possession of consumer i at purchase of game p	170.82	223.12	2.00	1862.00
$Gini_{i,p}$	Gini coefficient of the usage distribution of all games in possession for consumer i at purchase of game p	.76	.10	.00	.96
$ReviewScore_{i,p}$	Review score of game p at purchase by consumer i	84.87	12.93	23.08	100.00
$SimilarUsage_{i,p}$	Total usage (minutes) of similar games to game p for consumer i at time of purchase	1548.85	8416.81	.00	459420.00
$InverseMillsRatio_{i,p}$	Inverse mills ratio of consumer i for purchase of game p	2.59	1.88	.00	13.08

*Prices are measured as a price index in order to make differences in currencies comparable. For each currency, the price is divided by the highest observed price for a game.

Gini. Consumers can either have a preference for some favorite games in their possession that they play all the time or consumers can distribute their time equally on all games in possession. For consumers that have a strong preference for some "all-time favorite" games in their possession, the likelihood that a newly purchased game is used is lower compared to consumers who have an equal distribution. Therefore, we include the variable Gini, which is the gini coefficient of the usage distribution of all games in possession for a consumer at the time of purchase. The variable Gini is bound between 0 (equal usage distribution) and 1 (unequal usage distribution).

Table 3.3 and 3.4 provide a summary of our dependent and independent variables.

3.5 Model

The main research aim of this study is to access the direct effect of price on usage above and beyond potential selection and screening effects. As previously defined, selection effects may occur because consumers non-randomly choose whether or not to buy. Further, the screening effect may occur because consumers choose at which price they are willing to purchase. Therefore, in a first step, we model the selection process in which a consumer decides whether or not to adopt a game. The resulting adoption probability is then used in the second step in which we analyze the influence of price on usage. In order to capture the screening effect, we control for unobserved fix heterogeneity across consumers and games and additionally use a set of control variables. In a subsequent robustness check, we treat the price as an endogenous variable and model it through an instrumental variable approach.

We outline our conceptual framework in Figure 3.1.

More specifically, in step 1, we estimate the selection process through a logit regression with game random effects and consumer specific control variables. As dependent variable, we model whether or not a consumer (i) chose to adopt the respective game (p) (Figure 3.1).

$$y_{i,p} = \begin{cases} 1, & if\ consumer\ i\ purchases\ game\ p \\ 0, & otherwise \end{cases} \tag{1}$$

$$logitP\left(y_{i,p} = 1 \middle| X_i, X^1_{i,p}, MeanPrice_p, c^r_p, \mathrm{e}_{i,p}\right) \tag{2}$$

As independent variables, we use a vector of consumer specific variables X_i ($Level_i$, $Groups_i$, $Friends_i$, $Country_i$) and a vector of consumer-game specific variables $X^1_{i,p}$ ($SimilarUsage_{i,p}$, $UsageFriends_{i,p}$, $ReviewScore_{i,p}$, $NumberofGames_{i,p}$, $Gini_{i,p}$, $TotalUsage_{i,p}$). We use the variable $MeanPrice_p$ to capture price differences between different games. Finally, we include game specific random effects c^r_p. The error term of our model is $\mathrm{e}_{i,p}$.

As we are interested in the purchase probability for consumer i and game p, we calculate the inverse mills ratios $\lambda_{i,p}$ and include them in step 2 as an additional regressor to control for selection biases as proposed by Heckman (1979).

In step 2, we try to address potentially remaining screening effects in different approaches. We estimate the influence on usage using a linear regression with game plus consumer fixed effects. As accounting for endogeneity is potentially costly because of poor sampling properties, like substantial finite sample bias and large sampling errors (e.g., Rossi

2014), we decide against treating price as endogenous in equation 3 but analyze the impact of accounting for endogeneity in our robustness check (e.g., unobserved utility influences prices). To safeguard against screening effects, where consumers chose prices based on unobserved characteristics like e.g., expected utility, we follow a two-pronged approach. First, we include game and consumer fixed effects in step 2 to capture all unobserved effects that may lead to a screening effect on the consumer and game level. Second, to mitigate remaining screening effects on a consumer-game level, we utilize our extensive set of control variables (e.g., usage of similar games, friends' usage). There are (1) consumers who are in general willing to pay more for games based on their expected utility and (2) games for which consumers are in general willing to pay more. After controlling for (1) and (2), we assume that a specific consumer's willingness to pay for a specific game based on his/her expected utility is negligibly after introducing our control variables. We relax this assumption in a subsequent robustness check.

The dependent variable in step 2 is the total usage (minutes) $Usage_{i,p}$ of consumer i for game p in the first month of possession. As independent variables, we use the focal variable $Price_{i,p}$, a vector of consumer-game specific variables $X_{i,p}^2$ ($TotalUsage_{i,p}$, $UsageFriends30_{i,p}$, $NumberofGames_{i,p}$, $Gini_{i,p}$, $ReviewScore_{i,p}, SimilarUsage_{i,p}$) and the inverse mills ratios $\lambda_{i,p}$ from our purchase model. Finally, we include game c_p^f and consumer c_i^f specific fixed effects. The error term of our model is $u_{i,p}$.

$$Usage_{i,p} = \beta_1 Price_{i,p} + \beta_2 X_{i,p}^2 + \beta_3 \lambda_{i,p} + c_p^f + c_i^f + \mathrm{u}_{i,p} \quad (3)$$

As we are not only interested in the single effect of price on usage but also how this effect is influence by the experience of a consumer in the marketplace – measured by the number of games in possession –, we extend equation 3:

$$\begin{aligned} Usage_{i,p} = {} & \beta_1 Price_{i,p} + \beta_2 Price_{i,p} * NumberofGames_{i,p} \\ & + \beta_3 X_{i,p}^2 + \beta_4 \lambda_{i,p} + c_p^f + c_i^f + \mathrm{u}_{i,p} \end{aligned} \quad (4)$$

In equation 4, we mean centered all variables that are included in the interaction to ease interpretation.

Endogeneity. In our case, screening effects could translate to an endogeneity problem for the estimation of price-usage effects. Unobserved characteristics e.g., a consumer's expected utility for a game could be correlated with the price that a consumer pays.

To safeguard against endogeneity, we include game and consumer fixed effects and utilize our extensive set of control variables. This is in line with the data rich approach proposed, e.g., in Germann et al. (2015). In a subsequent robustness check, we additionally model price as a function of exogenous and instrumental variables. Besides controlling for endogeneity due to unobserved game and consumer characteristics, this allows us to control for unobserved consumer-game specific effects. However, accounting for potential endogeneity through an instrumental variable approach is costly due to the potentially poor sampling properties (see e.g., Rossi 2014), which implies that the cure (instrumental variables) can be worse than the disease (endogeneity). To assess the robustness of our model, we estimate equation 3 and 4 without an instrumental variable approach as our focal models, but test the impact of accounting for endogeneity in a subsequent robustness check.

Estimation. In step 1, we use a logit random effects model and estimate it with maximum likelihood estimation. There are 280,709 observations that consist of 55,622 purchases and 225,087 randomly by game selected non-purchases. Purchases per game range from 2 to 666 observations with an average of 55.

In step 2, we use a fixed effects linear regression. Observations per game range from 2 to 620 with an average of 18. Observations per consumer range from 2 to 381 with an average of 18.

3.6 Empirical Results

3.6.1 Step 1: Controlling for Selection Effects

Table 3.5 reports the results of equation 2-4. The logit random effects model shows the influence on the decision to purchase a game. Consistent with an economic rational, the mean price of a game has a negative (-.53) and significant influence on purchase propensity. The level of the consumer across all games has a positive influence (.30). Consumers with a higher level are potentially more involved with the distribution platform and previously purchased games and have therefore a higher propensity to purchase games. The number of friends has no influence on the purchase propensity, however the number of group memberships has a negative (-.02) and significant impact. Further, not the number of friends but the behavior of friends seems to be important for purchase decisions. For the usage of friends, we find a positive (.06) and significant effect. The more positive a game is perceived by consumers, the more likely are consumers to buy it. This is reflected in the positive (10.16) and significant effect of the review score. The more games a consumer has purchased in the past, the more likely it is that s/he will purchase an additional game. We find a positive (.94) and significant effect of number of games. For the gini coefficient, which measures how equally the usage distribution across all games in possession is, we find a positive (1.99) and significant effect. This means that the more unequal (higher gini coefficients indicate unequal distributions) the usage distribution is, the more likely is a consumer to make a purchase. Potentially, the usage of the games in possession is unequal because the consumer has a small liking of some games in possession. This makes the purchase of new games more attractive compared to consumers who like and play more of their games. The total past usage of all games in possession has a negative (-.45) and significant effect. Potentially, heavy users either stick to formerly purchased games that they play heavily or they get bored of video games in general due to the heavy usage which makes the purchase of new games unattractive. For the usage of similar games, we find a positive (.18) and significant effect. Consumers seem to have a liking for specific types of games and this liking is reflected in the higher propensity to purchase a new game that is similar to heavily played games in possession.

3.6.2 Step 2: The Influence on Usage

3.6.2.1 The Influence of Price on Usage

Price. We find a positive and significant effect of price on usage in both, equation 3 and equation 4. After controlling for selection effects and the introduction of game and consumer fixed effects plus control variables to capture screening effects, we still find a price-usage elasticity of .09. This implies that for a 1% higher price, we can expect .09% higher usage. Consequently, our analysis provides evidence for positive sunk cost effects above and beyond selection and screening effects. The more a consumer pays for a game, the more intense s/he will use it due to the high price.

Price X NumberofGames. For the moderation of price and the number of games in possession, which we use as a proxy for the experience of the consumer in the marketplace, we find a significant negative effect (-.04). As we mean centered all variables in equation 4 that are included in the interaction, the main effect of price at the average level of number of games is .09. However, this effect diminishes the more games a consumer has in possession in relation to the average number of games in possession across all consumers. We find support for the notion that consumers improve their decision making with a higher level of training and experience (e.g., Fennema and Perkins 2008). Especially unexperienced consumers seem to use mental budgeting and are less aware of biases in their decision making (e.g., Heath 1995). Based on the results of main price effect and the interaction (equation 4) – the total price effect is the combination of main effect and interaction –, we can predict the effect of price on usage for different levels of NumberofGames. At 180 games in possession, the effect of price on usage reaches an effect size of zero. Consequently, the higher the experience of a consumer in the marketplace, the smaller is the sunk cost effect. However, for unexperienced consumers in the marketplace with less than 25 games in possession (9% in our data), we predict price-usage elasticities of .18.

3.6.2.2 Selection Effects

InverseMillsRatio. To control for selection effects, we included the inverse mills ratios from our selection model (step 1) in the outcome model (step 2). We find that the propensity to purchase a game has a positive (.19) and significant effect on usage. This suggests that sample selection is likely to be present.

3.6.2.3 Control Variables

UsageFriends30. The usage behavior of friends has a positive (.07) and significant effect on usage. The more intense the friends of a consumer play the focal game within the first 30 days, the higher is the usage of the consumer. Potentially, a higher usage of friends increases peer pressure and provides more opportunity to engage in multiplayer activities.

SimilarUsage. We find a positive (.06) and significant effect of the usage of similar games on the usage of the focal game. Consumers have a liking for specific kinds of games and this liking is reflected in higher usage.

ReviewScore. The review score of the purchased game has a positive (2.38) and significant effect on usage. Consumers play games more heavily, for which they get a more positive external clue for product quality.

NumberofGames. The number of games in possession at the time of purchase has a negative (-.64) and significant impact on usage.

Table 3.5: Regression Results

	Logit RE (Equation 2)			Linear FE (Equation 3)			Linear FE Moderation** (Equation 4)		
	$Purchase_{i,p}$			$Usage_{i,p}$			$Usage_{i,p}$		
Variable*	**Coef.**	**SE**	**p**	**Coef.**	**SE**	**p**	**Coef.**	**SE**	**p**
$Price_{i,p}$				**.09**	.02	.00	**.09**	.02	.00
$InverseMillsRatio_{i,p}$				.19	.06	.00	.20	.06	.00
$UsageFriends30_{i,p}$				.07	.01	.00	.07	.00	.00
$SimilarUsage_{i,p}$	.18	.00	.00	.06	.01	.00	.06	.01	.00
$ReviewScore_{i,p}$	10.16	.23	.00	2.38	.64	.00	2.42	.64	.00
$NumberofGames_{i,p}$	.94	.01	.00	-.64	.08	.00	-.64	.08	.00
$Gini_{i,p}$	1.99	.13	.00	.49	.55	.37	.50	.55	.37
$TotalUsage_{i,p}$	-.45	.01	.00	-.07	.06	.24	-.07	.06	.27
$Price_{i,p}$ X $NumberofGames_{i,p}$							-.04	.01	.00
$MeanPrice_p$	-.53	.09	.00						
$UsageFriends_{i,p}$	.06	.00	.00						
$Level_i$	.30	.02	.00						
$Groups_i$	-.02	.01	.03						
$Friends_i$	-.01	.01	.33						
$Country_i$	Included								
Game Intercepts	Included			Included			Included		
Consumer Intercepts				Included			Included		
Obs.	280,709			55,622			55,622		

*We take the log of all non-categorical dependent and independent variables to be able to interpret coefficients as elasticities.
**In equation 4, we mean center all variables that are included in the interaction.

Gini and *TotalUsage*. Both variables, gini coefficient of the usage distribution and the total past usage of a consumer have no significant effect on usage.

3.7 Robustness Check

In equations 3 and 4, we assumed that the introduction of game and consumer fixed effects plus control variables captures the screening effect. We relax this assumption in the robustness check and control additionally for screening effect by treating the price variable as endogenous. Potentially, remaining unobserved factors may still influence price. There may be not only (1) consumers who are in general willing to pay more for games based on their expected utility or (2) games for which consumers are in general willing to pay more because it has a general high level of utility. There may also be specific consumers who are willing to pay more for a specific game based on a consumer-game specific expected utility. E.g., a consumer who usually derives not much utility from video games purchases a game that provides a general low level of utility. However, because the game meets exactly the consumer's preferences, he expects to derive a high level of utility from the game although the consumer in general derives not much utility from games and the game in general provides not much utility. To account for this endogeneity, we use an instrumental variable approach and use the following instruments for price:

3.7.1 Instruments for Price

To estimate the potentially endogenous variable price with instruments, we use variables from different sources of game (TimeSinceRelease), consumer (PastPrices, PastSpending) and store (Promotion) variation. Requirements for our instruments are that they are related to price but uncorrelated with the error term (e.g., expected utility) and influence usage only through price.

TimeSinceRelease. The variable TimeSinceRelease captures the number of days between release and purchase of a game. As video games typically follow a price skimming strategy, we expect that prices for older games are lower. Further, the expected usage should be independent of the "age" of a game, i.e., we expect that games purchased right after release can and will be used as much as games bought some weeks after release. Hence, the expected utility of consumers should be independent of how old the game is as game characteristics do not change with growing age (especially in early phases of the game life cycle).

PastPrices. We use the average price that a consumer paid for all previously purchased games as an instrument for the price that a consumer pays for the next purchase. The average price of all previously purchased games changes for each new purchase. Consumers with a high average price are more likely to spend more on a game compared to consumers who purchased every game at a low price. Consequently, prices for high-spending consumers should be higher. As this variable derives from past purchases, it is unrelated with the error term (e.g., expected utility of the focal game).

PastSpending. The variable PastSpending measures the total spending of a consumer during the last month before purchase. E.g., for a purchase in mid-August the variable PastSpending covers all spending from mid-July to the day of purchase in mid-August. The total spending refers to the total amount spent in US dollar. Other currencies are converted to US dollars. We expect that consumers who spent more in the past month are prone to spend more in the future as they are in a temporary heavy spending period.

Promotion. As a store variable, we use a dummy variable that indicates a purchase during a heavy promotion period. The distribution platform has two heavy promotion periods each year: summer and winter sale. Importantly, consumers do not have any knowledge on which games will be on promotion. Hence, we argue that the only effect that this promotion variable may have on consumers' usage is via the price that a consumer pays because the decision which games to include in a promotion cannot be based on consumer-game specific unobservables.

We provide descriptive statistics for our instruments in Table 3.6.

Table 3.6: Descriptives Instruments

Variable	**Description**	**Mean**	**SD**	**Min**	**Max**
$TimeSinceRelease_{i,p}$	Time since release of game p at purchase by consumer i	1174.57	1498.07	.00	10729.00
$PastPrices_{i,p}$ *	Average price index consumer i paid for all previously purchased games at purchase of game p	.63	.23	.01	1.00
$PastSpending_{i,p}$**	Total spending of consumer i during the last month before purchase of game p	80.86	171.85	.05	8266.13***
$Promotion_{i,p}$	Dummy for a purchase during a heavy promotion period for game p of consumer i	.26	.44	.00	1.00

*Prices are measured as a price index in order to make differences in currencies comparable. For each currency, the price is divided by the highest observed price for a game.
**All currencies are converted to USD.
***We keep extreme values for PastSpending. Our results are not influenced by their elimination/inclusion.

3.7.2 Model for Robustness

In the robustness check, we treat price as endogenous and model it through an instrumental variable approach. We estimate the influence on usage using a two-stage least squares regression with game plus consumer fixed effects and price as endogenous variable.

In our first stage, we model the endogenous variable $Price_{i,p}$, through a vector of instruments $Z_{i,p}$ ($TimeSinceRelease_{i,p}$, $PastPrices_{i,p}$, $PastSpending_{i,p}$, $Promotion_{i,p}$) and all other variables included in stage two ($X^2_{i,p}$ plus $\lambda_{i,p}$). Finally, we include in both stages game c^f_p and consumer c^f_i specific fixed effects. The error term of our model is $r_{i,p}$.

$$Price_{i,p} = \beta_1 Z_{i,p} + \beta_2 X^2_{i,p} + \beta_3 \lambda_{i,p} + c^f_p + c^f_i + r_{i,p} \quad (5)$$

The dependent variable in our second stage is the total usage (minutes) $Usage_{i,p}$ of consumer i for game p in the first month of possession. As independent variables, we use the vector of consumer-game specific variables $X^2_{i,p}$ and the inverse mills ratios $\lambda_{i,p}$ from our purchase model (equation 2). The error term of our model is $u_{i,p}$.

$$Usage_{i,p} = \beta_1 \widehat{Price}_{i,p} + \beta_2 X^2_{i,p} + \beta_3 \lambda_{i,p} + c^f{}_p + c^f{}_i + u_{i,p} \quad (6)$$

3.7.3 Endogeneity and Model Estimation

Endogeneity. The F-test of excluded instruments shows that the IVs are sufficiently strong with an F-value of 3,122 (d.f.1 = 4; d.f.2 = 49,322; $p < .01$). However, after the introduction of game and consumer fixed effects plus control variables, the Hausman test for the presence of endogeneity is not significant ($p = .61$).[11]

Estimation. In equations 5 and 6, we use a fixed effects instrumental variable regression estimated with two-stage least squares.

3.7.4 Results of Robustness Check

We report the results of our robustness check in Table 3.7. All instruments utilized in the first stage instrumental variable regression (equation 5) are significant and show expected signs. This supports our choice of instruments. For the potentially endogenous variable price, we still find a positive (.07) and significant effect. The price usage elasticity above and beyond selection and screening effects (equation 6) is .07. This implies that for a 1% higher price, we can expect .07% higher usage. This supports the notion that above and beyond selection and screening effects, a positive sunk cost effect of price on usage exists. The price effect in our robustness check is not significant on a 5% level and only significant on a 10% level. However, the Hausman test for the presence of endogeneity – that tests if the coefficients of the model with and without endogeneity correction are significantly different – is not significant ($p = .61$).

[11]In the robustness check, we find positive price-usage elasticities for different combinations of our instruments.

Consequently, the difference between a statistically significant coefficient (equation 3) and a coefficient that leans towards insignificance (equation 6) is not significant in our case. As more weight should be assigned to the statistical significance of the difference and not the difference between the significance levels, we treat both, results from equation 3 and 6 as meaningful estimates (e.g., Gelman and Stern 2006).

As the results of the inverse mills ratio and control variables in equation 6 are identical to the results of equation 3, we put aside a discussion of these variables.

Table 3.7: Results Robustness Check

	IV FE Regression (Equation 5)			**IV FE Regression (Equation 6)**		
	$Price_{i,p}$			**$Usage_{i,p}$**		
Variable	**Coef.**	**SE**	**p**	**Coef.**	**SE**	**p**
$\widehat{Price}_{i,p}$				**.07**	.04	.07
$InverseMillsRatio_{i,p}$	.19	.02	.00	.19	.06	.00
$UsageFriends30_{i,p}$	.01	.00	.00	.07	.01	.00
$SimilarUsage_{i,p}$	.03	.00	.00	.06	.01	.00
$ReviewScore_{i,p}$	1.66	.15	.00	2.42	.64	.00
$NumberofGames_{i,p}$	.03	.02	.06	-.64	.08	.00
$Gini_{i,p}$	.31	.13	.01	.50	.55	.36
$TotalUsage_{i,p}$	-.07	.02	.00	-.07	.06	.22
$TimeSinceRelease_{i,p}$	-.03	.00	.00			
$PastPrices_{i,p}$	.10	.01	.00			
$PastSpending_{i,p}$	.15	.00	.00			
$Promotion_{i,p}$	-.52	.01	.00			
Game Intercepts	Included			Included		
Consumer Intercepts	Included			Included		
	55,622			55,622		

F-test of excluded instruments: F-value of 3,122.21 ($d.f._1 = 4$; $d.f._2 = 49{,}322$; $p < .01$).
Hausman test for the presence of endogeneity: $p = .61$.

Additional to the described models, we estimate supplemental models to access the impact of controlling for selection effects, screening effects and game plus consumer heterogeneity. We outline a summary of the effect of price on usage across these models in Table 3.8.

As expected, we find evidence for a general positive effect of price on usage. All analyzed model choices lead to positive price-usage elasticities (from .337 to .071) and all models are significant with a maximum p-value of .07. Consequently, we find empirical support for the expectation that higher prices are associated with higher usage. We show that this effect is due to price and not due to e.g. the expected utility that may shape the price that a consumer pays.

Table 3.8: Impact of Model Choices on the Price-Usage Effect

	Price-Usage Elasticity		
Model	**Coef.**	**SE**	**p**
OLS	.337	.01	.00
2FE	.092	.02	.00
2FE IMR	.088	.02	.00
2FE IV	.083	.04	.03
2FE IV IMR	.071	.04	.07

2FE: Include game and consumer specific intercepts.
IV: Estimate price with instruments.
IMR: Include inverse mills ratio from selection model.

3.8 Discussion and Implications

This study builds on a stream of articles that analyze the influence of price on post-purchase behavior, including accelerated usage and the reduction of stockpiled goods (e.g., Ailawadi and Neslin 1998), tariff structures (e.g., Iyengar et al. 2011; Ascarza et al. 2012), payment equity (e.g., Bolton and Lemon 1999), payment plans (e.g., Gourville and Soman 2002) and isolated effects of price on usage (e.g., Arkes and Blumer 1985; Ashraf et al. 2010). We contribute to the literature by analyzing the direct effect of price on usage plus taking into account screening and selection effects. An additional special aspect of our research is that we observe the actual usage of each purchased product for a huge set of consumers. Further, as we have information about the usage behavior of a consumer's friends, we are able to analyze a consumer's usage behavior in the context of her/his social group.

The analysis of 3,161 consumers plus 63,821 friends over 18 months provides evidence for a positive effect of price on usage above and beyond selection and screening effects. We find a price-usage elasticity of .09. This effect diminishes with a rising experience of the consumer in the marketplace. However, for unexperienced consumers we predict price-usage elasticities of .18.

We provide a predictive (equation 3 and 4) and descriptive (equation 6) model to assess the influence of price on usage. Although our instruments in the descriptive model are sufficiently strong, the Hausman test for the presence of endogeneity is not significant.

Potentially, we are able to capture the influence of unobserved factors (e.g. expected utility) through consumer and game fixed effects plus the introduction of control variables. Consequently, we prefer the predictive model as accounting for endogeneity in our descriptive model is costly (e.g., Rossi 2014; Ebbes et al. 2011) and the difference between the predictive and descriptive model is not significant.

Further, we can generate insights from our set of control variables. The positive effect of friends' usage suggests that consumers derive utility not only from individual but also social aspects. Consumers can play games together with friends or exchange experiences through social media. Not being in possession of a popular game among friends can isolate consumers. Consequently, the usage of friends does not only influence the propensity to purchase the game but also the usage after purchase. Further, we find evidence for consumers increasing positive emotions such as a game's liking with rising mastery of the game (e.g., Holbrook et al. 1984). The effects of the total usage of similar games are positive. Consequently, consumers derive more utility from games that are similar to already mastered games (e.g., Murray and Bellman 2011). This effect is reflected in the positive effect of similar usage on both, usage and propensity to purchase the game.

A positive impact on usage and the propensity to purchase have the review score that a consumer observes at the time of purchase and the mean review score. We control for the general level of game quality by introducing game intercepts. Consequently, the only variation comes from the perception and rating of the game by other consumers. The better it is rated, the stronger is the effect on usage. Potentially, when making the purchase, consumers create a mental account (e.g., Thaler 1985) for the game in which they store price but also review information. These stored information can then drive the post-purchase behavior.

The negative effect of the number of games that a consumer has in possession can be an indicator for cannibalization effects. With a rising number of games, consumers have to distribute their available time across a larger set of alternatives – this can lead to lower usage. Further, with a growing experience in the marketplace consumers are less effected by the sunk cost effect of price on usage.

The future usage of recently purchased games seems to be independent of the usage distribution of games in possession and the total past usage of all games. Potentially, each new game has the chance to become a heavily played game independent of the usage-gini coefficient. For the total past usage, possibly the opposing effects that consumers get bored of video games or show a tendency to play heavily balance.

3.8.1 Implications for Managers and Researchers

Managers are interested in a high usage as past usage may be related to future purchase behavior (e.g., Park et al. 2010; Murray and Bellman 2011). Especially in the entertainment sector (e.g. video games, movies, books), in which the publication of prequels or sequels is an important strategy, managers should be aware of the effect of price on usage. Further, a higher usage provides more opportunity for additional revenue streams like e.g., in-game purchases. With knowledge about the price-usage elasticity, managers are able to manage customer behavior through price and are able to find new possibilities to foster customer satisfaction (e.g., Bolton and Lemon 1999). With the increase of usage, potentially, brand attachment, brand attitude and customer loyalty increase which can lead to a more positive word of mouth.

Consequently, knowledge about the influence of price on usage enables managers to account for purchase and post-purchase effects when setting prices. One major implication of this study is to be careful with price promotions. Beside other negative effects like the influence on reference prices (e.g., Blattberg et al. 1995), price promotions also decrease consumers' usage. Therefore, it is important to not manage products as silos. Without taking into account the influence of marketing decisions (e.g. pricing) on post-purchase behavior, potential spillover effects on other products of the company e.g., through brand attachment or loyalty are neglected.

Further, companies should design their price discrimination strategies additionally on the basis of a consumer's peer and past usage behavior. As the usage of friends and the usage of similar games positively affects the propensity to purchase and the subsequent usage behavior, the willingness to pay should be higher, (1) the more heavily a consumer's friends used the game and (2) the more heavily a consumer used similar games in the past.

The review score has a positive impact on the propensity to purchase and strong positive impact on usage. Consequently, companies should induce marketing actions to encourage especially consumers with a high liking of the game to submit a review. As a high usage is typically achieved for consumers with a high liking, induced encouragements should be designed to be attractive only for consumers with a high usage (e.g., access to end-game content after review).

Additionally, companies can anticipate the positive price-usage relation and should target specifically consumers who paid lower prices with communication that fosters usage like e.g., a reminder that the game is not yet used or a hint that a special game event takes place.

Finally, our results help researchers to calibrate their models and expectations.

3.8.2 Limitations

As any research, this study is not free from limitations that offer fruitful opportunities for future research.

First, we analyze only one industry in the entertainment sector. Future research has to qualify how our results can be generalized across different industries. However, as the sunk cost effect is a general concept that is not linked to one specific industry, we expect future research to find similar results in other industries e.g., books or subscription services.

Second, as we have only information about price and purchase but not cost or profit margin data, we are not able to analyze the impact of price changes on a company's long-term profit. This is a fruitful opportunity for future research to analyze the impact of prices on usage and the subsequent impact on company success.

Our research provides an indication that companies should not only look at the impact of price changes on purchase but also post-purchase behavior.

4. The Effect of Usage on Cross-Buying

Chapter 4 is a single author paper by Johannes Auer.

Abstract

Previous research on cross-buying has identified a substantial set of drivers but neglects a driver in the field of consumer behavior: the impact of consumers' product usage. In this study, I analyze the impact of a product's usage on the propensity to cross-buy another product within the same franchise. Based on a panel dataset of 793 consumers, I find for a digital good that higher product usage leads to a higher propensity to purchase an additional product within the same franchise. This effect increases for consumers with low levels of category experience. The results of this research have relevant implications for researchers in adding a new cross-buying driver: product usage. Practitioners profit from my findings as knowledge about the relationship between product usage and purchase propensity fosters new ways of e.g., consumer targeting.

Keywords: Usage; Cross-Buying; Post-Purchase Behavior

4.1 Introduction

Leveraging a firm's brand value in order to maximize revenues and profits is of growing importance for firms and to achieve this goal, companies can sell different products under the same brand (e.g., Kumar et al. 2008). E.g., in the movie industry several films and television series are published under the Star Wars brand. Offering different products under the same brand is popular as it serves as a new product development strategy that offers the opportunity to leverage parent brand equity, reduce cost and risk (e.g., Aaker and Keller 1990; Reddy et al. 1994; Sullivan 1992; Swaminathan 2003) and further increase acceptance and growth potential (e.g., Tauber 1988; Völckner and Sattler 2006). This strategy can extend the brand and transfer associations of the brand to new products (e.g., Kim and Sullivan 1998).

Consequently, firms' focus has changed from solely keeping customers to the field of cross-selling additional services and products as a valuable field of customer relationship management (e.g., Verhoef et al. 2001). Therefore, it is important to understand the motivation of consumers to cross-buy – purchase different products from the same firm – and to identify drivers of cross-buying (e.g., Kumar et al. 2008). Enhanced cross-buying is associated with an enhanced profitable lifetime durations of consumers (e.g., Reinartz and Kumar 2000) and has a positive impact on the customer lifetime value (e.g., Blattberg et al. 2009). As companies cannot always target all their customers with marketing actions, it is a necessity to identify consumers with a higher propensity to cross-buy (e.g., Kumar et al. 2008). Previous research covers a set of drivers that influence consumers' propensity to cross-buy (e.g., customers' attitude towards the firm, socio-demographic characteristics and marketing effort) but it neglects an important driver in the field of consumer behavior: consumer's usage of the base product. In this study, I analyze how the usage of a product influences consumers' decision to purchase an additional product from the same brand, i.e., to cross-buy.

I test my research questions in the context of the video game industry. As of 2016, 17 of the top 20 bestselling video games were sequels – successors of established products under the same brand –, the industry seems to rely on exploiting established brands. Consumers who purchase a game potentially also purchase sequels or prequels – predecessors of established products under the same brand. Over a 25 year period, the video games industry could achieve annual growth rates of 10-15% (e.g., Zackariasson and Wilson 2010) and generated revenues of \$23.5 billion in 2016 (ESA 2016). This makes the video games industry a fruitful and relevant field for the analysis of consumer's cross buying – the decision to purchase an additional game within a franchise. I define a franchise as a group of games under the same brand.

My data consists of a panel of 793 consumers whose purchasing behavior on one of the leading online distributors of video games is observed in 15 countries over a time period of 18 months. The distribution platform fulfills two functions for users: (1) users obtain access to games in the shop and (2) the platform is a community in which users can join groups and communicate or play with friends. Consequently, the dataset includes a set of consumer and game variables. Further, I am able to track not only a consumer's behavior but also the behavior of his/her friends within the community. The video games in my data are purchased through a one-time payment. Further, games can be purchased only once and have no usage restrictions after purchase.

In this paper, I analyze consumers who purchase a base game which I define as a game within a franchise that has at least one sequel or prequel e.g., Super Mario Bros. 2 as base game, Super Mario Bros. 1 as prequel and Super Mario Bros. 3 as sequel. I define a sequel (prequel) as the subsequent (preceding) game within the franchise in terms of the distribution platform's release date. In my context both, sequels and prequels of the base game are relevant targets for consumers' cross-buying. Each consumer's purchase is set as base game to analyze subsequent purchases within the franchise. Consequently, I want to analyze the impact of the base game's consumer behavior on the decision to cross-buy other games within the franchise.

Previous research suggests that past consumer behavior (e.g., past consumption dynamics or practice with a product) is related to future purchase behavior, e.g., via brand attachment, brand attitude and customer loyalty (e.g., Park et al. 2010; Murray and Bellman 2011; Iyengar et al. 2007). Further, a higher involvement and investment of consumers in the relationship can increase switching cost (e.g., Kumar et al. 2008; Pick and Eisend 2014) and consumers increase positive affects such as liking with rising mastery of a product (e.g., Holbrook et al. 1984). Additionally, the quality of a video game cannot be accessed prior to purchase. However, if consumers have already purchased and used a game of the franchise, they can transfer the perceived quality of the base product to other games of the franchise (e.g., Wernerfelt 1988). Consequently the usage of the product should have a positive impact on the purchase of another game within the franchise.

Nijssen (1999) finds that category experience and variety seeking of consumers have a negative effect on the success of brand extensions – the introduction of a new product labeled with an established brand (e.g., Keller and Aaker 1992). As consumers with a high level of category experience are better aware of alternatives (e.g., Smith and Park 1992), they have to rely less on experience with the base product. Consequently, the effect of the base product's usage could be heterogeneous for consumers with different levels of category experience.

The goal of this study is to capture factors that determine consumers' purchases of other games within the franchise. The main research questions are the following: (1) What effect has the base game's usage on the decision to purchase other games within the franchise. (2) How is the effect of usage on purchase moderated by the level of category experience.

On the basis of my data, I estimate a logit model that assesses the decision of a consumer to buy another game within the franchise.

I contribute to the literature by providing evidence for insights that are based on actual post-purchase behavior and I add a new driver for consumers' cross-buying: the base product's usage. Both, the usage behavior of the focal consumer and all of his friends are analyzed and I find that usage of the base game significantly influences the decision to purchase another game within the franchise positive. Further, this effect increases for consumers who have low levels of category experience.

My findings allow me to draw new implication as I have information about the post-purchase behavior of consumers. First, managers should optimize and induce higher levels of consumers' usage with the base product to boost cross-buying. Second, in markets where consumers' cross-buying is rare, managers may want to focus on convincing consumers with a high base product's usage as they have a higher propensity to cross-buy. Finally, if managers evaluate if they should introduce a new brand extension, the brand extension's likelihood of being successful is higher if consumers heavily use the base product. However, managers have to account for both, consumers' product usage and category experience. Especially for consumers with a low level of category experience, managers can utilize the effect of product usage on cross-buying. Managers must be aware, that consumers with a high level of category experience rely less on product experience when deciding on an additional purchase within a franchise.

4.2 Contribution to the Literature

Kumar et al. (2008) classifies previous literature (e.g., Verhoef et al. 2001; Ngobo 2004; Verhoef and Donkers 2005) on the drivers of cross-buying and cross-buying intension in three areas: studies that consider customers' attitude towards a firm plus its products, socio-demographic characteristics, and marketing effort by the firm. In the field of customers' attitude Verhoef et al. (2001) find that consumers' perceived payment equity – perceived price fairness – has a positive impact on cross-buying because the perceived fairness associated with previously purchased products has a positive effect on the perceived fairness of products purchased in the future. Further, consumers' willingness to continue the relationship with the firm, trust and consumers' evaluations of the ability of the firm to provide different products have a positive effect on cross-buying intention (e.g., Ngobo 2004; Aurier and N'Goala 2010). Additional drivers of cross buying in the field of socio-demographic characteristics are income, education age and gender (e.g., Verhoef et al. 2001; Li et al. 2005). Finally, for marketing efforts, previous literature argues that especially the extent of direct mail and loyalty programs are important drivers of cross-buying. Further drivers are average interpurchase time, focused buying, product category, ratio of product returns (e.g., Kumar et al. 2008), channel of acquisition (e.g., Verhoef and Donkers 2005) and switching costs of households (e.g., Li et al. 2005). However, previous literature is inconclusive about the effect of consumers' satisfaction or perceived quality and value of offered products on cross-buying (e.g., Verhoef et al. 2001; Ngobo 2004; Li et al. 2005).

Consumers engage in cross-buying as the purchase of unknown products is associated with uncertainty. Consequently, consumers rely on previous experiences with the base product to reduce risk and uncertainty for the purchase of an unknown product (e.g., Kumar et al. 2008). The higher the quality of the base product, the more successful is cross-buying because of positive spillover effects from the base product to the cross-bought product. This improves consumers' perception of the cross-bought product (e.g., Keller and Aaker 1992).

Offering additional products under one brand can leverage brand equity, reduce cost and risk (e.g., Aaker and Keller 1990; Reddy et al. 1994; Sullivan 1992; Swaminathan 2003) and further increase acceptance and growth potential (e.g., Tauber 1988; Völckner and Sattler 2006). Finally, consumers engage in cross-buying because consumers' involvement and investment in a relationship can increase switching cost (e.g., Pick and Eisend 2014). This makes the purchase of products outside of the brand less attractive.

Further, companies can signal category expertise to consumers through a high number of branded products within one category. This higher level of category expertise can influence consumers' choice (e.g., Berger et al. 2007).

Cross-selling can also increase risk for brands as extensions may dilute the brand equity (e.g., Loken and John 1993; John et al. 1998) or cannibalize purchases of the base product. However, on an aggregate level, previous literature finds evidence that the increase in incremental sales seems to dominate cannibalization effects (e.g., Reddy et al. 1994). Further, consumers with adverse behavioral traits (e.g., limited spending or excessive service requests) have a negative impact on firm profitability when engaging in cross-buying (e.g., Shah et al. 2012).

Finally, previous research suggests that if consumers have already purchased a firm's product, the usage of an additionally purchased product of the firm is lower compared to consumers who purchase a firm's product for the first time (e.g., Krishnamurthy and Shainesh 2017).

Consequently, the literature lacks a driver of cross-buying in the field of consumer behavior: consumers' usage of the base product. I am not aware of any study that analyzes how the usage of the base product impacts the purchase propensity of additional products. Further, several studies on the drivers of cross-buying are based on surveys (e.g., Verhoef et al. 2001; Ngobo 2004). The unique feature of this research is that I can link actual consumer and peer behavior to the propensity to cross-buy. In contrast to e.g., Swaminathan (2003) I do not rely on purchase frequency of FMCGs as experience measure but am able to observe how much the base product and the category is actually used. I observe usage for both, a consumer and all friends of the consumer. Consequently, I add to the literature by providing insights on the relationship between consumers' actual usage behavior and the purchase of additional products within the same brand.

4.3 Conceptual Framework and Research Questions

In order to identify the effect of usage on purchase decisions, I use the framework shown in Figure 4.1. The focal outcome variable in my framework is cross-buying – the decision of a consumer to purchase an additional game within the franchise. I model the decision to purchase as a function of the base product's usage and control variables. As controls I utilize variables from the areas of consumer behavior and base game characteristics. Further, I introduce a moderating effect between base game's usage and a consumer's category experience because I expect the effect of usage to be heterogeneous for different levels of category experience.

Figure 4.1: Conceptual Framework

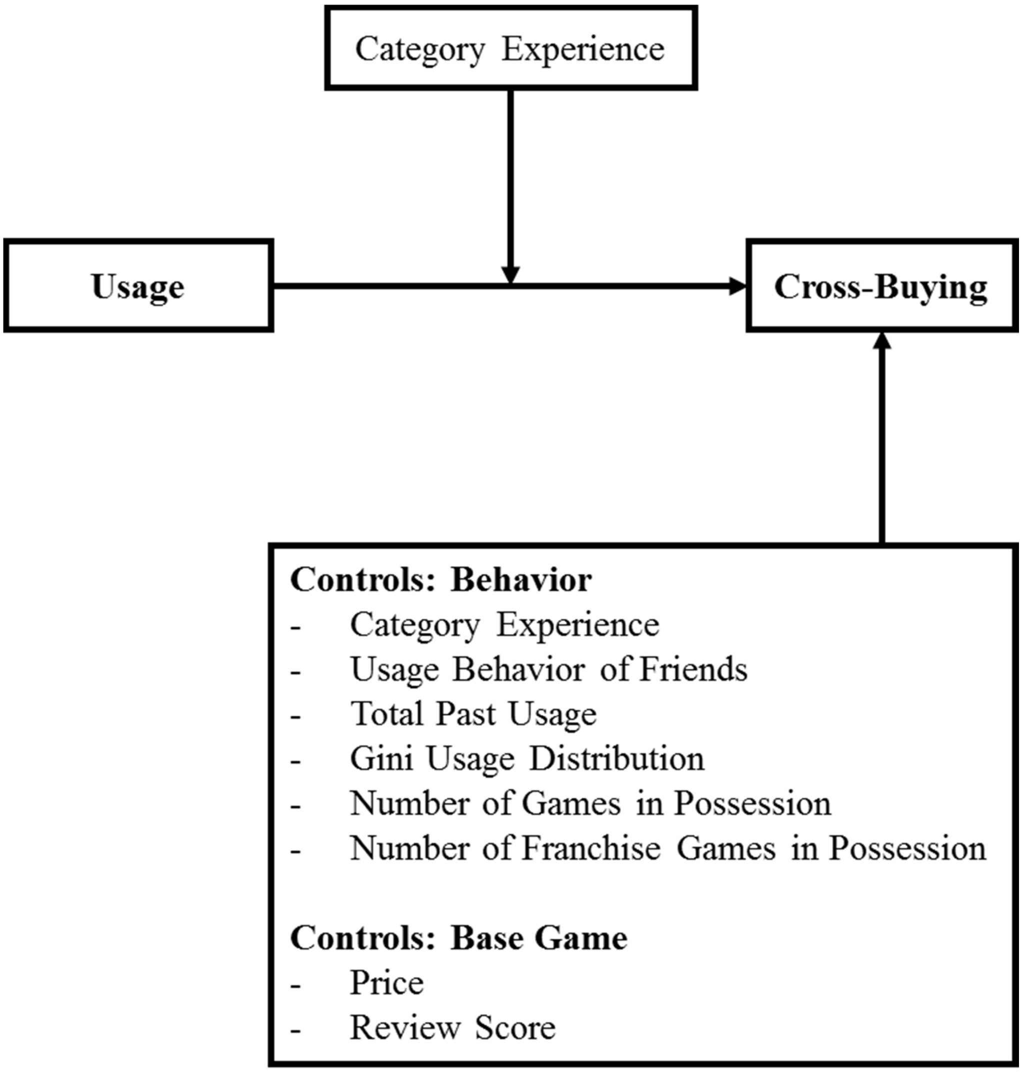
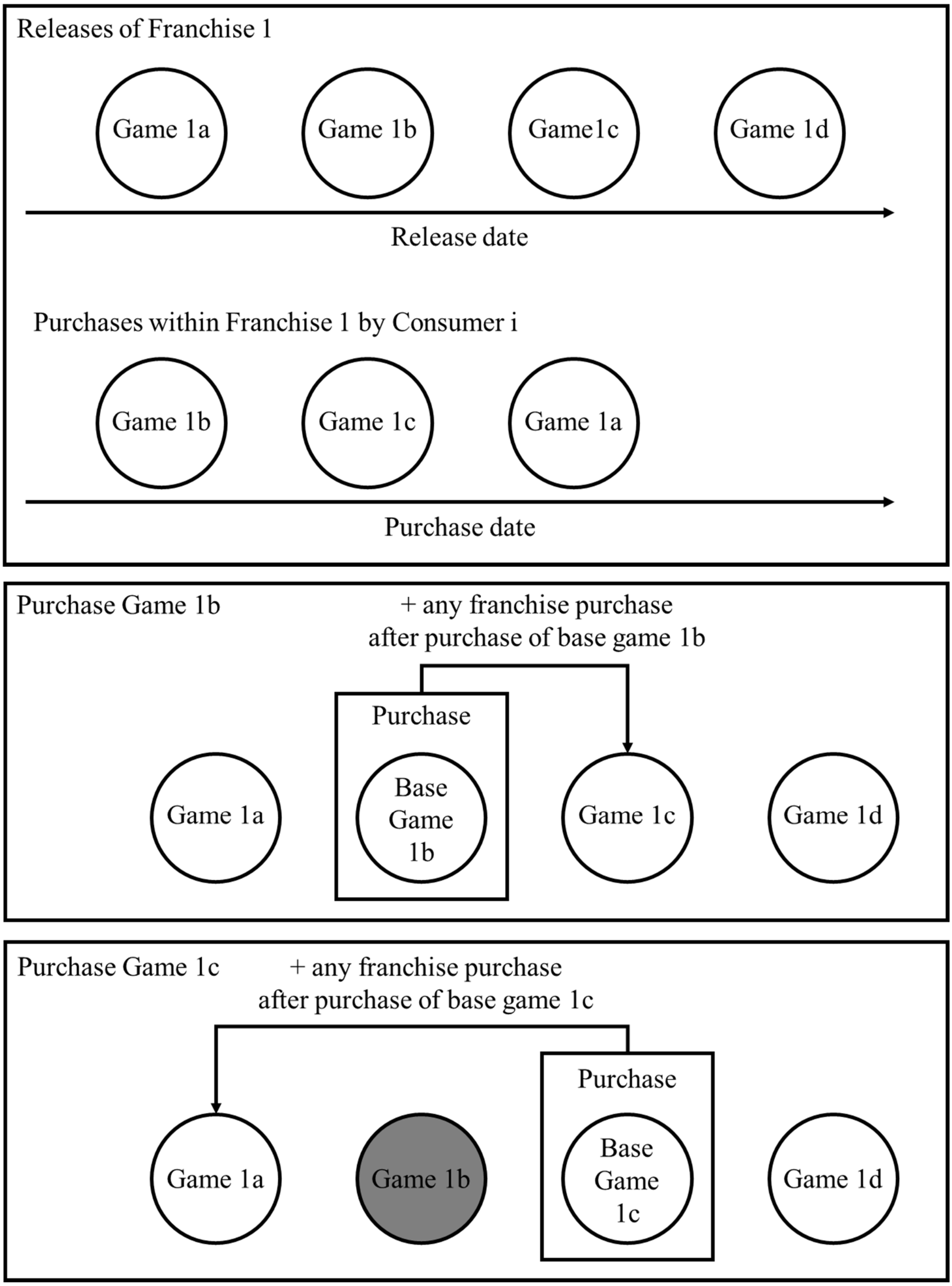


Figure 4.2 shows an exemplary purchase process for one franchise and one consumer. A Franchise 1 consecutively releases Games 1a-1d. Consumer i purchases Game 1b first, Game 1c second and finally Game 1a during my observation period. After the purchase of Game 1b – which is now my base game – I am interested in the question, if consumer i purchases any other games within Franchise 1. Consumer i purchases Game 1c and Game 1a after the purchase of Game 1b. Consequently, I observe for base game 1b at least one additional purchase. As consumer i purchases multiple games within the Franchise 1 during my observation period, I consecutively analyze for each game that is purchased if consumer i makes an additional purchase. Each game that consumer i purchases becomes consecutively the base game.

Figure 4.2: Exemplary Purchase Process



After the purchase of Game 1c – which is now my base game – I observe that consumer i purchases Game 1a. Finally, if I take Game 1a as my base game, I do not observe an additional purchase within the franchise. I conclude that for base games 1b and 1c I observe an additional purchase by consumer i within the Franchise 1. For base game 1a I do not observe the purchase of an additional game within the franchise. For my analysis, it is necessary that the consumer at least purchases one base game.

Higher levels of usage could serve through multiple ways as facilitator of additional purchases. (1) Usage of the base game can be used as risk reduction mechanism by consumers. The quality of a video game cannot be accessed prior to purchase. However, if consumers have purchased and used a game of the franchise, they can transfer the perceived quality of the base product to other games of the franchise (e.g., Wernerfelt 1988; Smith and Park 1992). Further, information created from experiencing the base product are more memorable and reliable than external information (e.g., Kempf and Smith 1998; Völckner and Sattler 2006). (2) Higher levels of consumers' involvement and investment in a relationship – reflected in higher usage – can increase switching cost (e.g., Pick and Eisend 2014) and consumers increase positive affects such as liking with rising mastery of the game (e.g., Holbrook et al. 1984). Further, the more experience consumers have with the base product, the more positive is their expectation of the additional product's quality (e.g., Kim and Sullivan 1998; Hem and Iversen 2003). This could lead to (3) higher brand attachment, brand attitude and customer loyalty (e.g., Park et al. 2010; Murray and Bellman 2011; Iyengar et al. 2007). Further, a higher usage leads to a more positive perception of payment equity which has a positive influence on consumers' probability of cross-buying (e.g., Verhoef et al. 2001).

Therefore, I expect:

H_1: The usage of the base game has a positive effect on the decision to purchase an additional game within the franchise.

Smith and Park (1992) argue that consumers are better aware of alternatives the larger their experience with the category is. In the context of video games, I define category experience as the accumulated usage of similar games. Nijssen (1999) finds that larger variety seeking of consumers has a negative effect on the purchase of additional products under the same brand. Further, variety seeking of consumers with a high level of category experience could be higher as they derive less marginal utility from an additional game from the same category. Consequently, I expect that there is heterogeneity in the effect of usage on additional purchases. The more heavily a consumer has used similar games, the larger is the consumer's category experience. With higher category experience, the consumer is better aware of alternatives and needs to rely less on experience with the base product as risk reduction device. Therefore, the effect of the base game's usage on additional purchases should be lower for consumers with a high level of category experience compared to consumers with lower levels.

Therefore, I expect:

H_2: The effect of usage on additional purchases of the franchise is stronger for consumers with a low level of category experience.

I have information about the following control variables that I observe at the time of the base game's purchase: The total usage of similar games, the total usage of all friends for the base game, the total usage of all games in possession, the gini coefficient of the usage distribution of all games in possession, the number of games in possession, the number of franchise games in possession, the price at which the base product is purchased and the review score of the base game.

As I include these variables as controls in my models, I refrain from formulating expectations about the effect on my dependent variable.

4.4. Data and Measures

The object of my study are computer games that are part of a game franchise and are purchased through an online distribution platform. The online distribution platform has over 125 million consumer accounts and is one of the leading online distributors of video games. Every consumer of the platform has an own publicly accessible profile webpage. This profile provides information about the consumer (e.g., country, friends) and the consumer's games library. In order to be able to use a purchased game, consumers have to install a software on their devices. This software automatically registers the games consumers purchase as well as the usage behavior and updates the user's profile webpage. Further, consumers can connect with other consumers – friends – on the platform to communicate or play together.

I randomly select 5,000 users with publicly available profiles from 15 countries. I select my sample based on two criteria: (1) the user was active within the last 30 days; (2) the user is connected within the network which means that s/he has at least one "friend" or has joined at least one "group". I clean my sample of 5,000 users based on the criterion that (3) the user has made at least one purchase of a game that is part of a franchise within my observation period. This results in a core dataset of 793 consumers. Additionally, I have information about all "friends" of the 793 focal customers. This leads to an additional 10,605 friends whose purchase and usage behavior I observe daily. I use the behavior of friends to explain the behavior of the 793 core consumers. As I am interested in subsequent purchases of any additional game within the game franchise, I analyze games with at least one additional game in the game franchise. In total, I observe 9,540 purchases by consumers of games that are part of a franchise. In 7,777 instances do the consumers purchase a base game but no other game within the franchise. In 1,763 instances do the consumers purchase a base game and subsequently another game within the franchise. I collect my data for the period February 2015-July 2016. An observation in my data is always a consumer-base game combination: a game that is purchased by a consumer. For each game that a consumer purchases, I look at if the consumer subsequently purchases another game within the franchise. I observe for one consumer multiple purchases of different games and for one game multiple purchases by different consumers.

I have information about consumers from the following countries: United States (39.6%), Russia (12.6%), UK (7.3%), Canada (7.1%), Germany (6.7%), Australia (5.0%), Brazil (4.1%), France (3.6%), Spain (3.5%), Poland (3.2%), Sweden (2.5%), Netherlands (2.0%), South Korea (1.3%), Ukraine (.9%), Turkey (.7%).

4.4.1 Dependent Variables

Purchase. As dependent variable, I analyze the binary variable *Purchase* that takes the value 0 if a consumer purchases the base game but no other game of the franchise and 1 for consumers who purchase the base game plus an additional game of the franchise. As I am interested in the effect of the base game's usage on additional purchases, I analyze for each game that a consumer purchases (base game) if the consumer purchases another game within the franchise. In the example in Figure 4.2, I would observe a 1 for the consumer-base game combinations "Consumer i"-"Game1b", "Consumer i"-"Game1c" and a 0 for "Consumer i"-"Game1a".

4.4.2 Independent Variables

Usage. As central independent variable, I operationalize usage as the cumulated usage minutes within the first 30 days of possession for a consumer-base game combination. If consumers purchase another game within the franchise, the average time between purchase of base game and the additional game of the franchise is 55 days. Consequently, my measurement captures usage of the base game prior to the purchase of the additional game. The base game's usage within the first 30 days of possession is defined independent of whether or not the consumer purchases an additional game. I include in my analysis only consumer-base game combinations that I observe for at least 30 days.

Table 4.1: Descriptives

Variable	Description	Mean	SD	Min	Max
$Usage_{i,g}$	Total usage (minutes) of consumer i for game g in the first month of possession	7.51	20.82	.00	411.00
$CategoryExperience_{i,g}$	Total usage (minutes) of similar games to game g for consumer i at time of purchase	1546.63	7547.84	.00	229560.00
$UsageFriends_{i,g}$	Total usage (minutes) of game g for all friends of consumer i at the end of the first month of possession	42.44	301.65	.00	17216.70
$Price_{i,g}$*	Price index of consumer i for game g	.55	.36	.02	1.00
$ReviewScore_{i,g}$	Review score of game g at purchase by consumer i	86.94	11.00	15.17	100.00
$NumberofGames_{i,g}$	Number of games in possession of consumer i at purchase of game g	167.65	208.74	3.00	1862.00
$Gini_{i,g}$	Gini coefficient of the usage distribution of all games in possession for consumer i at purchase of game g	.76	.09	.00	.96
$TotalUsage_{i,g}$	Total usage (hours) of all games for consumer i at purchase of game g	1644.54	1364.59	1.40	11703.80
$NumberofFranGames_{i,g}$	Number of franchise games in possession of consumer i at purchase of game g	1.02	1.51	.00	12.00

*Prices are measured as a price index in order to make differences in currencies comparable. For each currency, the price is divided by the highest observed price for a game.

4.4.2.1 Consumer Behavior

CategoryExperience. The variable CategoryExperience captures for each consumer's base game purchase the cumulated usage of the five most similar games to the base game. The distribution platform offers information to consumers on the shop site of a game about the five most similar games. I adopt this definition and measure for each base game purchase of a consumer how much the consumer has played similar games. Two possible effects of a high usage of similar games are possible. First consumers have a general liking for certain types of games that they will continue to purchase in the future. Second, variety seeking effects could lead to consumers switching to other kind of games or other franchises.

UsageFriends. One advantage of my dataset is that I am not only able to observe a consumer's behavior but that I also observe the behavior of his/her friends. Choi and Kim (2004) find that the experience of consumers is positively influenced by the interaction with friends. Consequently, consumers should be more attached to games that many friends have played. Potentially, they transfer this attachment to the whole franchise (e.g., Kim and Sullivan 1998). The variable UsageFriends provides information about the total usage of all friends for a specific base game within the first 30 days of possession. This variable is defined independent of whether or not the consumer purchases an additional game and captures and includes friends' usage prior to the potential purchase of an additional game.

TotalUsage. The variable TotalUsage captures the total past usage of all games in possession for a consumer at the time of the base game's purchase. Two possible effects of a high total usage of games in possession are possible. First, consumers get bored by video games and turn to other activities. Second, a high total usage of games in possession is an indicator of a tendency to play heavily and to derive more utility from the purchase of additional games.

Gini. Consumers can either have a preference for some favorite games in their possession that they play all the time or consumers can distribute their time equally on all games in possession. An equal distribution can be a sign for variety seeking which can decrease success chances of purchasing additional products (e.g., Nijssen 1999). Consequently, consumers with an equal distribution should be more prone to try new games and franchises compared to consumers who have developed an "all-time favorite" game or franchise. Therefore, I include the variable Gini, which is the gini coefficient of the usage distribution of all games in possession for a consumer at the time of the base game's purchase. The variable Gini is bound between 0 (equal usage distribution) and 1 (unequal usage distribution).

NumberofGames. The variable NumberofGames captures how many games a consumer has in possession at the time of the base game's purchase. A high number of games can either be an indicator for a consumer who derives a lot of utility from video games. It can also be an indicator of cannibalization effects. With a growing number of games, consumers have to divide their available time on more games. Potentially, some games in possession are not yet used by the consumer and this makes the purchase of new games less attractive.

NumberofFranGames. The variable NumberofFranGames captures how many games of the franchise a consumer has in possession at the time of the base game's purchase. A high number of franchise games can be an indicator for a high liking of the franchise by the consumer. In contrast, it can increase the probability that the consumer grows bored of the franchise and searches for alternatives.

I provide a descriptive summary in Table 4.1.

4.4.2.2 Base Game

Price. I obtain daily price information from the online distributor's shop and match them with the time of purchase for each consumer's purchase. In my data, price variation for a game comes from two sources: (1) regular price changes (2) price promotions. Consequently, I observe different prices for the same game depending on the circumstances under which the consumer made the purchase. As I observe consumers in different countries with different currencies, I decide to use a price index as price variable. The price index measures for each country and game the relation of the price to the highest observed price in my observation period. Consequently, my price variable is bound between 0 (low prices) and 1 (highest price) and allows me to compare the effect of prices across several currencies.

ReviewScore. For external cues of the base game's quality, I use the review score that a consumer observes in the shop of the online distributor before making the purchase. The review score is created by other consumers who up vote or down vote the game after purchase. I match each game purchase with the day-specific review score for that game. The review score is calculated by taking the relation of up votes to total votes.

4.5 Model

I rely on a model that assesses the impact on the decision to purchase an additional game within the franchise. To test my research questions, I use a logit model which is in line with other studies e.g., on consumers' decision to purchase a brand extensions (e.g., Swaminathan 2003). More specifically, to allow for game and consumer specific intercepts, I apply a logit model estimated with hierarchical Bayes (Stan Development Team 2016). This approach accounts for the fact that multiple observations (i.e., purchases) originating from one game or one consumer may share common, unobserved characteristics. For the priors of my logit model, I use a set of normal distributions with mean 0 and unknown scale parameter as proposed by Gelman et al. (2008). For the unknown scale parameter, I use cauchy(0, 5) priors and run four chains with 50,000 draws for warmup and 4*50,000 draws for inference. The sampling approach uses Markov Chain Monte Carlo, in particular Hamiltonian Monte Carlo. The results are robust against different prior selections, and all chains are well converged and mixed with a potential scale reduction factor ($\hat{R}$) of 1. For 9 out of 11 coefficients, I achieve effective sample sizes of 200,000. For the other two coefficients, the lowest effective sample size is 102,717.

As dependent variable, I model whether or not a consumer i chose to adopt the respective game plus any other game within the franchise of base game g. I only analyze games for which at least one other additional game within the franchise exists.

$$y_{i,g} = \begin{cases} 1, & if\ consumer\ i\ adopts\ the\ base\ game\ g\ plus\ any\ other\ game\ within\ the\ franchise \\ 0, & if\ consumer\ i\ adopts\ the\ base\ game\ g\ but\ no\ other\ game\ within\ the\ franchise \end{cases}$$

$$logitP\left(y_{i,g} = 1 \middle| \beta X_{i,g}, \beta_2 Usage_{i,g} * CategoryExperience_{i,g}, c_i^r, c_g^r, \mathrm{e}_{i,g}\right) \quad (1)$$

As independent variables, I use a vector of consumer-base game specific variables $X_{i,g}$ ($Usage_{i,g}$, $CategoryExperience_{i,g}$, $UsageFriends_{i,g}$, $TotalUsage_{i,g}$, $Gini_{i,g}$, $NumberofGames_{i,g}$, $NumberofFranGames_{i,g}$, $Price_{i,g}$, $ReviewScore_{i,g}$). Further, as I expect the impact of $Usage_{i,g}$ to vary for different levels of $CategoryExperience_{i,g}$, I add an interaction of these two variables. In order to ease interpretation, I mean center all variables that are included in the interaction. Further, I take the log of all non-categorical dependent and independent variables to harmonize variable scaling. The error of my model is $\mathrm{e}_{i,g}$.

Unobserved heterogeneity. To safeguard against unobserved factors of consumers and games that may drive the decision to purchase additional games of the franchise, I introduce consumer c_i^r and game specific intercepts c_g^r. These intercepts control for unobserved fix heterogeneity that arises e.g., because (1) there are some consumers who are in general more prone to purchasing additional games within a franchise (2) there are some games for which the purchase of additional games within the franchise is in general more attractive.

4.6 Empirical Results

4.6.1 The Influence of Usage on Additional Franchise Purchase

My first main research question is (1) what effect has usage on the purchase of other games in the franchise. I report the results of my main model in Table 4.2. In line with H_1, I find a positive (.32) and significant effect of usage on additional franchise purchases as the 95% posterior interval excludes zero. Consequently, the more a consumer has used the base game, the more likely is it that the consumer purchases another game within the franchise. Potentially, higher switching cost through higher levels of consumers' investment (e.g., Pick and Eisend 2014) and a more positive expectation of the additional product's quality through more experience with the base product (e.g., Kim and Sullivan 1998; Hem and Iversen 2003; Völckner and Sattler 2006) lead to a higher probability of purchasing the additional product. Further, a higher usage is an indicator for a higher liking for the game. As other games of the franchise are potentially similar, chances are high that the consumer also likes these games.

I report the predicted probabilities for different specifications of the base product's usage in Table 4.3. For my main model, I find a predicted probability for purchasing another game within the franchise of .168 if all variables are set to their mean. Everything else set to their mean, I predict for a usage level above the 75% quantile (heavy-users) a probability of .267 and below the 25% quantile (non-heavy-users) a probability of .130. Consequently, the predicted probability of purchasing another game within the franchise is twice as high if I compare heavy-users to non-heavy-users.

Table 4.2: Results Hierarchical Logit for Additional Franchise Purchase

	Hierarchical Logit		
	Additional Franchise Purchase$_{i,p}$		
		95% Posterior Interval	
Variable*	**Median**	**2.5%**	**97.5%**
Usage$_{i,g}$	**.32**	.26	.37
CategoryExperience$_{i,g}$	-.02	-.04	.00
Usage$_{i,p}$ X CategoryExperience$_{i,g}$ **	**-.02**	-.03	-.01
UsageFriends$_{i,g}$	.02	.00	.04
TotalUsage$_{i,g}$	**-.14**	-.23	-.06
Gini$_{i,g}$	.09	-.32	.65
NumberofGames$_{i,g}$	**-.28**	-.37	-.19
NumberofFranGames$_{i,g}$	**.19**	.06	.33
Price$_{i,g}$*	.08	-.01	.17
ReviewScore$_{i,g}$	-.23	-.75	.13
Constant	1.63	-.08	4.01
Game Intercepts	Included		
Consumer Intercepts	Included		
Obs.	9,540		

In bold are the parameters whose 95% posterior interval excludes zero.
*I take the log of all non-categorical dependent and independent variables to harmonize variable scaling.
**I mean center all variables that are included in the interaction.

4.6.2 Direct and Moderating Effect of Category Experience

Reinartz and Kumar (2000) argue that more experienced consumers are more value conscious which can lead to a negative effect on purchasing behavior. I find a negative effect (-.02) of the usage of similar games on the propensity to purchase an additional game within the franchise. However, this effect is associated with some uncertainty as the 95% posterior interval includes zero and only the 90% posterior interval excludes zero. Previous research argues that variety seeking has a negative effect on additional products under the same brand (e.g., Nijssen 1999). A higher usage of similar games could trigger variety seeking and therefore, I find a negative effect of CategoryExperience (e.g., Nijssen 1999).

Table 4.3: Predicted Probabilities

	Predicted Probabilities			
		Robustness Check		
Usage Specification	**Additional Franchise Purchase**	**Sequel1 Purchase**	**Conditional on Used**	**Usage Dummy**
Usage > 75% Quantile	.268	.045	.024	
Usage Mean	.168	.017	.016	
Usage < 25% Quantile	.130	.009	.011	
Used Yes				.205
Used No				.130

All other variables are set to their mean.

My second main research questions is (2) how is the effect of usage on purchase moderated by the level of category experience. In line with H_2, I find that the positive effect of usage on additional purchases significantly decreases (-.02) for consumers with a high level of category experience; that is the more the consumer has used similar games. The 95% posterior interval of this effect excludes zero. As consumers are better aware of alternatives with a higher level of category experience (e.g., Smith and Park 1992), consumer have to rely less on the experience with the base product. This leads to the negative moderation between the usage of the base game and the usage of similar games.

4.6.3 Controls

UsageFriends. The usage of friends has a positive effect (.02) on the purchase of an additional game within the franchise. However, this effect is associated with some uncertainty as the 95% posterior interval includes zero and only the 90% posterior interval excludes zero. With a higher usage of friends, consumers may develop a higher attachment to the franchise. Further, the usage of friends for the base game can be an indicator that friends also use additional purchases of the franchise. This makes the purchase of additional franchise games more attractive because the interaction with friends facilitates a more positive consumer experience (e.g., Choi and Kim 2004).

TotalUsage. A major change in total usage can be a sign for a tendency to play heavily and to derive a lot of utility from video games or it can lead to consumers switching to other activities because they derive less marginal utility from an additional game. In line with the latter argument, I find that a higher level of total usage significantly decreases (-.14) the propensity to purchase an additional game within the franchise.

Gini. I find that the usage distribution of a consumer's library has no effect on the propensity to purchase an additional game within the franchise.

NumberofGames. The number of games that a consumer has in possession has a negative and significant effect (-.28). Potentially, with a higher number of games consumer have more opportunity to use an already purchased game before making a new purchase. This can lead to cannibalization effects because consumer have to divide their available time on a larger set of alternatives which makes a new purchase potentially less attractive.

NumberofFranGames. The effect of number of franchise games is positive (.19) and significant. I find that the more games of the franchise a consumer has in possession, the more likely is it that the consumer purchases another game within the franchise. In contrast to the variable CategoryExperience, the variable NumberofFranGames captures not the amount that a consumer has invested in the franchise or similar games but it solely captures how many games are in possession. Consumers do not need to have a high usage of franchise games just because franchise games are in possession. Consequently, the effect of owning more franchise games is positive and the effect of having used similar games is negative.

Price. I find that the price that a consumer pays for the base game has a positive effect (.08) on additional purchases within the franchise. However, this effect is associated with some uncertainty as the 95% posterior interval includes zero and only the 90% posterior interval excludes zero. Potentially, consumers are well aware of their expected utility for a specific franchise and adjust their willingness to pay (e.g., Nunes 2000; Tanner and Carlson 2009; Hamilton et al. 2011). Consequently, consumers with a higher expected utility have a higher willingness to pay and pay higher prices. As consumers' expected utility is potentially correlated with actual experience, higher prices are associated with a higher propensity to purchase other games within the franchise.

Review Score. The review score of the base game at the time of purchase has no significant effect on additional purchases within the franchise. Potentially, consumers' own experience with the base game has a higher impact compared to external cues for quality.

4.7. Robustness Checks

My main research questions are linked to the effect of usage on the purchase of an additional game within the franchise. I chose this setting as managers are potentially interested in the effect of a base game's accumulated usage on the whole franchise. I decide to analyze the franchise and not e.g., the first sequel, as analyzing the franchise is the more general approach. However, other settings to analyze the effect of usage on e.g., brand extension purchases are possible. Managers may be also interested in (1) the effect of the base game's usage on the purchase of the base game's first sequel (2) conditional on having used the base game: what is the effect of base game's usage on additional franchise purchases (3) the effect of having used the base game at all on additional franchise purchases. I analyze these settings in the subsequent robustness check. For each model in the robustness check I run logit models with 5,000 draws for warmup and 4*5,000 draws for inference. The results are robust against different prior selections, and all chains are well converged and mixed with a potential scale reduction factor ($\hat{R}$) of 1. For all models in the robustness check effective sample sizes are sufficiently large. All robustness checks are altered versions of equation 1.

First Sequel. Managers may be interested in the effect of base game's usage on the purchase of the direct sequel as the establishment of new products may be more relevant compared to the exploitation of previously released games. For the dataset of sequel purchases, I observe 8,583 consumers who purchase a base game but not the first sequel and 649 consumers who purchase a base game plus the first sequel. I use the same model as shown in equation (1) but replace the dependent variable with a consumer's decision to purchase the first sequel after purchasing the base game. Table 4.4 left panel shows the results of base game's usage on the decision to purchase the first sequel. I find similar results compared to my main analysis. A consumer's usage of the base game has a positive (.26) and significant effect. Further, the usage of similar games has a negative (-.14) and significant effect. For the effect of the interaction of usage and category experience, I find a negative tendency. However, this effect is associated with uncertainty as both, the 95% and 90 % posterior interval include zero. For the decision to purchase the first sequel, the effect of product experience seems not to be strongly diminished by a consumer's category experience.

Table 4.4: Robustness Check for First Sequel and Conditional on Used

	First Sequel Purchase$_{i,p}$			Additional Franchise Purchase$_{i,p}$		
				Conditional on used		
Variable*	**Median**	**2.5%**	**97.5%**	**Median**	**2.5%**	**97.5%**
Usage$_{i,g}$	**.26**	.21	.30	**.29**	.21	.37
CategoryExperience$_{i,g}$	**-.14**	-.18	-.10	-.02	-.06	.01
Usage$_{i,p}$ X CategoryExperience$_{i,g}$ **	.00	-.01	.01	**-.02**	-.04	-.01
UsageFriends$_{i,g}$	.00	-.03	.04	**.03**	.01	.06
TotalUsage$_{i,g}$	-.11	-.24	.02	**-.18**	-.28	-.08
Gini$_{i,g}$	.26	-1.22	1.82	.10	-.36	.73
NumberofGames$_{i,g}$	.08	-.05	.22	**-.21**	-.32	-.10
NumberofFranGames$_{i,g}$	**2.61**	2.34	2.89	**.40**	.22	.58
Price$_{i,g}$*	.04	-.11	.19	**.14**	.03	.26
ReviewScore$_{i,g}$	**1.62**	.45	3.04	-.17	-.72	.23
Constant	**-12.53**	-19.03	-7.11	**1.31**	-.66	3.86
Game Intercepts	Included			Included		
Consumer Intercepts	Included			Included		
Obs.	9,232			4,868		

In bold are the parameters whose 95% posterior interval excludes zero.

*I take the log of all non-categorical dependent and independent variables to harmonize variable scaling.

**I mean center all variables that are included in the interaction.

Conditional on used. As 49% of the consumers in the dataset of my main analysis have not used the base game within my observation period, the results may mainly be driven by the fact that several consumers have not used the base game at all. Managers may be interested in the effect of base game's usage on purchase behavior for consumers who have started using the base game. Consequently, I restrict the analysis of equation (1) to consumers who have used the base game. In total I observe 4,868 purchases of base games. In 3,819 instances do the consumers purchase the base game but no additional game within the franchise. In 1,049 instances do the consumers purchase the base game plus an additional game within the franchise. Table 4.4 right panel shows the result conditional on having used the game. The effect of the base game's usage – conditional on having used the base game – on the decision to purchase additional games within the franchise is positive (.29) and significant. Consequently, the positive effect that I find in my main analysis is not driven by the fact that several consumers do not use the game at all. Like in my main analysis, category experience measured through similar usage has a negative (-.02) effect. However, this effect is associated with uncertainty as both, the 95% and 90 % posterior interval include zero. Further, I find for the interaction that the effect of having used the base game increases for lower levels of category experience.

Table 4.5: Robustness Check Usage Dummy

	Additional Franchise $Purchase_{i,p}$		
	Usage Dummy		
Variable*	**Median**	**2.5%**	**97.5%**
$Used_{i,g}$	**.55**	.41	.69
$CategoryExperience_{i,g}$**	-.01	-.04	.02
$Used_{i,p}$ X $CategoryExperience_{i,g}$	-.03	-.07	.01
$UsageFriends_{i,g}$	**.02**	.00	.04
$TotalUsage_{i,g}$	**-.11**	-.19	-.03
$Gini_{i,g}$	.07	-.48	.69
$NumberofGames_{i,g}$	**-.33**	-.42	-.24
$NumberofFranGames_{i,g}$	**.21**	.07	.34
$Price_{i,g}$*	**.10**	.01	.18
$ReviewScore_{i,g}$	-.34	-.91	.08
Constant	**1.85**	-.17	4.43
Game Intercepts	Included		
Consumer Intercepts	Included		
Obs.	9,540		

In bold are the parameters whose 95% posterior interval excludes zero.
*I take the log of all non-categorical dependent and independent variables to harmonize variable scaling.
**I mean center $CategoryExperience_{i,g}$ as it is part of an interaction.

Usage dummy. In the dataset of my main analysis, I find that 49% of all consumers who purchase the base game do not use it within my observation period. Managers may be interested in the effect of having used the base game at all to adapt marketing actions like e.g., incentives to familiarize with the product. Consequently, I am interested in the question, whether the results of my main analysis can be generalized to a case in which I only analyze if – and not how much – a consumer uses the base game. I run the same model as shown in equation (1) but replace the variable Usage with a dummy variable Used that indicates whether or not a consumer i has used the base game g within my observation period. As in my main analysis, I observe 7,777 instances where consumers purchase a base game but no other game within the franchise and 1,763 instances where consumers purchase a base game plus another game within the franchise. Table 4.5 shows the results having used the base game on the decision to purchase an additional game within the franchise. I find similar results compared to my main analysis. The effect of having used the base game at an average level of category experience has a positive (.55) and significant effect. The direct effect of similar usage is negative but associated with uncertainty as both, the 95% and 90 % posterior interval include zero. As the variable is part of an interaction, the “direct effect” of similar usage is the effect of category experience if the base game was not used. Consequently, for consumers who have not used the game, the amount of similar games’ usage seems to be of less importance. Further, I find a negative effect of the interaction between having used the base game and the amount of similar usage. The lower a consumer’s usage of similar games, the higher is the effect of having used the base game on the decision to purchase the first sequel. However, this effect is also associated with uncertainty. Combined with the results from the previous robustness check (result conditional on used), I find that (1) consumers who use the base game have a higher propensity to purchase another game within the franchise and (2) for consumers who use the base game the propensity to purchase another game within the franchise gets higher the more the consumer uses the base game.

I report the predicted probabilities for different specifications of the base product’s usage in Table 4.3. Compared to my main model, I find similar results for the models in the robustness check. For the analysis of the purchase probability of the first sequel (Sequel1 Purchase), I find that overall predicted probabilities are lower compared to my main model. By definition, the propensity to purchase any additional game within the franchise must be higher or equal to the propensity to purchase only one specific game – the first sequel – within the franchise. However, I find that the predicted probability for heavy-users (.045) is five times as high compared to non-heavy-users (.009). If I only look at consumers who have started using the game (Conditional on Used), I find lower overall predicted probabilities compared to my main model but the predicted probability for heavy-users (.024) is twice the size compared to non-heavy users (.011).

Finally, the predicted probabilities for my model with a usage dummy mirror the results of my main model.

4.8 Discussion and Implications

This study builds on a stream of literature that identifies drivers of cross buying (e.g., Verhoef et al. 2001; Ngobo 2004; Verhoef and Donkers 2005; Kumar et al. 2008). I contribute to the literature by introducing a new driver of cross-buying: consumers' usage behavior. A beneficial aspect of my research is that I observe the actual usage of each purchased product for a huge set of consumers. Further, as I have information about the usage behavior of a consumer's friends, I am able to analyze a consumer's usage and purchase behavior in the context of her/his social group. Consequently, I derive my insights from field data and not from data based on surveys (e.g., Verhoef et al. 2001; Ngobo 2004).

The analysis of 793 consumers plus 10,605 friends over 18 months provides evidence for a positive effect of consumers' base game usage on the propensity to purchase another game within the franchise. For consumers who use the base game heavily, the predicted probability of purchasing another game within the franchise is twice as high compared to users with a low level of usage. Further, the positive effect of the base product's usage increases for consumers with low levels of category experience.

I estimate one main model and three additional models as robustness check and control for unobserved consumer and game heterogeneity with consumer and game specific intercepts. The results for the impact of base product's usage on the propensity to purchase an additional game are consistent across all models. However, I find that the moderating effect of category experience is of less importance when I analyze only purchases of the first sequel.

Further, I can generate insights from my set of control variables. The negative main effect of category experience suggests that consumers potentially are more prone to variety seeking – not purchasing games within the franchise but outside the franchise – when the level of category experience is high (e.g., Nijssen 1999). This has a negative effect on the propensity to purchase an additional game within the franchise. Further, consumers seem to be influenced by their social surrounding and derive utility not only from individual but also social aspects. Consequently, the usage of friends has a positive impact on purchase propensity because not being in possession of popular franchises among friends can isolate consumers. Consumers with a strong change in the total usage of games have a smaller propensity to purchase additional games. Potentially, the more a consumer has used games in total, the lower is the utility that the consumer derives from an additional game. Consequently, it is less attractive for the consumer to purchase additional games. Comparable to the effect of total usage, the number of games that a consumer has in possession has a negative effect on the propensity to purchase. The more games a consumer has in possession the less attractive it is to purchase an additional game because the consumer can come back to her/his previous purchases. This leads to cannibalization effects between the usage of previously purchased games and the purchase of new games. However, the more games of the focal franchise a consumer has in possession, the higher is the propensity to purchase another game within the franchise. It is notable, that the usage of similar games has a negative effect but the possession of more franchise games has a positive effect on purchase propensity. Potentially, the need of consumers to complete their collection of games within the franchise is higher the more games of the franchise the consumer has previously purchased. However, the negative effect of the usage of similar games – including franchise games – counteracts this effect. If consumers are aware of their high liking for a game and expect a high utility, this can result in a higher willingness to pay for that game. I find that the base game's price has a positive effect on the propensity to purchase another game within the franchise. The gini distribution of a consumer's usage of games in possession and the base game's review score seem to have no effect on the propensity to purchase an additional game.

4.8.1 Implications for Managers and Researchers

Especially in the entertainment sector (e.g. video games, movies, books), in which the publication of prequels or sequels is an important strategy, managers should be aware of the effect of usage on cross-buying. Managers should not only be interested in a higher usage as it provides more opportunity for additional revenue streams like e.g., in-game purchases but it has also a positive effect on purchases within the whole franchise.

My findings allow me to draw new implications as I have information about the post-purchase behavior of consumers. First, managers should optimize and induce higher levels of consumers' usage with the base product to boost cross-buying. Second, in markets where consumers' cross-buying is rare, managers may want to focus on convincing consumers with a high base product's usage as they have a higher propensity to cross-buy. Finally, if managers evaluate if they should introduce a new brand extension, the brand extension's likelihood of being successful is higher if consumers heavily use the base product. However, managers have to account for both, consumers' product usage and category experience. Especially for consumers with a low level of category experience, managers can utilize the effect of product usage on cross-buying.

Further, it is important to not manage products as silos. Managers have to take into account the influence of marketing decisions (e.g., pricing) on post-purchase behavior because otherwise potential spillover effects to other products of the company e.g., through a higher cross-buying propensity are neglected.

Finally, companies should design their price discrimination strategies additionally on the basis of a consumer's individual and peer usage behavior. As the consumer's usage of the base game and friends' usage of the base game have a positive effect on the propensity to purchase an additional product within the franchise, the willingness to pay should be higher, (1) the more heavily a consumer uses the base game and (2) the more heavily a consumer's friends use the base game.

4.8.2 Limitations

As any research, this study is not free from limitations that offer fruitful opportunities for future research. First, as I analyze only one industry in the entertainment sector, future research has to qualify how my results can be generalized across different industries. However, as the effect of usage is potentially caused by general concepts like switching cost (e.g., Pick and Eisend 2014), brand attachment, brand attitude and customer loyalty (e.g., Park et al. 2010; Murray and Bellman, 2011; Iyengar et al. 2007) and a more positive expectation of quality (e.g., Kim and Sullivan 1998; Hem and Iversen 2003; Völckner and Sattler 2006), I expect future research to find similar results in other industries. Second, as I have only information about purchases but not cost or profit margin data, I am not able to analyze the impact of usage on a company's long-term profit. This is a fruitful opportunity for future research to analyze the impact of usage on company success.

My research provides an indication that companies should not only look at the impact of marketing-mix instruments that are directly linked to purchase (e.g., price) but have to take into account post-purchase behavior because it is related to future purchases.

5. Conclusion

In this dissertation, I analyze and combine two fields that are especially relevant for managers and researchers in the area of marketing: consumers' purchase and post-purchase behavior. More precisely, price effects and usage effects. In the field of consumers' purchase behavior, I analyze how consumers react to price changes of competing brands. Therefore, I conduct a meta-analysis of cross-price elasticities to generate knowledge about an average effect size and determinants that shape the size of cross-price elasticities (Chapter 2). In the field of post-purchase behavior, I analyze how the price that a consumer pays for a product influences the consumer's usage (Chapter 3) and how usage is related to future purchases (Chapter 4).

This dissertation contributes to the literature by providing generalizing insights about cross-price elasticities (price effects), by providing insights of price on post-purchase behavior (price-usage effects) and by providing an understanding of the influence of post-purchase behavior on subsequent purchases (usage effects).

In Chapter 2, we analyze the impact of pricing on the purchase behavior of consumers. Therefore, we conduct a meta-analysis to derive empirical generalizations on cross-price elasticities. Factors that motivate this research are that the domain of pricing has seen two important developments over the last years. First, firms are facing a changed competitive environment. Second, research on pricing issues has benefitted from several important modelling advances. Because the most recent publications that summarize research on cross-price effects considers research that was published until 1996, both developments are not reflected in our knowledge about cross-price effects. To address this void, we provide empirical generalizations using a meta-analysis of prior econometric estimates of cross-price effects. As effect size, we use (1) cross-price elasticities, which is the percent change in demand of one product due to the percent change in price of a different product. This metric is easy to interpret and helps comparing findings from studies with different demand measures. As additional effect size, we use (2) absolute cross-price effects which is defined as the percentage change in demand of a target product when the price of a competing product is changed by one percent of the product category's price. In comparison to the cross-price elasticity, the absolute cross-price effect has a percentage-unit-change interpretation rather than a percentage-percentage-change. We analyze absolute cross-price effects because scaling effects – a 1% price change of a brand in a high price tier is larger in terms of dollars compared to a 1% change in a low price tier – may bias cross-price elasticities towards asymmetry. We analyze the impact of a set of determinants and asymmetries on the magnitude of cross-price elasticities and absolute cross-price effects. Asymmetric effects occur for instance due to differences in prices or market shares of competing brands. Therefore, we rely on three models to assess (1) the impact of determinants on cross-price elasticities (2) the impact of asymmetries on cross-price elasticities and (3) the impact of asymmetries on absolute cross-price effects. Based on 7298 cross-price elasticities from 114 studies, we identify 6 new main empirical generalizations. (1) We find an overall cross-price elasticity of .26, which is half the effect size of the previous meta-analytic mean. The median cross-price elasticity is .10. (2) Cross-price elasticities have decreased over time. (3) Cross-price elasticities decrease over the product life cycle. (4) High-stockpiling groceries have the highest cross-price elasticities. (5) Long-term are larger than short-term cross-price elasticities. (6) The asymmetric share effect only holds in high-share tiers.

However, in our data base of cross-price elasticities, we observe no cross-price elasticities from the online domain. Future literature could test the impact of including a larger number of online cross-price elasticities on the magnitude of cross-price elasticities. Further, we identify fruitful avenues for future research in the fields of (1) asymmetric effects that can occur because consumers may respond differently to price increases vs. decreases and (2) extending the data to countries with a more heterogeneous level of economic development to see if the results of this study hold globally.

In Chapter 3, we analyze the impact of pricing on the post-purchase behavior of consumers. More specifically, we analyze the impact of the price that a consumer pays on the consumer's post-purchase usage of that product. Factors that motivate this research are that although the strong impact of price promotions on demand is well documented in the literature, it is less clear how the price that consumers pay for a product is related to the way the product is used after purchase. Further, it is not clear how the effect of price on usage is influenced by screening and selection effects. Screening effects arise because consumers who plan to use a product heavily are willing to pay more for a product. Selection effects occur because only consumers who plan to use the product for an adequate amount purchase the product at all. The goal of this study is to assess the direct effect of price on usage above and beyond potential selection and screening effects. We attribute the remaining effect of price on usage to sunk cost. Sunk cost effects arise, if past expenses are incorporated in the current decision processes. We control for screening and selection effects by estimating two models: a selection and an outcome model. The selection model captures the propensity of a consumer to purchase the good. The outcome model captures the effect of price on usage.

Post-purchase usage is an important field of study, because it is potentially related to future purchase behavior. Further, usage is an antecedent of customer satisfaction and, therefore, managing customer usage levels is an important tool to sustain customer satisfaction and ensure long-term customer profitability. We show for a digital good, that above and beyond selection and screening effects, a positive sunk cost effect of price on usage exists. Based on 280,709 observations in our selection model and 55,622 observations in our outcome model, we find a price-usage elasticity of .09. This positive sunk cost effect increases for consumers with lower levels of experience in the marketplace.

However, we analyze only one industry in the entertainment sector. Future research has to qualify how our results can be generalized across different industries. Further, we have only information about price and purchase but not cost or profit margin data. Consequently, we are not able to analyze the impact of price changes on a company's long-term profit. This is a fruitful opportunity for future research to analyze the impact of prices on usage and the subsequent impact on company success.

In Chapter 4, I analyze the impact of consumers' post-purchase behavior on future purchase behavior. More specifically, I analyze the impact of consumers' product usage on the propensity to cross-buy – purchase another product from the same brand. The motivation for this research is that although literature on cross-buying has identified a substantial set of drivers, the driver of consumer's usage of previous products from the brand is neglected. Consequently, we contribute to the literature by introducing a new driver of cross-buying: consumers' usage behavior. A beneficial aspect of our research is that we observe the actual usage of each purchased product for a huge set of consumers. Further, as we have information about the usage behavior of a consumer's friends, we are able to analyze a consumer's usage and purchase behavior in the context of her/his social group. Based on a panel dataset of 793 consumers, we find for a digital good that higher product usage leads to a higher propensity to purchase an additional product. For consumers who use the base game heavily, the predicted probability of purchasing another game within the franchise is twice as high compared to users with a low level of usage. Further, the positive effect of the base product's usage increases for consumers with low levels of category experience. In subsequent robustness checks, we model (1) the influence of consumers' base product usage on the propensity to purchase the product's first sequel, (2) the influence of consumers' base product usage on the propensity to purchase an additional product within the franchise for consumers who have started using the product and (3) the influence of having used the game compared to not having used the game on the propensity to purchase an additional product within the franchise. For all models in the robustness check, a higher product usage has a positive impact on additional purchases.

The limitations of this research are similar to the limitations of Chapter 3: We analyze only one industry in the entertainment sector and we have only information about price and purchase but not cost or profit margin data. Consequently, future research has to qualify how our results can be generalized across different industries and what the impact of price changes on a company's long-term profit is.

In summary, the results of this dissertation have important practical and theoretical implications. One major implication of this study is to be careful with price promotions. Beside other negative effects, price promotions decrease consumers' usage. Lower usage has then a negative effect on future purchases. Further, it is important for managers to not manage products as silos. Without taking into account the influence of marketing decisions (e.g. pricing) on post-purchase behavior – as shown in Chapter 3 –, potential spillover effects on other products of the company e.g., through a higher cross-buying propensity – as shown in Chapter 4 – are neglected.

Further, we find that markets are characterized much less by brand-switching in response to price changes than previously thought. Researcher should therefore adjust their expectations of what constitutes a normal cross-price elasticity.

Managers and researchers are interested in understanding the full consequence of price changes. This dissertation adds knowledge to the consequence of price changes on purchase and post-purchase behavior. Consequently, managers have to account for purchase and post-purchase effects when developing pricing strategies and researchers have to further quantify, update and differentiate purchase and post-purchase price effects.

6. References

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