CROSS-CULTURAL DIFFERENCES IN ONLINE PRICE ELASTICITY

Research paper

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Abstract

This study empirically derives price elasticity estimates in fashion e-commerce in six European countries and explores their relationship within the given cultural context using Hofstede's cultural dimensions theory. The authors use a novel data set consisting of more than two million actual sales transactions provided by a leading European fashion e-commerce company for regression analysis and find considerable cross-country differences in price elasticity. Furthermore, cultural dimensions power distance, individualism, and masculinity relate to a less distinct price elasticity whereas long-term orientation pertains to the opposite. Lastly, the study analyzes profit implications for multinational corporations employing cross-country price discrimination.

Keywords: Price elasticity, E-commerce, Fashion, Big data, Cross-cultural, Hofstede, Data-driven competitive advantage

1 Introduction

In line with the Resource Based View (RBV) some scholars recognized the strategic importance of the pricing process as a capability to yield sustainable competitive advantage (Dutta, Zbaracki and Bergen, 2003; Kemper, Schilke and Brettel, 2013). Pricing strategy's profit implications are particularly relevant for multinational corporations (MNCs) operating in the online fashion retailing market and prominently employing markdown pricing strategies leading to billions in lost sales (Levy, Grewal, Kopalle and Hess, 2004). These companies have to purchase a whole seasons' stock in advance before actual demand manifests (Soysal and Krishnamurthi, 2012). If demand for certain products is less than expected, retailers reduce prices to boost sales (Soysal and Krishnamurthi, 2012). The challenge is to find the optimal discount rate clearing inventory levels at the highest possible price in order to maximize profits (P. Kopalle et al., 2009). So far, retailing companies predominantly have been using rather less sophisticated pricing techniques to tackle this challenge (Nijs, Srinivasan and Pauwels, 2007). A solution for MNCs is the employment of sophisticated information systems to enable spatial market segmentation by differences in price elasticity as a lever to significantly improve profitability (Steenkamp and Ter Hofstede, 2002; Grüschow, Kemper and Brettel, 2015).

According to a Retail Systems Research study only 13% of retailers around the world had pricing intelligence solutions deployed to improve their bottom line (Emarketer, 2013). While about a quarter of respondents plan to engage in this field, a vast number of companies lack awareness of the issue. Additionally, resistance to changing long-time practices and lack of required resources in terms of structured data and skilled workforce represent reasons for companies not executing dynamic pricing in their operations as (P. Kopalle et al., 2009; Emarketer, 2013).

Although crucial for firm success, research into pricing in international marketing literature has been scarce (Clark, Kotabe and Rajaratnam, 1999; Tan and Sousa, 2011). Due to lack of data a very limited number of studies have provided international comparisons of price elasticity (Clark et al., 1999; Engelen and Brettel, 2011), while reporting contradictory findings. Bolton and Myers (2003) examined antecedents for differences in price sensitivity for service offerings across various nationalities and found evidence for the existence of clearly distinguished customer segments defined by national borders. In addition, Bolton, Keh, and Alba (2010) detected cross-cultural differences in price perception while Tellis (1988) and Crouch (1996) identified cross-continent and cross-country variation in price elasticity in their meta-analyses. Bijmolt, Van Heerde, and Pieters (2005), however, did not find significant discrepancies in price sensitivity across continents in their meta-analysis.

The availability of comprehensive data in e-commerce enables detailed analysis of customers' behavior which is different to offline commerce (D. Schellong, Kemper and Brettel, 2016). This study thus aims at further investigating cross-national differences in the demand effect of price using a novel data set consisting of millions of actual sales transactions in six European countries in fashion e-commerce. The authors empirically estimate demand functions of numerous product categories to obtain differences in price elasticities across countries. In order to allow for better generalizability of the results and to account for the importance of considering differences in culture when developing marketing strategies (Dawar, Parker and Price, 1996; Ackerman and Tellis, 2001; Kemper, Engelen and Brettel, 2011), the study explores the role of national culture with respect to price elasticity. We use Hofstede's well-known cultural dimensions theory (Hofstede, 2001) and argue that cultural power distance, individualism, and masculinity increase social status needs and thereby lower price elasticity. Furthermore, we assert that cultures high in long-term orientation involve a more distinct thriftiness resulting in lower price sensitivity.

Additionally, this study contributes to the growing stream of research on pricing in e-commerce. Scholars particularly identified the fashion industry to offer great potential for further pricing studies in the online environment recently (P. Kopalle et al., 2009). Studies concerning pricing in e-commerce mostly focused on price dispersion (Brynjolfsson and Smith, 2000; Chellappa, Sin and Siddarth, 2011; Ghose and Yao, 2011) and price levels (Brynjolfsson and Smith, 2000; Brown and Goolsbee, 2002; Zettelmeyer, Morton and Silva-Risso, 2006) contrasting differences in online and offline settings. Papers examining price sensitivity in online environments mostly used clicks (Baye, Gatti, Kattuman and Morgan, 2009) and publicly available sales rank data to approximate price elasticities (Chevalier and Goolsbee, 2003; Brynjolfsson, Dick and Smith, 2010; Pathak et al., 2010) while some studies made use of records of actual sales transactions to explore the demand effect of price in different industries (Chu, Chintagunta and Cebollada, 2008; Ellison and Ellison, 2009; De Los Santos, Hortaçsu and Wildenbeest, 2012; Granados, Gupta and Kauffman, 2012; Granados, Kauffman, Lai and Lin, 2012). The previous studies, however, have not covered the online fashion retailing domain. To the authors' knowledge, this is the first paper estimating demand functions in this industry using actual sales records.

2 Conceptual framework and hypotheses development

According to classic economic theory price elasticity is the percentage change in demand following a one-percent change in price of a given product (Nagle, 1984). The terms price elasticity and price sensitivity are used interchangeably in this text. Most commonly a negative correlation between price and demand exists since consumers propensity to brand switching or doing without the desired product increases in the product's price (Nagle, 1984). The dual role of price explains differing extents of price elasticity across customer segments (Lichtenstein, Ridgway and Netemeyer, 1993). This concept entails two opposing effects of how the price level influences the purchase probability of a customer - that is, the sacrifice and the informational effect (Lichtenstein et al., 1993; Theysohn, Klein, Völckner and Spann, 2013).

First, the sacrifice effect of price, which is grounded in classic economic theory and Thaler's (1985) transaction utility theory, suggests a negative influence of the price level on demand through allocative effects and transaction utility. Allocative effects imply that customers maximize their utility by distributing a limited budget across a given selection of products (Nagle, 1984). The lower a product's price the more resources remain to be spent on other alternatives (Walters and Bommer, 1996). Hence, customers prefer reduced product prices since these facilitate extra purchasing possibilities and thereby maximize utility (Völckner, 2008). According to transaction utility theory customers compare the observed price with an internal memory-based reference price to decide whether the purchase at hand can be evaluated a good deal (Thaler, 1985; Jung, Cho and Lee, 2014). If the observed price is below the reference price, the deal is perceived as a gain (P. K. Kopalle, Kannan, Boldt and Arora, 2012). A lower product price is more likely to be below a customer's reference price, and therefore increases her utility from the given transaction (Thaler, 1985).

Second, in line with cue utilization theory the informational effect of price implies that consumers deduce information about a product's adequacy from its attributes (Völckner, 2008). One of the most important such attributes is the product's price (Lichtenstein et al., 1993). Customers infer quality or experience prestige and hedonism when evaluating a high-priced product (Lichtenstein et al., 1993; Amaldoss and Jain, 2005). The informational effect thus leads to a positive effect of the price level on demand (Lichtenstein et al., 1993; Amaldoss and Jain, 2005).

We further conceptualize that the cultural context in a given market amplifies or dampens the individual demand effects of price discussed above and thus help explain differences in price elasticity across countries. We use Hofstede's theory (Hofstede, 1980, 2001) to operationalize culture. Hofstede initially developed the framework to capture cultural differences of several nationalities in work life, but a number of studies also used the model to examine customer behavior (Roth, 1995; Soares, Farhangmehr and Shoham, 2007; Chui, Titman and Wei, 2010). The model categorizes numerous nationalities on five dimensions describing their culture - that is, "the collective mental programming that these people have in common" (Hofstede 1980, p. 43). Of the five dimensions power distance, individualism, masculinity, long-term orientation, and uncertainty avoidance the first four are particularly relevant to influence price elasticity.[1] Following we develop the hypotheses pertaining to the proposed dimensions of national culture.

[1] The uncertainty avoidance dimension is not included in the analysis as it does not influence status needs or thriftiness. Uncertainty avoidance relates to what extent members of a society try to cope and avoid ambiguity and uncertainty in their lives also concerning the future (Roth, 1995). Low uncertainty avoidance countries are open for changes and innovation whereas high uncertainty avoidance countries attempt to preserve their current state and act conservatively towards changes (De Mooij and Hofstede, 2011). Status needs are rather influenced

We hypothesize that national culture moderates the relationship between price and demand through the two factors social status needs and thriftiness. In the following we discuss these mechanisms, characteristics of corresponding dimensions of national culture, and their influence on price elasticity.

2.1 Social status needs

Some cultures emphasize the importance to show social status more than others. In line with the informational effects component of the dual role of price, customers can earn prestige and social status by purchasing high priced brands and products (Lichtenstein et al., 1993; Völckner, 2008). Hence, when people are more inclined to show off social status and prestige the importance of well-known and luxury brands increases (R. N. Bolton, 1989; Amaldoss and Jain, 2005). These brands typically possess a certain amount of market power and involve less price elasticity since customers infer the correctness of the price from the brands' famousness (Huber, Holbrook and Kahn, 1986; Kim, 1996) and are willing to pay a price premium to show their ability to purchase these kinds of products (R. N. Bolton, 1989; Völckner, 2008). By this means people are able to demonstrate their position in society (Roth, 1995). We argue that the distinctiveness of the national culture dimensions power distance, individualism, and masculinity influence the need to show social status and discuss each in turn.

High power distance cultures emphasize the social acceptance of a few people being independent and superior to the remaining part of society, meaning "everybody has a rightful place" (Hofstede 1980, p. 46). This fact also entitles the superior to privileges and contains the requirement to show social status (Roth, 1995; Millan, De Pelsmacker and Wright, 2013). In these cultures the superior members of society constantly strive to strengthen their position reinforcing social status needs and reducing price sensitivity.

H1. Price elasticity will be lower when power distance is high than when power distance is low.

The individualism dimension relates to how much people's identity is based in social groups or in the individual (Millan et al., 2013). Individualist cultures stress I-consciousness and people prefer to lead a life more independent of others and their opinions (Hofstede, 1980; Roth, 1995). Furthermore, people are hedonistic and seek variety and pleasure (Hofstede, 2001), decreasing the degree of price sensitivity. Conversely, collectivist societies emphasize the importance of belonging to socially defined and stable groups such as family or work teams (Roth, 1995). People's values and identity are embedded in the social system and the well-being of the group is the superior goal in life (Hofstede, 1980; Soares et al., 2007). This need for affiliation in collectivist societies also decreases social status needs since people do not strive for distinguishing themselves from their social system by owning expensive commodities and thereby amplifies price elasticity.

H2. The effect of price on demand will be lower when individualism is high than when individualism is low.

Countries characterized by a high masculinity index stress the significance of achieving in professional career to gain satisfaction (Hofstede, 1980; Soares et al., 2007). Other members of society admire achievers and people are more ego-oriented (Hofs tede 2001). Earning good money to be able to purchase expensive commodities and thereby show ones professional achievements is thus central in life (Millan et al., 2013). Hence, members of high masculinity cultures consider demonstrating their position in society highly important (Hofstede, 1980). This mechanism leads to lower price sensitivity in these countries.

H3. The effect of price on demand is less pronounced when masculinity is high than when masculinity is low.

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by differences in the power distance, individualism, and masculinity dimensions as discussed in the remainder of this text.

2.2 Thriftiness

Thriftiness motivates people to search for low prices (Urbany, Dickson and Kalapurakal, 1996; Völckner, 2008). Thrifty consumers are thus more likely to detect and purchase a discounted product. Hence, price elasticity is higher when thriftiness is more pronounced. Moreover, cultural long-term orientation implies perseverance, thrift, and proneness to save for the future as well as higher propensity for long-run investments (Hofstede, 2001). Short-term oriented cultures, on the contrary, place less emphasis on saving for the future and the pursuit of happiness is central in life rather than the pursuit of peace of mind (Hofstede, 2001). Hence, customers in long-term oriented cultures are more attentive in the purchasing process, compare prices more actively, and ultimately involve a more pronounced price sensitivity.

H4. Price elasticity is more pronounced when long-term orientation is high than when long-term orientation is low.

Figure 1 summarizes the conceptual model arising from the hypotheses.

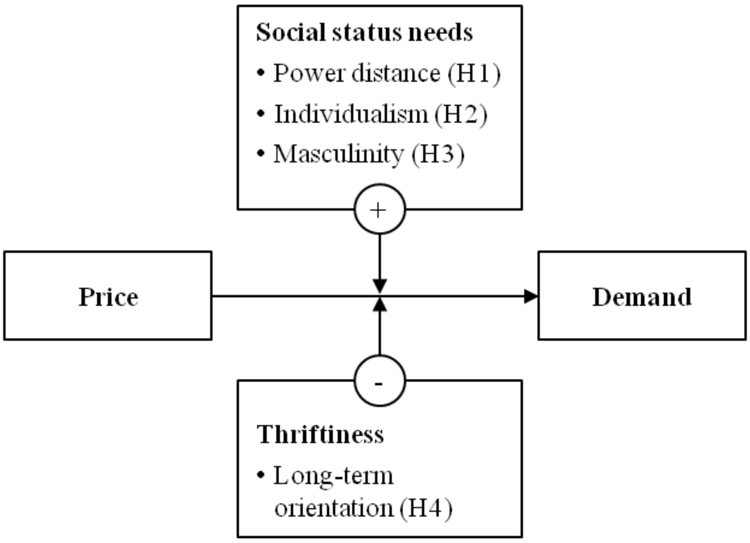

Figure 1. *Conceptual framework*

3 Methods

Going forward we conducted a two-step analysis. First, we derived brand-category price elasticities in six countries under study. In a second stage, we related obtained elasticity estimates to the proposed dimensions of national culture to test the hypotheses.

3.1 Data

A leading European fashion e-commerce company provided us with a novel data set consisting of more than two million actual sales transactions in Austria, Belgium, France, Germany, Netherlands, and Sweden. Weekly sales records span the fall-winter season from August 2012 to February 2013. They contain detailed quantity, sales price, purchase price, and availability data as well as brand and private brand information on SKU-level of seven apparel and three shoe categories for women (blouses, cardigans, coats, dresses, shirts, sweat wear, trousers, bootees, boots, and pumps) and men respectively (cardigans, coats, dress shirts, shirts, sweat wear, trousers, under wear, bootees, boots, and sneakers). In addition, we received information about periods of increased marketing spend per country.

In each country-category combination we selected up to five top selling private brands and 15 top selling national brands if available. We selected a set of top selling brands since these are most likely to best represent the taste of customers in each single country to allow for cross-country comparison. We subsequently deleted brand-category combinations without variance in the data. This course of action left us with a data set covering 2,090 brand-category combinations with a total of more than 1.2 million observations. Table 1 depicts the number of brand-category combinations clustered by broader product classes.

Furthermore, we used classifications of national culture from Hofstede (2001) to facilitate the exploration of cross-cultural effects. We controlled for cross-national differences in the economic situation using national real gross domestic product per capita values (in 2005 one thousand U.S. dollars) from the International Macroeconomic Data Set by the United States Department of Agriculture (2013). Table 2 depicts corresponding values.

	Women		Men	
Country	Apparel	Shoes	Apparel	Shoes
Austria	136	60	116	45
Belgium	122	59	101	42
France	135	60	117	53
Germany	137	60	119	55
Netherlands	139	60	121	52
Sweden	124	46	98	33

Table 1. Number of brand-category combinations per product class

Country	Power distance	Indi-vidualism	Masculinity	Long-term orientation	GDP [1000 US$]
Austria	11	55	79	60	41.08
Belgium	65	75	54	82	39.06
France	68	71	43	63	34.17
Germany	35	67	66	83	37.40
Netherlands	38	80	14	67	40.97
Sweden	31	71	5	53	45.80

Table 2. Country ratings based on Hofstede and GDP per country

3.2 Estimating brand-category-level price elasticities

Consistent with previous literature (Baye et al., 2009; Pathak et al., 2010; Granados, Gupta, et al., 2012) we used the log-log specification to model demand on SKU-level in order to derive price elasticities (Bijmolt et al., 2005).

3.2.1 Econometric model.

The model captures sales on a brand-category level since customers' reaction to price changes likely differs across brands and categories (Narasimhan, Neslin and Sen, 1996; van Heerde, Gijsenberg, Dekimpe and Steenkamp, 2013). The demand model has the following form:

$$\ln(\text{sales})_{i,t} = \beta_1 \cdot \ln(\text{price})_{i,t} + \beta_2 \cdot \ln(\text{availability})_{i,t} + \beta_3 \cdot \text{time}_t + \beta_4 \cdot \text{pre-Christmas}_t + \beta_5 \cdot \text{Christmas}_t + \beta_6 \cdot \text{final sale}_t + \beta_7 \cdot \text{mid-season sale}_t + \sum_i \sigma_i \cdot \text{SKU}_i + \varepsilon_{i,t} \qquad (1)$$

The sales variable captures the number of sold items of product i in week t belonging to a given brand-category-country combination. Price represents the average selling price per product and week weighted by the number of sold items. The availability variable captures the average availability of all sizes of a product in a given week. We included this variable because other scholars identified availability to have a significant effect on sales (Soysal and Krishnamurthi, 2012). In order to precisely measure the effect of availability on sales, we would need real-time data of SKU-specific inventory levels for each purchasing occasion (Soysal and Krishnamurthi, 2012). The data set contains availability information on SKU-level averaging day-end values over the length of one week. Thus, the availability measure represents an approximation consistent with previous literature using retail distribution proxies for availability (Bruno and Vilcassim, 2008; Soysal and Krishnamurthi, 2012).

In seasonal goods industries sales of products usually follow a decreasing pattern in the course of a season, if they are not discounted (Heching, Gallego and van Ryzin, 2002; Soysal and Krishnamurthi, 2012). The time variable accounts for this decreasing pattern in sales quantity. This variable is a continuous variable taking on the value of the respective week in which an observation occurred. Pre-Christmas and Christmas represent dummy variables capturing increased demand during the pre-Christmas period and decreased demand around Christmas, respectively. The pre-Christmas period is defined as the first three weeks of December when the Christmas season peaks in retailing. The dummy variables mid-season sale and final sale control for increased marketing spend during periods of mid-season sale and final sale, respectively. Furthermore, SKU fixed effects in terms of the SKU variable allow us to control for substantial demand differences between products. β_1 is the price elasticity of a given brand in a given category in a given country, β_2 to β_7 represent elasticities of the other variables in the model. Parameter σ_i reflects SKU-specific demand patterns. Finally, ε is the error term. We estimated model (1) using ordinary least squares regression (OLS).

3.2.2 Multicollinearity

We computed pairwise correlations of the model variables in each of the 2,090 different demand models. We further investigated variable relationships, if a correlation value is above the threshold of .80, indicating high correlation between variables (Kennedy, 2008). Correlation figures between the price and time variable were problematic in two cases. Subsequently, we computed the variance inflation factor (VIF) for the time variable in the two models and found one critical value above the threshold of 10 (Kennedy, 2008). Hence, we kept all variables for further examination in case the VIF was smaller than 10 and deleted the time variable in the model involving multicollinearity.

3.2.3 Heteroskedasticity

We conducted a Breusch-Pagan test for heteroskedasticity for every model individually (Breusch and Pagan, 1979). In 1,276 instances we rejected the hypothesis of homoskedasticity ($p < .05$) and assumed heteroskedasticity to be present in the respective models. Going forward we report parameter estimates using Huber-White robust standard errors in the affected models in order to account for heteroskedasticity (Baye et al., 2009; Granados, Gupta, et al., 2012).

3.2.4 Endogeneity

An imminent risk of price endogeneity in modeling demand in seasonal goods industries exists that could bias elasticity estimates (Bijmolt et al., 2005) since prices can strongly depend on the quantity sold until a given point in the season. We performed a Hausman test for every model under study to test whether the OLS estimator is consistent (Granados, Gupta, et al., 2012). In case we could not reject this hypothesis ($p < .05$) we concluded price endogeneity to be present and applied a standard instrumental variable approach for price (Berry, Levinsohn and Pakes, 1995). Therein, the cost-side variables purchase price and time in season as well as their interaction served as instruments. Retailers determine the final selling price of a product by applying a mark-up on its purchase price. This mark-up follows a rather constant pattern within a brand. As managers frequently mark down prices of products with less than expected demand in the course of a season (Levy et al., 2004) the relative time in the season is a good approximation for decreasing average price levels of products. Going forward we estimated model (1) using two-stage-least-squares (2SLS) regression in 23 instances to account for price endogeneity. Estimation of all 2,090 models yielded a satisfactory fit with a median adjusted R^2 of 62.1 %.[2]

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[2] R^2 descriptive statistics: minimum -.55, mean .59, maximum .98.

3.3 Uncovering cross-cultural differences in price elasticity

In order to shed light on cross-cultural differences in price elasticity, we followed the approach employed by Deleersnyder et al. (2009) in a different marketing application. We first aggregated the obtained brand price elasticity estimates (β_1) to category level c and pooled these across all countries j. The aggregation to category level followed the method of added Zs (Rosenthal, 1991). Therein, the mean elasticity is computed as a weighted mean of the underlying price elasticities. We used the inverse of the standard error of the price elasticity estimates as weights. Hence, the mean elasticity translates to a reliability weighted measure (van Heerde et al., 2013). We aggregated 2,090 elasticity estimates to 10 categories per gender and country, leaving us at 120 different category values. We deleted three of these estimates for further analysis since their meta-analytic p-value was above .05.

In a second step, we related the aggregated figures on the following dimensions of national culture: power distance, individualism, masculinity, and long-term orientation. The real per capita income (GDP) controls for country-specific economic situations since differences in the disposable income are likely to influence the demand effect of price. In line with the allocative effect of price this higher available budget leads to a less distinct price elasticity. In addition, a dummy variable for categories controls for category-specific demand effects. μ is the error term. These modeling preliminaries lead to equation (2):

$$\beta_{1,c,j} = \delta_1 + \gamma_1 \cdot \text{power distance}_{c,j} + \gamma_2 \cdot \text{individualism}_{c,j} + \gamma_3 \cdot \text{masculinity}_{c,j} + \gamma_4 \cdot \text{long-term orientation}_{c,j} + \gamma_5 \cdot \text{GDP}_j + \sum_{c=1}^{20} \lambda_c \cdot \text{category}_c + \mu_{c,j} \quad (2)$$

We estimated equation (2) using OLS regression. We tested model (2) for multicollinearity by computing pairwise correlations of the regressors (compare Table 3) and did not find critical values above the threshold of .80. In addition, we performed a White test to test for heteroskedasticity (Deleersnyder et al., 2009) and found that this is not of concern (p > .10).

Variable	Mean	SD	1	2	3	4	5	6
1. Elasticity (β_1)	-1.39	.77	1.00					
2. Power distance (γ_1)	41.31	19.96	-.13[a]	1.00				
3. Individualism (γ_2)	44.07	26.50	-.38[a]	-.18	1.00			
4. Masculinity (γ_3)	69.77	7.87	.07[a]	.63[a]	-.73[a]	1.00		
5. Long-term orientation (γ_4)	68.24	10.88	-.53[a]	.37[a]	.45[a]	.21	1.00	
6. GDP (1.000$) ($\gamma_5$)	39.65	3.55	.65[a]	-.61[a]	-.47[a]	-.03[a]	-.50[a]	1.00

Values of category dummies excluded for reasons of brevity. The highest correlation between category variables and any other variable is .13; [a] = p < .001;

Table 3. Mean, standard deviation and correlations of model variables

4 Results

We first present results pertaining to the demand effect of price in the six examined markets using demand model (1). Subsequently, we outline the effect of national culture on price elasticity figures resulting from model (2).

4.1 Price elasticity estimates

Figure 2 depicts price elasticity estimates in Austria, Belgium, France, Germany, Netherlands, and Sweden. Aggregation of brand-category estimates to higher order levels follows the method of added Zs (Rosenthal, 1991). The values reveal whether customers react elastically (< -1) or inelastically (> -1) to price changes in a given country. The aggregated price elasticity value (M) across all categories in all countries under study is -1.46 (meta-Z = -232.71, p < .001) indicating a moderately price elastic online fashion retailing market in Europe. Therein, substantial cross-country differences are apparent. German customers react most distinctly to price changes (M = -2.74, p < .001) followed by French (M = -1.76, p < .001), Dutch (M = -1.22, p < .001), and Austrian (M = -1.07, p < .001) customers. The Belgian (M = -.92, p < .001) and Swedish (M = -.48, p < .001) market on the contrary react inelastically to price changes.

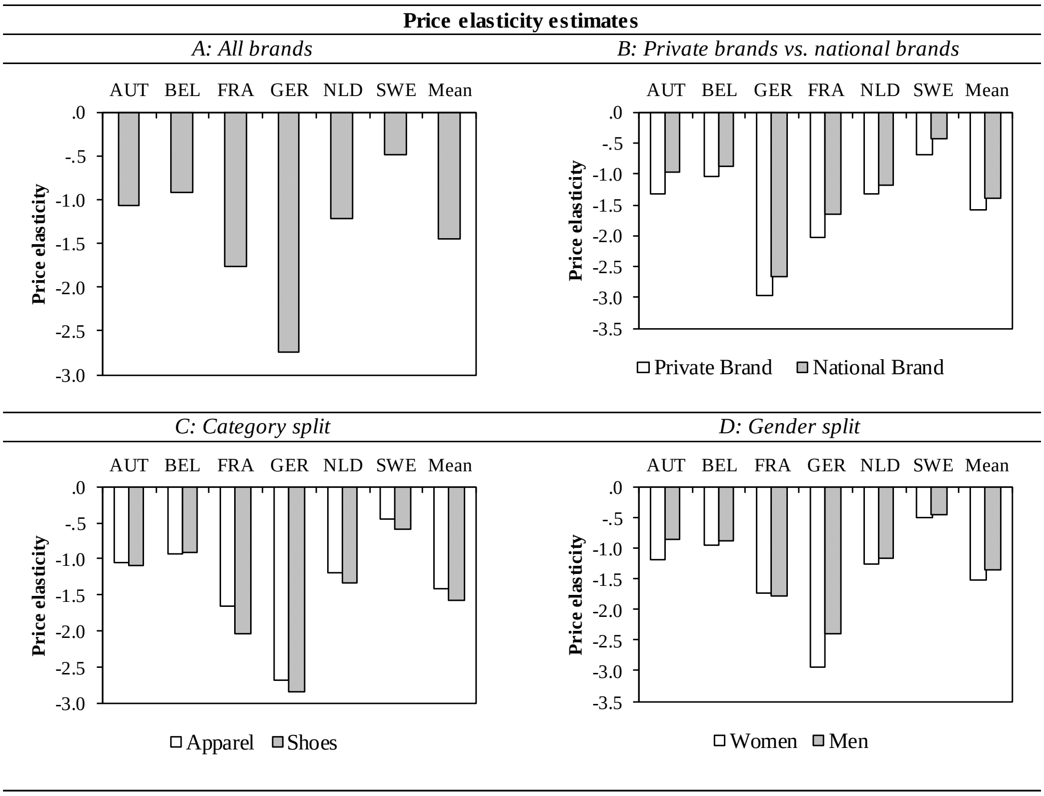

Figure 2. Across-country comparison of price elasticity estimates

Price elasticities of national and private brands (panel B), aggregate apparel and shoes categories (panel C) and both genders (panel D) show the same order. Overall demand of private brands (M = -1.57, p < .001) reacts more distinctly to price changes than sales of national brands (M = -1.39, p < .001), which is in line with previous research (R. N. Bolton, 1989; Amaldoss and Jain, 2005). Women (M = -1.53, p < .001) are more price sensitive than men (M = -1.35, p < .001) and shoes categories (M = -1.58, p < .001) on average show higher price elasticities than apparel categories (M = -1.41, p < .001).

Table 4 summarizes meta-analytic regression results. All the obtained values have a negative sign as expected and the order of magnitude is in line with related literature (Bijmolt et al., 2005). Individual category values range between -3.24 for women shirts in Germany and -.34 for trousers in Sweden, which translates to a deviation of 2.9 elasticity points. In addition, considerable intra-country variability in category price elasticities exists. Elasticity estimates in France differ by as much as 1.81 elasticity points between -2.52 (men boots) and -.71 (men underwear).[3]

4.2 National culture's influence on price elasticities

Table 5 depicts parameter estimates of model (2) representing aggregated values across all categories under study. Negative parameter values indicate an amplification effect of the given variable on price elasticity since the latter carries a negative sign as well. Parameter values of the main effects are

[3] The presentation of effects of control variables to account for time-specific effects in model 1 was omitted for brevity.

highly significant at the .001-level. Power distance has a positive influence on price elasticity lowering the demand effect of price ($\gamma_1 = .02$). This result confirms hypothesis 1.

		Rosenthal's Weighted Zs	
	# Models	Mean Elasticity (M)	Meta-Analytic Z
Country			
Austria	357	-1.07[a]	-72.78
Belgium	324	-.92[a]	-51.10
France	365	-1.76[a]	-133.19
Germany	371	-2.74[a]	-193.25
Netherlands	372	-1.22[a]	-87.07
Sweden	301	-.48[a]	-19.37
Product type			
National brand	1,666	-1.39[a]	-184.39
Private brand	424	-1.57[a]	-153.83
Apparel	1,465	-1.41[a]	-188.78
Shoes	625	-1.58[a]	-136.44
Gender			
Women	1,138	-1.53[a]	-204.04
Men	952	-1.35[a]	-122.27
Overall	2,090	-1.46[a]	-232.71

[a] = Meta-analytic p-value < .001.

Table 4. Price elasticity estimates per country

The parameter of the individualism variable has a positive sign as well ($\gamma_2 = .06$) supporting hypothesis 2 that implies a negative influence of individualism on the magnitude of price elasticity. Hypothesis 3 finds support by the present results indicating a negative influence of cultural masculinity on the extent of price sensitivity ($\gamma_3 = .15$). Long-term orientation, on the contrary, has an amplifying influence on price elasticity supporting hypothesis 4 ($\gamma_4 = -.10$).

Furthermore, gross domestic product per capita has a dampening effect on price elasticity. In addition, some of the category-specific differences are significant. Men underwear represents the least price elastic category whereas the women coats category unfolds to be most reactive to price changes in the set of product groups under study. Lower price elasticity categories in the data set under study are men underwear and dress shirts. The former category is represented by a low average purchase value and thus induces low effort for price comparison and switching (Thaler, 1985). The latter products are used in professional live and thus comprise a high prestige value dampening the demand effect of price (Völckner, 2008). Higher price elasticity categories are represented by more browsing-related categories such as women boots, coats, sweat wear as well as men sneakers.

5 Discussion

This study empirically derives price elasticity figures by estimating demand functions of numerous apparel and shoe categories in six European countries. Therein, substantial variation across markets is apparent. Elasticity estimates are related to dimensions of national culture in order to examine the role of cultural in this context. The authors conceptualize that social status needs and thriftiness are more pronounced in certain cultures leading to the demonstrated deviations in price elasticity. Furthermore, we hypothesize that the distinctiveness of the proposed dimensions of national culture, in turn, influences the degree of both social status needs and thriftiness. All hypotheses find support implying that countries high in cultural power distance, individualism, and masculinity involve more social status needs also translating to a less distinct price elasticity (H1 to H3). In addition, cultures high in long-term orientation include a certain degree of thriftiness resulting in a more pronounced price elasticity (H4). These findings have both academic and managerial implications.

Variable	Hypothesis	Value	Standard Error
Intercept		-20.84[a]	.97
Dimensions of national culture			
Power distance (γ_1)	H1: +	.02[a]	.00
Individualism (γ_2)	H2: +	.06[a]	.00
Masculinity (γ_3)	H3: +	.15[a]	.01
Long-term orientation (γ_4)	H4: -	-.10[a]	.01
N		117	
R^2		91%	

Category dummies omitted for brevity. Women blouses served as reference category in fixed effects regression; [a] = $p < .001$.

Table 5. Parameter estimates of cross cultural regression

5.1 Implications

First, knowledge about cross-cultural differences in price sensitivity remains scarce, primarily because of data availability issues. In order to shed light on this topic, we use a large data set containing SKU-level data from numerous product categories in the estimation procedure to account for category and brand level heterogeneity. The results suggest that MNCs should take differing customer behavior with regard to pricing across cultures into account when developing marketing strategies. The present findings give a good indication of how customers will likely react to price changes in a given cultural context, and thus can help managers making marketing decisions.

Second, Bijmolt et al. (2005) emphasize the need to analyze price elasticities in newly developing or changing environments such as the e-commerce domain since the magnitudes of elasticity estimates change over time and are affected by market characteristics. Although highly important for researchers and practitioners still little is known about the demand effect of price in online settings. Different scholars also call for more cross-cultural research on customer behavior in online (Nakata and Huang, 2005; Engelen and Brettel, 2011). The previous studies left open a gap in the e-commerce fashion retailing industry that the present study seeks to close by quantifying the demand effect of price pertaining to this setting.

Third, in order to disclose profit implications of cross-national market segmentation by exploiting differences in price elasticity we conduct a counterfactual analysis. We assert that country-specific discount differentiation yields better monetary results compared to overall-level price setting. To test this assertion we employ demand model (1) developed in section 3.2. to simulate the markdown process of an exemplary brand with observations of 421 different SKUs that are sold in the six countries under study over the course of one season. Therein, we compare the monetary outcome of executing the markdown process using an overall price elasticity to the outcome using country-individual figures. We utilize values of a brand in the women shirts category. Table 6 summarizes respective figures. Therein, across-country variability is substantial with elasticity values ranging between -.55 in Sweden and -2.47 in Germany. In addition, we have access to inventory data for the given brand.

We assume that items in stock can only be sold online and the cost for purchasing these items are sunk costs. The value of leftover stock after the season is zero. Furthermore, we assume constant fulfillment cost independent of the market to which the goods are shipped. The season consists of 26 weeks in total. We examine the situation after six weeks into the season. The revenue from selling the remaining items in stock until season end represents the variable that we seek to maximize by employing either a markdown process using an overall price elasticity or country-specific figures.

Country	Elasticity	Standard Error	t-value
Austria	-1.11[a]	.11	-9.67
Belgium	-.82[a]	.16	-5.12
France	-1.61[a]	.12	-13.67
Germany	-2.47[a]	.10	-23.58
Netherlands	-1.03[a]	.11	-9.40
Sweden	-.55[a]	.15	-3.79
	Mean Elasticity	# Models	Meta-Analytic Z
Overall	-1.33[b]	6	-76.31

[a] = $p < .001$; [b] meta-analytic p-value < .001

Table 6. Price elasticity breakdown of exemplary brand by country

First, we describe the process using an overall price elasticity (OPE) value: We use the moving average of sales of the past three weeks as the sales forecast for the remaining season and select weights of .7, .2, and .1 to compute the moving average per period. Going forward, we compare this value to the ratio of remaining stock and periods in the season, which translates to the number of sold items per period necessary to clear the inventory. If the sales forecast, which is based on the manifested recent demand, is too small to clear the inventory until season end, prices of the products need to decrease to increase sales. Therein, we use the price elasticity to compute optimal prices. The result of this step is an overall discount rate that is applied to all products in every market under study. On the contrary, if demand turns out to be higher than required to sell off the entire inventory, prices increase to lower sales. Prices cannot exceed the initial price and drop below the purchase price of the respective items. We use demand model (1) introduced in section 3.2. and corresponding parameter estimates of the brand under study to determine the demand that would have materialized considering the newly computed prices. We repeat this procedure every period until the end of the season.

In the second case we use country-specific price elasticity (CPE) figures in the markdown process. The key difference to the OPE case is the weekly determination of the price necessary to clear remaining inventory. Therein, we compute the optimal discount rate per country for the upcoming period by maximizing the expected period revenue by changing the price individually for every examined market based on the local price elasticity.

The extra revenue obtained by employing CPE compared to OPE steering translates to 4.1 % of total season revenue and 5.3 % of the total revenue earned during the markdown periods within the season. Since no additional costs are incurred to generate extra sales these numbers are equivalent to an increase in profit. This outcome represents a substantial improvement considering only very small margins predominant in the fashion retailing industry.

The analysis thus clearly advocates price differentiation on country level as a lever to improve profitability. This is a crucial insight since in e-commerce an increased likelihood of multinational business activity exists compared to traditional settings. Multinational accessibility, lower costs, and effort necessary greatly simplify company expansion by entering new markets (Singh and Kundu, 2002; Biswas and Biswas, 2004). In addition, borders defined by national culture regarding customer behavior in e-commerce will likely persist in the future (de la Torre and Moxon, 2001). However, online retailers face the challenge of changing prices of a high number of products very frequently. Companies usually carry large assortments, menu costs are lower compared to traditional channels, and price comparison sites increase transparency of the supply side (Biswas and Biswas, 2004).

Despite presented profit implications, a vast number of companies still do not make use of dynamic pricing practices, due to a lack of awareness and resources as well as internal resistance to change (P. Kopalle et al., 2009; Emarketer, 2013). Hence, strategies to tackle these challenges need to be developed. First, it is required to create awareness so company executives decide to introduce more sophisticated processes. The scientific community as well professional networks and associations with access to retailing executives are demanded to educate companies regarding bottom line implications of dynamic pricing and possible integration strategies. In a next step, company executives need to educate their workforce to create acceptance of new processes to avoid failure of integration due to internal resistance.

In a third step required resources need to be acquired to introduce dynamic pricing systems. A first option is represented by licensing one of the readily available Software-as-a-Service (SaaS) products offered by different vendors. While this strategy saves resources in the short-term, better results can be achieved by developing a dynamic pricing system in-house taking into account company-specific conditions and making use of all available data points that most of the SaaS products miss (P. Kopalle et al., 2009). Developing a custom solution requires hiring skilled personnel or internally educating employees to be able to structure vast amounts of data and develop an IT system dealing with a highly complex problem. To begin with, retailers need to develop a sophisticated forecasting method reliably predicting future sales of the assortment in stock. This forecast ideally takes place on a detailed level capturing product-specific demand patterns. Next, based on the forecast an optimization algorithm calculates the optimal discount rate per market and period to optimize operating profit. Therein, the algorithm needs to take different boundary conditions into account stemming from stakeholders internal and external to the company such as legal restrictions, supply characteristics, and firm goals.

5.2 Limitations and avenues for further research

We next report four limitations of this study that also represent opportunities for further research. First, the data set comprises observations from six countries inside the European Union, which can be considered a rather homogenous region. Expanding the study to countries outside Europe, especially to the US and Asia to validate results with more diverse data sets comprising also more variance in dimensions of national culture would thus represent a valuable contribution. In a similar vein, a single company provided the data set opening up the possibility of common source bias. Future studies could thus be based on sales data of more than one company per country to generalize results to industry level. Nevertheless, the data set at hand comprises sales transactions of more than 500,000 customers easing concerns of common-source bias.

Second, customers likely compare prices at competing retailers before purchasing the desired items at the retailer offering the best value for money. Price comparison sites and generally low search costs on the internet facilitate this customer behavior. Hence, varying price differences across retailers possibly lead to certain demand fluctuations. Further research could thus incorporate prices of competing retailers into analyses of price elasticities in order to account for customers comparing prices and possibly switching retailers.

Third, customers' purchase and brand choice decisions are likely influenced by on-site factors such as product reviews left by other customers. Taking into account these factors when developing demand models is a promising way to enhance validity of analysis.

Fourth, we took a first step in accounting for customer heterogeneity in estimating demand models on brand-category level individually while also distinguishing between genders. Future studies, however, could model customer heterogeneity on a more detailed level. Therein, using household level data to analyze the composition of the customer base over the season to account for consumer heterogeneity would improve the understanding of what drives the magnitude of price sensitivity in online fashion retailing and provide managers with valuable information for customized marketing strategies. In addition, examining demand patterns longitudinally in the online setting could help explain the evolution of e-commerce and changing customer behavior over the past decades.

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