Brand competition in fashion e-commerce

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1. Introduction

It is essential for retailers to take into account substitution and complementary effects within their assortment when making pricing decisions to improve overall firm profitability (Song and Chintagunta 2006). Successful pricing strategies should thus recognize interdependencies on brand level within and across related categories (Wedel and Zhang 2004). Knowledge of these in-store competitive effects can be very valuable for online fashion retailing companies as they oftentimes apply markdown pricing strategies offering potential for substantial profit gains (Levy et al. 2004). Due to industry-specific supply characteristics, these companies receive the majority of stock prior to season start and before actual demand is evident (Soysal and Krishnamurthi 2012). Moreover, products in this setting are highly perishable as fashion becomes obsolete when new styles are introduced to the market (Varadarajan and Yadav 2002). To clear excess stock of poorly selling products and to boost sales, retailers apply discounts by season end (Levy et al. 2004). These price reductions influence the sales of competing products in the same shop thereby possibly shifting demand between high- and low-margin items (Kopalle et al. 2009). In a category management setting the target is to optimize the overall outcome of a category. This requires a multiproduct pricing strategy accounting for price-induced substitution and complementary purchase across items (Song and Chintagunta 2006).

The e-commerce space offers a promising setting for this type of pricing strategy as retailers can leverage inexpensive tools to track supply and demand on a detailed level; at the same time low menu costs allow for reactive action in terms of frequent price changes (Biswas and Biswas 2004, Varadarajan and Yadav 2002). Highly frequent price changes, in turn, amplify the potential profit gain generated by applying a sophisticated markdown strategy (Varadarajan and Yadav 2002).

So far, retailers have often neglected cross-price effects in their pricing decisions (Hall et al. 2010, Levy et al. 2004). Some companies also lack the data, the ability, or the time to conduct cross-price elasticity analyses which are essential to be able to cope with the above challenge (Kopalle et al. 2009). Additionally, consistent with the resource-based view (RBV), scholars have identified the strategic importance of the pricing process as a capability to improve competitiveness in the marketplace (Dutta et al. 2003, Kemper et al. 2013). Although it is highly important for academics and practitioners, there has been only scarce research examining cross-price effects in e-commerce settings (Kopalle et al. 2009). Extant literature largely focuses on brick-and-mortar situations involving fast-moving consumer goods (Leeflang and Parreño-Selva 2012). As increased information availability exists online altered patterns of customer behavior with respect to product substitution are likely to occur which renders an examination of this topic in the e-commerce context an interesting extension to...
existing literature (Kopalle et al. 2009, Varadarajan and Yadav 2002).

With this study we seek to make the following contributions. First, we analyze demand interdependencies among brands in two independent pairs of related product subcategories in online fashion retailing. Hence, we examine the impact of price cuts on the market share of other brands in the same product cluster. In our analyses we use a unique data-set consisting of more than 3 million sales observations which was provided by a European fashion e-commerce company. Second, this research helps obtain a fuller picture of price elasticities prevailing in e-commerce. In this context the online fashion retailing setting has not received sufficient attention so far (Kopalle et al. 2009) leaving a gap we seek to close with the present study. Third, we derive insights for category management considerations as we analyze detailed patterns of cross-competitive effects found in this distinct setting.

2. Conceptual framework and hypotheses development

In the following we develop our conceptual framework and derive hypotheses to examine cross-price elasticities in fashion e-commerce. Price elasticity “measures the percentage sales loss (gain) from a certain percentage price increase (decrease)” (Nagle 1984, p. 9). Moreover, cross-price elasticities refer to the percentage shift in the demand for a product when the price of a related product is changed (Levy et al. 2004). This change in demand is positive for substitutes and negative for complementary goods (Mulhern and Leone 1991). Moreover, competition among brands is called asymmetric when the effect of a price change of brand A on the demand for brand B is different from the effect of brand B on brand A (Carpenter et al. 1988). In this context extant literature refers to a brand’s price changes influencing another brand’s sales (gaining market share) as clout and, similarly, to a brand’s sales being affected by another brand’s price movements (losing market share) as vulnerability (Kamakura and Russell 1989).

Four factors constitute the underlying effects responsible for price-induced sales shifts. First and second, there is current and future brand switching within the same as well as in other stores in the same category (Ailawadi et al. 2007, 2007). Third, a possible result are sales shifts in other categories in the same store (Ailawadi et al. 2007, 2007). Fourth, increased category or brand consumption is likely to occur following a price promotion (Ailawadi et al. 2007, 2007). In a similar vein, customers get detraeted from purchasing in the focal product category when prices increase (Ailawadi et al. 2006).

Previous research on cross-price effects focuses on brick-and-mortar settings where fast-moving consumer goods—mostly groceries—constitute the center of attention. In these studies, evidence of substitution and complementary effects among different brands and categories becomes apparent (Mulhern and Leone 1991, Walters and MacKenzie 1988). In addition, cross-price effects are found to be less pronounced compared to own-price effects (Leeflang and Parreño-Selva 2012). Furthermore, significant cross-brand effects exist among a substantial share of brands within a category. In this context different studies consistently find a two-digit percentage ratio of significant effects over all possible brand-to-brand effects within a category (e.g. Bezawada et al. 2009, Kamakura and Kang 2007, Leeflang et al. 2008, Song and Chintagunta 2006). In contrast, cross-competitive effects across categories are found to exist only among a fraction of the examined product categories. (Duvvuri et al. 2007, Leeflang and Parreño-Selva 2012). Moreover, research has revealed that there is asymmetric competition among price tiers and national as well as private brands (Blattberg and Wisniewski 1989, Wedel and Zhang 2004).

One major difference between offline and online retailing can be seen in increased supply side transparency in e-commerce since most online retailers offer a multitude of different searching, filtering, and comparison possibilities for their products to create a more convenient shopping experience (Biswas and Biswas 2004, Rubin and Mantin 2012). Early predictions theorize the emergence of frictionless commerce characterized by highly competitive markets, enabling customers to easily obtain an overview of the products offered by a retailer within seconds (Bakos 1997, Varadarajan and Yadav 2002). Although information availability is high in fashion e-commerce brand competition is still not likely to exist between all brands within a category for these kind of products because of fashion products’ distinct characteristics.

The classification of goods devised by the American Marketing Association groups products into either convenience, shopping, or specialty goods, with the respective category depicting an item’s importance to the customer as well as the effort invested to purchase it. Given this classification, fashion products are considered specialty goods (American Marketing Association 1948, Copeland 1923, Murphy and Enis 1986). Customers have to invest little effort into buying convenience products, whereas the opposite is true for specialty products. They are generally very important to customers, and they thus invest substantial physical effort to be able to purchase these items (Murphy and Enis 1986). Nevertheless, customers avoid canvassing information about substitutes when it comes to shopping this type of product (Kaish 1967). There are two reasons for this customer behavior. First, customers ascribe the potential to satisfy their distinct needs only to a small set of brands, which leads to less substitution among alternatives as customers decline all but the preferred items and are willing to make an extra effort to obtain them (Bucklin 1963).

The blocking of dissonance reduction serves as a second explanation for the lack of shopping activity. In a shopping context, cognitive dissonance occurs post-purchase if an item is important to the customer and turns out to have one or more inappropriate attributes (Kaish 1967). People generally seek to reduce dissonance in order to achieve consonance regarding their attitudes and mental accounts as well as their actions (Festinger 1970). Collecting product information helps reduce the anxiety that a product’s inappropriateness is only detected post-purchase, thereby reducing dissonance in the first place (Kaish 1967). Nevertheless, certain conditions exist when the possible anticipated dissonance is high but engaging in any activity does not promise to solve this dissonance (Festinger 1970). In this case, people refuse dissonance reduction and live with its discomfort (Festinger 1970). When shopping for fashion merchandise, product comparisons often do not yield sufficient information to reduce dissonance as for these goods, “the physical characteristics of the product do not reflect directly its functional characteristics” (Kaish 1967, p. 31). As a result, customers avoid comparing products as items are “purchased on the basis of brand preference stemming from habit or recommendation” (Kaish 1967, p. 30). Given this lack of extensive shopping activity, it is likely that customers do not extensively search for substitutes either.

De Figueiredo (2000) developed a more current product classification scheme in which products are categorized based on the difficulty to judge an item’s quality on the web (Nikolaeva 2005, Walter et al. 2006). The continuum of product classes includes commodity products, quasi-commodity products, “look-and-feel” items, and “look-and-feel” items with variable quality (De Figueiredo 2000). The difficulty to judge a product’s quality

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2 Later on, a fourth dimension, preference goods, was added to the framework (Murphy and Enis 1986). In addition, the product classification was based on two dimensions—risk of making a faulty purchase and effort invested in the purchasing process (Murphy and Enis 1986).
online increases in the same order (Walter et al. 2006). Fashion items are considered to belong to the “look-and-feel” category containing differentiated goods as the evaluation of their appropriateness requires personal examination (Jung et al. 2014, Lal and Sarvary 1999). Moreover, customers are subject to higher degrees of perceived risk in online shopping situations (Biswas and Biswas 2004, Kirmani and Rao 2000). One possible reason is the inability to inspect products personally, leading to the risk of buying functionally inappropriate products. Another likely reason is the risk of dealing with a fraudulent seller not delivering purchased items after the customer has paid for them (Biswas and Biswas 2004, Laroche et al. 2005). The former reason specifically applies to “look-and-feel” goods (De Figueiredo 2000). Hence, customers strongly rely on signals on the web which help reduce perceived risk (Kirmani and Rao 2000). Extant research identifies branding as one of the strongest signals customers use in e-commerce (Baye and Morgan 2009, Kwon and Lennon 2009, Smith and Brynjolfsson 2001). Consequently, buyers regularly adhere to their individual choice sets of brands as they feel they are able to deduce a product’s adequacy based on brand reputation and thus do not have to attempt to judge item quality based on information available on the internet (De Figueiredo 2000).

Summarizing, although information availability is high online customers have a rather small choice set for fashion products for which intense substitution occurs. This behavior stems particularly from increased perceived risk towards functional inappropriate-ness of fashion items as evaluating product quality is more difficult for differentiated “Look-and-Feel” products as a result of spatial distance between buyer and seller in e-commerce. The latter aspect is particularly different from brick-and-mortar settings. We therefore predict:

**Hypothesis 1.** Cross-brand competition is less pronounced in fashion e-commerce compared to the order of magnitude found in offline settings.

Previous studies have shown that asymmetric competition is present in brick-and-mortar settings; particularly among different price tiers as well as between private brands and national brands (Blattberg and Wisniewski 1989, Song and Chintagunta 2006, Wedel and Zhang 2004). The preference distributions which cause the trade-off between quality and price prevailing in most markets lead to asymmetric competition among price tiers. In this context, promotions of high-price high-quality brands attract the majority of the customer base whereas price promotions by low-price, low-quality brands result in only a small share of customers who substitute these for upper-price-tier brands as customers do not receive an adequate alternative in terms of quality when purchasing discounted low-price brands (Blattberg and Wisniewski 1989). The same relationship holds for private brands and national brands as private brands are oftentimes characterized by lower price levels compared to national brands (Wedel and Zhang 2004). Hence, private brands are associated with lower clout and higher vulnerability when being subject to cross-competitive effects as has been shown empirically in different offline applications (Blattberg and Wisniewski 1989, Pauwels and Srinivasan 2004).

In line with the big middle theory, there is evidence that large online retailers move towards a strategy of offering an assortment comparable to their offline counterparts (Ganesh et al. 2010). In addition, the majority of Western-world customers engage in online shopping and customer profiles are mostly similar online and offline (Ganesh et al., 2010; Kukar–Kinney et al., 2009). With similar assortments and customer profiles in place we predict similar quality distributions of brands and corresponding preferences among customers also to be present online. These aspects should thus result in asymmetric competition in the online context as well. Moreover, private brands usually pertain to lower price tiers in fashion e-commerce as well making asymmetries between private brands and national brands a likely outcome in this environment. Replicating results in existing literature we predict:

**Hypothesis 2a.** In fashion e-commerce, national brands induce higher levels of competitive clout compared to private brands.

**Hypothesis 2b.** In fashion e-commerce, private brands are subject to higher vulnerability compared to national brands.

### 3. Data

A leading European online fashion retailer provided us with a novel data-set consisting of more than 3.3 million observations of numerous apparel and shoes categories. Going forward, we choose two categories for further analyses of competitive patterns—women’s cardigans and men’s sneakers. We select this subset of two categories since we need to assume their independence in terms of competition. This is most likely the case as the above categories pertain to different genders as well as product groups (apparel and shoes respectively) and thus do not represent substitutes. The data cover the period between August 2013 and January 2014, spanning almost 150 days with about 290,000 observations for the two categories under study. On SKU level they contain information on actual demand, undiscounted price, and offer price of both private and national brands in the German web shop. Due to the high number of SKUs belonging to the categories under study (about 3000 SKUs each), the retailer split each further into two subcategories. Since this split is also visible for customers on the website, we use it in our analysis as well.

Going forward we select the 10 top selling brands per subcategory and aggregate data to brand level. Subsequently, we delete one brand per subcategory in the cardigans cluster since for these two brands we do not have sales observations for every day in the examined period which could pose difficulties in the estimation strategy. The number of SKUs per brand can vary in the course of a season since some styles become available in a later part of a season. This aspect may change the composition of a brand’s assortment on the website and may also change the average brand price. We therefore compute a price index per brand and day to control for this aspect. The price index is calculated as the average offer price divided by the average undiscounted price of all SKUs within a brand’s assortment. Price indexes generally follow a decreasing pattern over the season as a result of markdown practices.

In addition, price levels are heterogeneously distributed between private and national brands in both examined product categories, which facilitates the detection of asymmetric patterns in the competitive structure. The vast majority of discounts in our data-set are not accompanied by a specific promotion prominently communicating the price reduction as they mostly stem from markdown practices. Price reductions, however, can easily be identified since a red price and a sales sign are attached to the product. In addition, we compute the revenue share per brand and day which is positive for every observation. **Table 1** depicts descriptive statistics.

Additionally, we determine a composite of all remaining brands per subcategory to control for price and revenue share movements outside the subset under study (Song and Chintagunta 2006). The revenue share of the composite is computed as the sum of the revenue shares of all underlying brands. The price index, again, is defined by the average offer price divided by the average undiscounted price. This leaves us with a total of 18 brands and 2 composites (cardigans) as well as 20 brands and 2 composites (sneakers) per category for further analysis.
4. Methodology

In this section we outline the model employed to estimate cross-brand effects in the data-set under study while also accommodating asymmetric competition among brands. For this purpose both hierarchical and non-hierarchical models exist involving aggregate data as is the case in our setting (Leeflang et al. 2000).

We follow Leeflang and Parreño-Selva (2012) approach and use the asymmetric market share model devised by Carpenter et al. (1988) (CCHM model in the following). The CCHM model was developed to reduce the number of parameters to be estimated to a reasonable amount while still allowing for the accommodation of complex competition among brands in a category (Carpenter et al. 1988). It is based on the assumption that “a brand’s market share is equal to its attraction relative to all others” (Carpenter et al. 1988, p. 395). A brand’s attraction, in turn, is conditional on marketing activity and other dynamics of brand competition that can formally be illustrated as follows (Cooper et al. 1996):

\[
\begin{align*}
RS_{it} &= \frac{A_{it}}{\sum_{j=1}^{C_i} A_{jt}}, \\
A_{it} &= \exp(x_i + \epsilon_i) \cdot \prod_{k=1}^{\pi} f_{k}(X_{ik})^{\mu_{kk}} \cdot \prod_{(k') \in C_i} f_{k}(X_{i'k'})^{\mu_{i'k'i}},
\end{align*}
\]

where \(RS_{it}\) is the revenue share of brand \(i\) on day \(t\); \(A_{it}\) is the attraction of brand \(i\) on day \(t\); \(\pi\) is the number of marketing instruments; \(\epsilon_i\) is the error term; \(X_{ik}\) is the level of marketing instrument \(k\) of brand \(i\) on day \(t\); \(f_k\) is a transformation function; \(\mu_{kk}\) represents the own-effect of marketing instrument \(k\) of brand \(i\); \(\mu_{i'k'i}\) is the cross-effect of marketing instrument \(k\) of brand \(j\) on brand \(i\); \(C_i\) represents a subset of brands with possible cross-brand effects on brand \(i\).

The application of the CCHM model proceeds in three steps (Carpenter et al. 1988). First, a differential effects model without...
cross-brands effects is individually estimated for every brand under study. The resulting model has the following form:

\[ A_{it} = \exp(\alpha_i + c_{it}) \cdot \prod_{k=1}^{m} \beta_{ik} \cdot (X_{0kt})^{k_h}. \]  

(2)

We use log-centering to transform the attraction model in Eq. (2) for parameter estimation (Nakanishi and Cooper 1982). We particularly focus on the marketing instrument price as price is considered to be the most influential instrument (Carpenter et al. 1988). We thus utilize price indexes per brand and day for further analysis that were derived as presented in the previous section. The transformed model to be estimated for every brand under study has the following log-linear form (Carpenter et al. 1988):

\[ \log(\text{RS}_{it}) = \alpha_i + \sum_{t=2}^{m} \gamma_{it} \cdot d_t + \sum_{t=2}^{m} \gamma_{it} \cdot \log(P_{it}) + c_{it}, \]  

(3)

where \( \alpha_i \) is the intercept; \( \alpha_i \) is a brand-specific intercept; \( d_t \) is a dummy variable taking the value on the 1 if \( t \neq \tau \); \( \gamma_{it} \) is a period-specific effect; \( c_t \) is a dummy variable taking the value of 1 if \( t = \tau \); \( P_{it} \) is the price index of brand \( i \) on day \( t \).

Second, the residuals of the differential effects model are cross-correlated with the price indexes of all other brands in the examined category (Carpenter et al. 1988). A significant correlation between these variables points to a potential cross-brand effect. Therein, not the magnitude of correlation but the level of significance (\( p < 0.1 \)) is used to evaluate possible cross-price relations. Executing the second step, we find 18 and 15 significant correlations (\( p < 0.1 \)) is used to evaluate possible cross-price relations. Executing the second step, we find 18 and 15 significant correlations (van Heerde et al. 2013). The average own-price elasticity of all brands is equal to \(-1.62\) (standard error 0.02). In contrast, the average cross-price elasticity is 1.87 (standard error 0.02), pointing to a high level of substitution among brands in case a significant relationship exists.

Figs. 1 and 2 depict elasticity figures on the brand level for the categories cardigans and sneakers, respectively. These figures illustrate the within-category competitive structure in more detail. There are substantial asymmetries apparent in both categories under study.

In the following we refer to a brand’s price index, which has an impact on another brand’s revenue share as clout and also as active effect. Similarly, we use the terms vulnerability and passive effect if a brand’s revenue share is affected by another brand’s price index. The brands in one cardigan subcategory cause 10 of 14 active effects overall. Moreover, two national brands belonging to either subcategory seem to be particularly influential as they combine 12 of 14 active cross-price effects. In total, six brands induce active effects, whereas nine brands are not affected by other brands at all. Additionally, no brand is influenced by more than three other brands.

Brands in one sneaker subcategory combine 12 of 14 active cross-brand effects. In total, only five brands involve active effects on other brands’ revenue share. The maximum number of active effects originating from one single brand is seven. In contrast, no brand is affected by more than two different brands. 11 brands are not affected by other brands at all and 17 brands do not induce active effects.

Next, we review both clout and vulnerability of private and national brands to test Hypothesis 2 that predicts a higher clout value pertaining to national brands (Hypothesis 2a) and a larger vulnerability value associated with private brands (Hypothesis 2b) as a result of asymmetric cross-competitive effects. First, contrary to our expectations, the average clout of private brands is higher (mean 3.13; standard error 0.76) than that of national brands (mean 1.84; standard error 0.02). Nevertheless, the private brand value is characterized by a large standard error resulting in the 95% confidence intervals of both values to intersect. The clout values are only different at the 0.1-level. In addition, the private brand value stems from two significant effects only originating from two brands. We conclude that we are not able to make valid inference on deviations in clout between private and national brands as we cannot thoroughly evaluate a difference in active effects between these two clusters. We thus reject Hypothesis 2a. Second, the mean vulnerability of private brands is higher compared to the respective value associated with national brands

\[ e_{ij} = \beta_{ij} \cdot (1 - \text{RS}_{it}) \cdot X_{j} \cdot j \in C_{i}. \]  

(5)

A positive value means brand \( j \) is a substitute for brand \( i \); a negative value indicates brand \( j \) represents a complementary good for brand \( i \). The own-price elasticity for brand \( i \) can also be derived by applying Eq. (5) with \( j = i \).

5. Results

In order to test the hypotheses, we estimate the CCHM model (Eqs. (1–4)) and subsequently derive price elasticity figures using Eq. (5). The SUR estimation procedure yields a satisfactory fit with a McElroy \( R^2 \) of 66% and 56% for cardigans and sneakers respectively. Table 2 summarizes the corresponding results. We find significant cross-price elasticities in 28 of 842 brand relationships. This translates to a quota of about 3.3% and thus represents only a small share of all possible effects. In support of Hypothesis 1, this value is well below the two-digit values found in offline settings.

The mean effects depicted in Table 2 are derived by applying the method of added Zs (Rosenthal 1991). To this end, all significant cross-price effects pertaining to one of the displayed clusters are aggregated by computing a weighted mean with the inverse of the standard errors of each effect serving as the respective weights. The aggregated effects thus represent reliability-weighted measures (van Heerde et al. 2013). The average own-price elasticity of all brands is equal to \(-1.62\) (standard error 0.02). In contrast, the average cross-price elasticity is 1.87 (standard error 0.02), pointing to a high level of substitution among brands in case a significant relationship exists.
private brands: mean 2.46; standard error 0.11 vs. national brands: mean 1.73; standard error 0.02). The 99% confidence intervals of both effects do not intersect. We thus conclude that private brands are more vulnerable towards cross-brand effects, hence Hypothesis 2bis supported.

6. Discussion

In this study we empirically derive own-price as well as cross-price elasticity estimates in two categories in an e-commerce fashion retailing setting. We predict the extent of brand competition to be rather small since e-commerce fashion customers tend to have a rather small but clear-cut set of brands they consider for purchase which prevents large-scale substitution among all brands in a category (Hypothesis 1). Furthermore, replicating results in extant research, we predict that asymmetries in competitive patterns among brands—particularly between national and private brands—exist since differences in brand attributes inducing asymmetric competition in brick-and-mortar settings are also present in the online channel (Hypotheses 2a and 2b).

Table 2
Overview of elasticity estimates. a

<table>
<thead>
<tr>
<th>Cluster</th>
<th>Total # of effects</th>
<th># positive effects</th>
<th># negative effects</th>
<th>Mean effect</th>
<th>Mean effect on NB</th>
<th>Mean effect on PB</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cardigans women</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Own-price elasticity</td>
<td>9 (45.0%)</td>
<td>3</td>
<td>6</td>
<td>–1.50</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Cross-price elasticity</td>
<td>14 (3.7%)</td>
<td>12</td>
<td>2</td>
<td>1.33</td>
<td>1.27</td>
<td>1.51</td>
</tr>
<tr>
<td>Cross-price elasticity of NB</td>
<td>12 (4.2%)</td>
<td>10</td>
<td>2</td>
<td>1.25</td>
<td>1.16</td>
<td>1.51</td>
</tr>
<tr>
<td>Cross-price elasticity of PB</td>
<td>2 (2.1%)</td>
<td>0</td>
<td>0</td>
<td>3.13</td>
<td>3.13</td>
<td>–</td>
</tr>
<tr>
<td>Sneaker men</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Own-price elasticity</td>
<td>16 (72.7%)</td>
<td>4</td>
<td>12</td>
<td>–1.70</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Cross-price elasticity</td>
<td>14 (3.0%)</td>
<td>11</td>
<td>3</td>
<td>3.00</td>
<td>2.52</td>
<td>6.72</td>
</tr>
<tr>
<td>Cross-price elasticity of NB</td>
<td>14 (3.3%)</td>
<td>11</td>
<td>3</td>
<td>3.00</td>
<td>2.52</td>
<td>6.72</td>
</tr>
<tr>
<td>Cross-price elasticity of PB</td>
<td>0 (0%)</td>
<td>0</td>
<td>0</td>
<td>3.13</td>
<td>3.13</td>
<td>–</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Own-price elasticity</td>
<td>25 (59.5%)</td>
<td>7</td>
<td>18</td>
<td>–1.62</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Cross-price elasticity</td>
<td>28 (3.3%)</td>
<td>23</td>
<td>5</td>
<td>1.87</td>
<td>1.73</td>
<td>2.46</td>
</tr>
<tr>
<td>Cross-price elasticity of NB</td>
<td>26 (3.7%)</td>
<td>21</td>
<td>5</td>
<td>1.84</td>
<td>1.67</td>
<td>2.46</td>
</tr>
<tr>
<td>Cross-price elasticity of PB</td>
<td>2 (1.5%)</td>
<td>2</td>
<td>0</td>
<td>3.13</td>
<td>3.13</td>
<td>–</td>
</tr>
</tbody>
</table>

a NB: national brand; PB: private brand. Table depicts number and magnitude of significant effects only. Percentage share of significant to possible effects in parentheses. Mean effects are represented by the means of all significant effects falling into the respective cluster obtained by applying Rosenthal’s method of added Zs. All mean effect values are significant at the 0.01 meta-analytic p-value.

Fig. 1. Women’s cardigans elasticity estimates on brand level.
We employ the model developed by Carpenter et al. (1988) to estimate cross-price elasticities while accommodating asymmetric competition among brands. To estimate our model, we draw on a large data-set consisting of millions of observations of sales transactions provided by a leading European e-commerce fashion retail company. Empirical results show significant cross-price elasticities in about 3.3% of all possible relationships which reflects a low level of brand competition. In addition, asymmetric and distinct competition between private and national brands is present. These results support most of our hypotheses (except for Hypothesis 2a) and have both academic as well as managerial implications.

6.1. Implications

With this study, we address a research gap pertaining to demand-side effects in e-commerce. Bijnol et al. (2005) emphasized the need to investigate price elasticities in online situations as these might be systematically different from brick-and-mortar settings. In addition, Kopalle et al. (2009) call for more studies on competitive price effects in fashion e-commerce since research on this topic has been scarce although “the ongoing focus on cross-category effects has great theoretical and substantive importance” (Lee and Parreño-Selva 2012, p. 584). To the knowledge of the authors, this is the first study to examine inter-brand competition in fashion e-commerce. We thus contribute to the marketing literature by finding unexpectedly small competition among brands and by identifying asymmetries in the competitive structure between private and national brands in two independent product categories. In addition, this study is among the first to use large-scale records of actual sales transactions to determine such competitive price effects in e-commerce. Previous research had only scant access to sales data and mainly used proxies instead (Granados et al. 2012, Grewal et al. 2010).

Moreover, we contribute to the literature on market efficiency and information economics by showing that online brand competition is small with cross-price effects being very distinct and highly pronounced only among a small share of all possible relationships. These results are in sharp contrast to early predictions of a frictionless electronic commerce due to increased information availability (Alba et al. 1997, Bakos 1997) and rather support the theoretical work of increased search cost online for differentiated goods (Lal and Sarvary 1999). In this context we also complement the empirical study by Ellison and Ellison (2009) in which they demonstrate how lower-quality memory modules can serve as loss-leaders for more expensive higher-quality items. The low price of low-quality items helps drag customers’ attention at a price comparison site to a web shop where they potentially switch to more expensive items. In contrast to the study by Ellison and Ellison on cross-competitive effects prevailing online we examine customer choice behavior in a situation involving a large differentiated goods assortment in e-commerce that is not as dependent on price comparison engines as product comparability is limited across brands and retailers (De Figueiredo 2000).

To this end, it would be highly interesting to study the effect of online fashion retailers’ attempts to increase tangibility of their product portfolio on brand competition within a product category. Retailers invest great effort into developing more advanced shopping aids such as mechanisms helping visualize clothes on customers’ bodies or measuring body shapes to determine best
fitting styles and sizes to further enhance the onsite shopping experience. A longitudinal study on cross-price effects in fashion e-commerce depicting increasing product tangibility would thus represent a fruitful extension to the ongoing discussion on market efficiency in e-commerce situations.

Extant research points out how important it is to consider inter-brand competition when making pricing decisions as this can serve as a lever to improve profitability (Grewal et al. 2011, Kopalle et al. 2009). This importance increases even more in the wake of intensified competition in e-commerce and emphasizes the necessity for managers to understand cross-brand effects. Considering our empirical results, firms need to take a category management perspective regarding the entire product portfolio when developing markdown pricing strategies in online fashion retailing since price cuts can lead to the opposite of the desired effect. Price reductions accompanied by inclining sales in one part of a category can thus lead to severe cannibalization of demand in other parts of the same category possibly leading to a deterioration of high-margin products’ sales. Cross-price effects therefore need to be incorporated into successful pricing strategies to sell off existing inventory while achieving the highest possible profit by gearing demand towards high-margin products. In this context, it is essential to reflect cross-price effects at a granular level to allow for the accommodation of asymmetries in the competitive structure of different brands. The resulting optimization problem involves high complexity with increasing assortment size that requires the employment of a sophisticated IT system.

Furthermore, some negative cross-price elasticity figures exist in our sample pointing to complementary purchase among per se competing brands. This represents a counterintuitive result at first sight. A possible explanation for this phenomenon is customer behavior implying extensive product returns. Customers might get attracted by discounted products of one brand and subsequently buy several similar items although they plan to keep only a fraction of their purchase and send all but the most-appealing items back. This behavior is facilitated as returns come at no cost to the customer at the retailer under study. Product returns have negative profit implications for retailers since they have to cover the costs incurred by cooperating logistic partners carrying out delivery. A successful markdown strategy should thus also incorporate patterns of product return behavior to improve bottom-line firm profit. This argument becomes increasingly important as more and more retailers are offering free product returns to compete in the marketplace. In particular, vendors selling products with non-digital attributes-items that need to be physically evaluated by customers to judge quality (Lal and Sarvary 1999)—need to find ways to cope with this challenge.

6.2. Limitations and avenues for further research

We next report limitations of our study that also include possible directions for further research. First, our study examines competitive price effects in two specific categories. It would be worthwhile to analyze different categories and, additionally, other product types such as undifferentiated goods in online settings to complement our findings. The comparability of undifferentiated goods makes within-store substitution a viable choice for customers and thus suggests highly pronounced substitution effects. The latter aspect could be analyzed on an even more granular scale by examining changes in price competition with products in varying stages of their life cycles as competition as well as product comparability may change over time. In a similar vein, it would be interesting to incorporate other marketing instruments than price such as targeted promotion campaigns and search engine marketing to quantify their impact on revenue shares. This could provide managers with a more holistic framework on which they can base their marketing decisions.

Second, we particularly investigate competition among different brands within two independent categories. Examining complementary purchasing across different related categories as well would help obtain a more complete picture of cross-brand effects present in fashion e-commerce. The combined findings would provide managers with valuable information which they can use to holistically evaluate the effectiveness of price promotions.

Another interesting extension of the present study would be the estimation of cross-price effects taking into account the distance between products or brands in terms of website location and sorting position. This would help answer the question whether retailers have to incorporate interaction effects for products that are very far apart in markdown algorithms. Previous research has shown that the distance between products influences competitive price effects in brick-and-mortar settings (Leefflang and Parreño-Selva 2012). Increased information availability online may alter this effect as customers are offered a multitude of searching and filtering options which potentially diminish the effect of distance.

Fourth, using household-level data to confirm the findings of the present study would be a worthwhile enhancement. Especially the differences in price sensitivity between comparing and non-comparing customer segments could be interesting for e-retailers. The e-commerce space offers opportunities to address customers individually depending on their distinct behavior. Subsequently, the design of on-site recommendation engines could benefit. This would facilitate customizing the set of products to be recommended to a customer depending on his or her affiliation with one of the opposite customer segments. Offering similar products with higher profit margin to the comparing customer segment while attempting to induce cross-selling to non-comparing customers with use complements represents an option to enhance both revenues and profits.

References
