Impact of Product Differentiation, Marketing Investments and Brand Equity on Pricing Strategies: A Brand Level Investigation

1. Introduction

Most companies use marketing-performance measures such as brand loyalty, market share, price premium and customer lifetime value, to determine their success or failure. Pricing is one of the most important elements of marketing mix and pricing strategies play an important role in a company’s marketing strategy (Kotler and Keller 2012; Tirole 1988). Hence, it is not surprising to see a large body of research on pricing in both marketing and finance areas on pricing; however the application of this type of research to both theory and practice has not been as prevalent as other marketing variables (Duke 1994; Christopher 2000).

One of the main reasons for this gap between theory and practice could be the difference in the orientations of marketing and finance researchers, with researchers in finance focusing on the impact of firm strategies and stakeholders’ short-/long-term expectations and marketing researchers on customer reactions and / or impact of branding on marketing strategies and decisions (Madden et al. 2006). A second reason could be that finance researchers typically use firm-level data from equity markets and the company’s financial statements, while marketing researchers generally use surveys or an experimental-research approach (Madden et al. 2006).

As a result, it is not usual for marketing researchers to deal with huge databases that can explain company, consumer or product (brand) patterns and behavior, nor is it usual for them to conceptualize their research using the findings from either industrial organizations (or any approach from a broad microeconomic theory) or other fields of economic science (such as finance, etc.). As scholars have studied neither pricing controversy (Myers et al. 2002) nor its
antecedents in detail (Christopher 2000), the pricing strategy is very often based on intuition and the working experience of managers rather than on empirical findings. We address this lack of empirical research on pricing using real-life data.

Many companies try to improve their marketing strategy through brand differentiation, using innovations in the technology or marketing domain. However, the question remains as to how do differentiations in pricing and branding relate with each other for different types of players in the market, such as Small and medium enterprises (SME), Multinational companies (MNC) and retailer (private label) brands. In fact, there is hardly any empirical research on how and whether brand differentiation and investments in brand building affect consumers’ willingness to pay a higher price, or to what extent these effects vary across different contexts. This is the second gap we address in this research.

In the words of Hanssens et al. (2009, p. 116), although the key marketing and financial metrics are influential factors in market valuation and, consequently, a firm’s market value, “how all these marketing assets, capabilities, and actions play out in determining market value remains somewhat of a mystery”. These issues are important because managers make decisions about these factors every day and the intention of our study is to give them more information to support this decision making process. The literature on the interaction among brands, price and differentiation is scant. There is no clear answer as to how drivers of brand equity influence a company’s competitive strategy in a brand performance context (Chu and Keh 2006, Peterson and Jeong 2010). We address this lack of evidence about the link between the drivers of brand equity and marketing performance.

To summarize, the aim of this study is twofold: First, to analyze the effects of brand equity, marketing investments and product differentiation on price. Second, to study the price in three
different innovation types (conventional, organic, functional) and for three different market players (SME, MNC and retailers). The food brands are clearly differentiated by the technology, quality and production standards applied; and conventional food has the lowest innovativeness applied, whereas functional food has the highest (Verbeke 2006; Sparke and Menrad 2009; Hamzaoui-Essoussi and Zahaf 2012; Dvcik 2013). In this process, this paper makes several contributions to the existing business literature. First, we estimate a model that empirically tests pricing, brand equity, marketing investments in the brand and several innovation variables. The literature (e.g., Duke 1994; Christopher 2000) has reported the need for empirically-based and overall solutions regarding relationships among brand price, brand equity and innovation. Second, we study the impact of product (brand) differentiation on price, based on innovation.

Our approach is in line with recent calls to study factors that determine the effects of marketing assets on financial metrics (e.g., Hanssens et al. 2009; Bharadway et al. 2011; Madden et al. 2006). Third, existing marketing and branding studies in the SME context (e.g., Keller 1993; Peterson and Jeong 2010; Sriram et al. 2007; Park and Srinivasan 1994; Simon and Sullivan 1993) mostly use a single-method (e.g., customer surveys, panel data, financial-report data, etc.), use a single unit of analysis (consumer, financial, organizational, etc.) and focus on one type of organizations (MNC or public companies).

In this study, we combine several research measures and methods to provide richer and deeper insights: (i) a consumer approach, using data from real-life consumers; (ii) a financial approach, employing financial data from the companies whose brands are part of the study; (iii) a marketing approach, using a brand dataset that forms the basis for the qualitative data employed in the study. Our methodology is based on a two-stage approach. In the first stage, we use a regression analysis to estimate how price performs in ‘Fast Moving Consumer Goods’ (FMCG)
context. After studying the role of price, we test its performance using a cluster analysis so as to determine how the product differentiation, driven by innovation, can lead to a premium price, as well as which player in the market (SME, MNC or retailers) may obtain this price. This is in line with Ketchen and Shook’s (1996) suggestion of not using cluster analysis in isolation but to augment it with additional statistical techniques, such as multivariate analysis.

This paper is structured as follows. We begin with a review of relevant pricing and branding literature to develop our framework and hypotheses. Next, we present the two-stage model with detailed descriptions of the dataset and the variables as well as estimation of the pricing model using regression analysis and analysis of product (brand) differentiation using cluster analysis. The final section describes and interprets the results of the study and concludes with implications for managers.

2. Conceptual background and research model

Companies usually compete in oligopolistic and open markets with similar technologies and marketing know-how. This implies creating competition on pricing is a dominant business strategy and this will lower profits in the long term. In order to defend its current position (i.e., price level and market share), an incumbent company has more incentives to introduce new brands than an entrant because of the “efficiency effect” that tends to bias market structure towards multi-brand situations (Tirole 1988). The other side of the coin is that an entrant has an incentive to proliferate and differentiate its brands in order to gain new market power and a better position in the market (Schmalensee 1982; Sriram et al. 2007). However, there are no clear guidelines on how to create an appropriate and efficient pricing strategy.
The theory of industrial organization (IO) suggests that consumers will be ready to pay a premium price if alternative brands do not have the same quality as the preferred brand, wherein the brands are differentiated and the cross-elasticity of demand is limited to equal prices (Tirole 1988). The principle of differentiation also explains why companies generally do not want to position their brands in the same market place as competing brands (Tirole 1988). The reason for this behavior is explained by the Bertrand paradox, because perfect and competing brand substitutes will face strong price competition which will jeopardize the prospects for profit and growth in the market. In IO terminology, product differentiation will create market niches and new markets, allowing entrants (first-time movers into the new market) and/or incumbents (dominant innovators in the existing market), to enjoy some market power over competing brands for a period of time.

Contemporary pricing theory is based on rational, classical economic behavior that views price as a signal of quality (Erdem et al. 2010; Ngobo 2011). This economic mechanism suggests that higher prices correspond to higher quality, which implies that a premium price might be achieved only by premium quality and differentiation based on innovation (Schmalensee 1982; Erdem et al. 2010; Kamakura and Russell 1993). The premium price represents consumers’ willingness to pay more than the usual or generally expected price. In a marketing context, this definition can be expanded and understood as consumers’ willingness to pay extra for the additional value that the brand offers. This mechanism takes place when a consumer is ready to pay for a product because he/she also wants to acquire certain benefits from a brand. Hence, a firm should set the price around the values that the brand offers to consumers.

The role of value in brand-level performance has rarely been investigated (e.g., Barth et al. 1998; Peterson and Jeong 2010), and little is known about how price depends on brand equity,
innovation activities, or marketing investments intended to improve brand performance. Pricing has a multi-decision consequence on a company’s performance. In a multi-brand organization, the price decision made about one brand will influence the performance of another. This is because of the internal competition and possible cannibalistic situations that can occur among brands within the multi-brand company. Firms must clearly differentiate their brands according to value cues and innovation, as well as different price categories and strategies among internally competing brands. The situation is similar in the marketplace, where competing brands are interconnected like water tanks; in general, if one organization lowers/raises prices, or introduces new enhancements or advertising campaigns, it will affect competing brands and change the existing market equilibrium.

In the context of this research, we understand that a premium price is a higher price than the average for a product category (i.e., cluster of products) in comparison to several other and similar categories across the same industry segment and market. The literature suggests that a firm’s brand success is associated with a strong brand in terms of its ability to achieve a premium price (Ambler et al. 2002). The “strong-success” correlation arises due to the customer perception that a recognized brand must equally reduce the risk associated with consumption and consumers’ inability to base their choice on experience due to frequent introductions of new models and improvements (Scitovszky 1944; Ambler et al. 2002; Madden et al. 2006); it is also due to the loyalty-switching cost, which appears because of a stronger relationship between a firm and its consumers. In order to gain the lucrative benefits of branding and premium pricing, an organization has to manage its brand portfolio so that a consumer can easily identify the unique brand values that are differentiated and sustained over a longer period of time.
In summary, we develop our conceptual approach based on Schmalensee’s (1982) analytical model, which explained the role of differentiation in brand performance outputs (i.e. price and market share\(^1\)). However, this model does not include the value of the brand (usually conceptualized through brand equity); nor does it empirically test its own premises. From marketing literature, we use the approach set forth by Peterson and Jeong (2010), who explained the role of brand value in a performance context, using the difference between brand assets and expenditures. However, this model is somewhat limited in scope because it focuses on the interrelationship between brand value and performance output, without including other explanatory effects of brand performance, such as how much a company invests in its marketing activities or differentiates its brands from the competition.

The second limitation is their focus on the performance of stock market brands, because they did not include small and non-public companies in their analysis. From finance literature, we benefit from Barth et al.’s (1998) work on the incremental contribution of brand value to price. Using the ordinary least squares (OLS) measurement approach, they related different layers of brand value (e.g., value of brand equity, advertising expenses, brand market share, etc.) to share prices. However, the conceptual foundations and theoretical justification of the constructs used are somewhat limited and unexplained. They have not defined the nuances of underlying brand forces, nor have they justified the causality between the employed constructs by using hypotheses / propositions.

As a result, it is not clear how different brand-value constructs – advertising effects and value of brand equity, among others – interact and contribute to share prices. However, their research idea and empirical approach is a valuable starting point for our study and we overcame

---

\(^1\) Price and market share are commonly used as measures of brand-performance. We focus on price in this manuscript, using market share as a control variable (Peterson and Jeong 2010; Slotegraaf and Pauwels 2008; Keller and Lehmann 2006).
these limitations by outlining clear and precise definitions of constructs and their causality. In the following subsections, we will establish research hypotheses and investigate how price performs in the market and across different types of innovation and companies.

2.1. Role of brand equity in price performance

Brand equity represents the value of the brand. This value is constituted by brand assets such as high brand loyalty, perceived quality, name awareness, strong brand associations, trademarks, patents (e.g., Kotler and Keller 2012; Aaker 1991; Park and Srinivasan 1994), production standards and applied innovation. From a marketing point of view, brand equity represents the customer mindset about the brand and includes perceptions, expectations, experiences, etc. (Ambler et al. 2002) and may yield specific outcomes such as incremental volume, price premium, profit, etc. (Ailawadi et al. 2003; Slotegraaf and Pauwels 2008). Brand equity may serve as a signal of the brand’s credibility in the market (Erdem and Swait 1998) and provide a goodwill value that can reduce uncertainty (Broniarczyk and Gershoff 2003), or it may be seen as an incremental contribution to the firm as consumer’s choice of the brand gives rise to the base product (Srinivasan et al. 2005; Park and Srinivasan 1994; Simon and Sullivan 1993).

Numerous sources, measures and theoretical approaches exist in the field of brand value, but there is no consensus on how to develop a unique measure of brand equity, or what the drivers of brand equity performance in the market are. There is fierce academic debate about the conceptualization of the appropriate theoretical and measurement approach in brand equity (Davcik 2013). The major cause of this debate is the numerous research approaches that define different – and in many instances conflicting – measurement approaches and research assumptions: customer-based, market-based, finance-based, etc. (Keller 1993; Ailawadi et al.
We follow the financial-based approach, because this research stream asserts the importance of financially based measurement and valuation of brand value (e.g., Simon and Sullivan 1993; Kamakura and Russell 1993; Park and Srinivasan 1994).

The stream of literature that is based on the customer-based brand equity concept (e.g., Keller 1993; Erdem and Swait 1998), suggests that price is an indicator of brand strength and brand equity. This research assumption is reasonable from the consumer perspective where researchers are trying to determine interrelated value factors in an experimental set-up. However, the financial-based approach (as used by us in this paper) suggests that innovation and brand quality drive brand equity through value propositions, which in turn allows marketers to draw a price premium (Simon and Sullivan 1993; Ailawadi et al. 2003; Kamakura and Russell 1993). In other words, according to this alternate view, brand equity is presented as an antecedent rather than outcome of pricing strategy. The contemporary research findings in marketing correlate higher brand equity with higher prices, if the latter are based on high quality and differentiation (Sriram et al. 2007; Suri et al. 2002; Knox 2000; Schmalensee 1982; Erdem et al. 2010; Stiglitz 1987). Price premium represents the effectiveness-orientated concept of a firm’s performance, because it is recognized in the literature as the value delivered to the consumer (Sandvik and Sandvik 2003). Park and Srinivasan (1994) explicitly address the importance of the impact and influence of brand equity on price premium.

**H1:** The likelihood of a higher price will increase with a focus on brand equity due to a greater emphasis on higher brand quality.

### 2.2. Role of marketing investments in price performance
Marketing investment in a brand represents expenses intended to increase its quality and reputation. These investments consist of advertising expenditures on the brand, promotional activities, etc. (Simon and Sullivan 1993; Sriram et al. 2007; Srinivasan et al. 2005; Peterson and Jeong 2010). A seminal paper by Schmalensee (1974) describes marketing investment as selling and promotional expenditures that are important sources of brand, which in turn has dynamic effects on demand through the pricing mechanism. These expenditures are important because of their influence on brand performance (Rust et al. 2004). For instance, promotion has a key role in obtaining the price premium because higher prices suggest better quality in the consumer’s overall assessment process of higher brand quality (Suri et al. 2002; Stiglitz 1987). A lucrative position in the market can yield price premium for a firm, but this market mechanism can also provide an entry barrier for companies who have to overcome the incumbent companies (Schmalensee 1974; Chu and Keh 2006).

Marketing investments may influence the consumers’ experience, utility and assessment of the brand quality (Fernandez-Olmos and Diez-Vial 2013), as well as their brand loyalty (Schmalensee 1974). Product quality affects price because a perceived higher quality allows a company to charge a higher price; in return, a higher price may enhance perceived quality of a brand, serving as a quality cue (Aaker 1991). Barth et al. (1998) addressed this problem and found that advertising expenditures, with an incremental effect on brand quality, have a negative relationship with the value of brand equity. The brand equity and marketing investment may intertwine, and their joint effects may boost revenues through higher prices and also serve as a barrier to entry (Srivastava et al. 1998). Thus:

**H2:** The likelihood of a higher price increases with a degree of higher marketing investments in a brand.
H3: There is a negative interaction between brand equity and marketing investment such that lower-quality brands generate a lower price performance than higher-quality brands with the same level of marketing investments.

2.3. Role of differentiation in price performance

Differentiation involves creating a brand that is perceived to be unique and distinctive in comparison to others on offer (Porter 1998a; Kotler and Keller 2012). Differentiation is an act of creating a set of meaningful differences that makes a company’s offers distinctive from those of competitors (Kotler and Keller 2012). The differentiated value provided by a firm, such as quality, reliability, service, etc., can create an image of a brand that might earn a 10-20% price premium (Kotler and Keller 2012). If differentiation is successfully applied, brands can reach a higher relative price (e.g., Knox 2000; Chaudhuri and Holbrook 2001; Tirole 1988; Dąbcik and Rundquist 2012). Successful brands are characterized by a higher brand value differentiation in comparison to less distinctive brands (Knox 2000). Differentiation (marketing domain) and innovation (technology domain) are the key elements of the brand paradigm, because they shape and drive a brand’s performance. For instance, Madden et al. (2006) call for further empirical insights into the relevant differentiation in the interrelationship between characteristics of strong brand and performance.

A company differentiates its brands through innovation because they want to soften any price competition (Schmalensee 1982; Tirole 1988). This mechanism implies that firms will have less incentive to differentiate brands when they do not compete on prices, which is not a very likely assumption in an open market. Distinctive brand differentiation among competing brands in the market can be achieved by more innovative brands, which may help a firm maintain its
dominant position for longer as it requires a new firm to have more resources to enter the market and/or to fill the innovation gap (Tirole 1988). In contrast, cheap brands are preferred by consumers that expect less differentiated and innovative brands (Sandvik and Sandvik 2003). In the FMCG context, differentiation can be achieved by the application of different innovation types, such as technology and production standards applied in the creation of a brand. If brand innovation is successfully applied by the company, that company will hold the existing price level and/or a monopoly for longer periods of time. Hence,

**H4:** The likelihood of obtaining a premium price increases as the degree of brand differentiation increases.

3. Methodology

3.1. Data description and measures

Several data sources have been employed in this research. The first is the scanner data from ACNielsen research into the food consumption of 10,282 Italian households. Data were used for the creation of different variables that describe consumption and market behavior, such as price, qualitative behavior of brands, etc. The Consumer Panel Solutions (CPS) and Homescan® panel tool were employed in order to obtain data from ACNielsen. The CPS consumer-centric marketing solutions were used to make in-depth analyses of purchase behaviors, demographic profiles, quantities sold, prices paid, etc. Second, data were obtained from the Bureau Van Dijk Electronic Publishing AIDA financial statements database for companies in the Italian market to develop the measures of brand equity that are used in this study. The research framework has been expanded to include quality independent variables, extracted from these data sources,
according to observed quality characteristics of brands and the technology applied in their creation. Table 1 shows the variables used in this research.

\{TAKE IN TABLES 1 and 2\}

We obtained panel data at the stock keeping unit (SKU) level, which we aggregated at the brand level. Single brands, rather than individual consumers, have been employed as units of observation in this study because aggregated consumer behavior at the brand level will produce more reliable results for the branding research (Hanssens et al. 2001; Chaudhuri and Holbrook 2001). In this way, the research avoids the potential pitfalls in experimental manipulations and obtains more accurate managerial implications, because decision-making is effective at the level of individual brands (Srinivasan et al. 2005).

The dependent variable is price, which represents the amount of money that consumers paid for a product in a store, aggregated at the brand level. We draw this information from ACNielsen data. Brand equity represents an asset that is calculated by a firm’s patents, licenses, etc. This value is taken from the BI position, intangible assets, in the company’s balance sheets from the AIDA database. This variable has been calculated using a single brand share indicator in order to allocate the brand equity value of a specific brand.

\[
(1) \quad v_{jk} = V_{jk} \left( \sum_{i=1}^{N} \frac{q_{ij}}{Q_{jk}} \right)
\]

where \(v_{jk}\) denotes brand \(j\)’s equity for firm \(k\); \(V_{jk}\) represents firm \(k\)’s equity from brand \(j\); \(q_{ij}\) is quantity of brand \(j\) sold to consumer \(i\); \(Q_{jk}\) denotes overall quantity sold by firm \(k\) of brand \(j\).
This measurement approach is conceptually based on Simon and Sullivan (1993) and in line with Park and Srinivasan (1994, p. 272) as it allows for estimation and “managing an individual brand in a multi-brand firm operating in multiple product categories”.

Marketing investments represent expenditure for the reputation of a brand, such as advertising and sales promotion as reported in a firm’s income statement. Prior research (e.g., Fernandez-Olmos and Diez-Vial 2013) relates marketing resources to the performance of a brand as the ratio of marketing-related expenses to total sales. However, this measure is not precise because it captures the overall marketing effects while neglecting the performance and influence of the individual brand. Hence, our measure is a better performance indicator because it captures the individual effect of marketing resources in a branding framework.

We use company and innovation type as indicators of quality. It has been suggested in the literature (e.g., Shepherd 1972; Chu and Keh 2006; Rubio and Yague 2009; Galdeano-Gomez and Perez-Mesa 2012) that product quality (e.g., technological standards and innovation) and company efforts (such as company culture, strategy, size, etc.) are important variables that influence profitability and overall brand performance. Product quality, based on innovation and company uniqueness, may provide the opportunity to charge a premium price (Aaker 1991) and create differentiation and market boundaries for new entrants (Sriram et al. 2007).

In the current study, applied innovation will be used as a proxy for product quality, because the consumer’s assessment of perceived value cannot be observed and measured directly (Kamakura and Russell 1993; Aaker 1991; Mamalis 2009; Davek and Rundquist 2012). The innovation type represents the variable, which is differentiated according to the technology and food standards applied, namely conventional brands, functional food (i.e., products with beneficial bacteria, etc.) and organic food brands (food stuff produced according to organic
standards: NOP [USA]; EC 834/2007 [EU], etc.). Dummy variables have been used in order to study the behavior of applied technology because marketing decisions should depend on production technology (Schmalensee 1989). It is possible to achieve this by estimating the organic and functional brands in comparison to conventional brands. Interested readers can assess this typology in detail from the food-orientated research articles (e.g., Sparke and Menrad 2009; Sorenson and Bogue 2007, Hamzaoui-Essoussi and Zahaf 2012; Davcik 2013).

In the present analysis, the difference between private-label brands, SME, and multinational food producers will be controlled (Choi and Coughlan 2006). The company type represents quality differences among private-label brands, brands that are managed by the Italian SME producers and brands that are managed by multinational companies. We use several control variables that are well established in the literature for this type of marketing study (e.g., Ailawadi et al. 2003; Slotegraaf and Pauwels 2008; Peterson and Jeong 2010). For instance, the importance of the control for market share effects and firm size when analyzing the explanatory power of brand equity has been reported in the literature (e.g., Keller and Lehmann 2006, Slotegraaf and Pauwels 2008). Following Ailawadi et al. (2003) and Slotegraaf and Pauwels (2008), we calculate market share as overall market revenue multiplied by brand share and we use parent-firm sales as a control variable.

The research framework uses quality independent variables that have been defined and created as a combination of existing empirical data (Einav et al. 2010) and observed brand quality characteristics, according to company and innovation type. The brand sample employed in this study includes 735 brands. The descriptive statistics of the variables used are presented in Table 2. The empirical results have been estimated using the Stata 12.1 SE statistical software.
3.2. Model and estimation procedure

OLS or regression analysis is a popular technique for estimating price and share-related phenomena, using panel data (e.g., Einav et al. 2010). The models are estimated here with standard OLSs. The $R^2$ and adjusted $R^2$ values have been reported to provide goodness-of-fit indicators of regression. In order to provide more stable estimates and to account for some eventual heteroskedasticity problems, we compute robust standard errors (White 1980; Zaman et al. 2001). We have used the Huber-White sandwich estimators to address concerns about data normality, heteroskedasticity and behavior of large residuals.

A logarithmic transformation of price, brand equity and marketing investments has been conducted. We have undertaken this transformation in order to reduce a large range of values in the dataset that may cause econometrical discrepancies in the estimation process. In order to test the behavior of the price model in line with hypotheses H1, H2 and H3, the brand price is introduced as a proxy and the effects of different variables on this are studied. Brand price is regressed on brand equity, marketing investment, market share, firm size, company and innovation types. The price performance model (PPM) at the aggregate level is:

$$ Y \ln (price_b) = c + \delta_1 \text{dummy company’s type(Italian)}_b + \delta_2 \text{dummy company’s type(foreign)}_b + \delta_3 \text{dummy innovation type(organic)}_b + \delta_4 \text{dummy innovation type(functional)}_b + \beta_1 \ln (marketing investment_b) + \beta_2 \ln (brand equity_b) + \beta_3 \text{interaction effect}_b + \beta_4 \text{market share}_b + \beta_5 \text{firm size}_b + u_b $$

where $b=1,…,B$ (brands). In the PPM, $\beta$ and $\delta$ are the parameters that will be estimated under the assumption that the variance of the error term $u_b$ is constant and conditional on
regressors. The marginal effects of the independent variables on brand price are measured by the \( \beta \) coefficients. In line with the above, parameters \( \delta \) measure the marginal effects of the quality independent variables on brand price. In order to control for possible multicollinearity problems, we have used the Stata regression collinearity diagnostic to test the variance inflation factors (VIFs) for all independent variables.

The possibility of reverse causality is a relevant concern in marketing modeling, and a well-known problem in econometrics. We address this issue and potential model misspecification with careful model formulation (Schmalensee 1989; Barth et al. 1998; Hanssens et al. 2009). For instance, we avoid potential endogeneity concerns with respect to the effects of independent variables, brand equity and marketing investments on price by using the Hausman specification test; following Hausman (1978) and Wooldridge (2001). We control for the statistical power of a significance test in competing models, as described in Cohen (1988; 1992). Sawyer and Ball (1981) defended the use of statistical power analysis in marketing research as a complement to the conventional use of statistical significance tests.

In order to explain brand differentiation, which is in line with hypothesis H4, innovation effects as well as the influence of company type on brand price are introduced and studied using cluster analysis. Studying the objective market data may give us a certain “picture” as to how price performs in a specific marketing-related context. However, this knowledge will be limited in its scope and descriptiveness because it is not possible to determine how specific brands behave in that context, nor is it possible to determine why brands behave in the ways observed. In the context of the present study, this problem is even more complex because different market players (SME, MNC, retailers) are included along with the innovation type analysis. There are examples in the literature (e.g., Pauwels et al. 2007) in which the price effects are explained by
price performance differences and market discrepancies. However, it is not clear what a benchmark price or brand property is, or how these benchmarks or properties behave under dynamic market conditions. This is why we cluster the innovation and company type on price.

The concept of clustering is widely discussed in management literature (e.g., Ketchen and Shook 1996; Porter 1998a/b). Clustering represents the grouping of a set of objects into clusters according to certain traits, so that the objects in a cluster have more similar properties than the objects in other clusters. The use of cluster analysis may raise some concerns because it does not offer a test statistics, and sorting ability might be so powerful that it provides clusters when the underlying theoretical rationale is otherwise missing (Ketchen and Shook 1996). We overcame this problem by using a two-step model that provides the criterion-related validity for the methodology used, together with the theoretical definition of cluster variables according to the technology applied. Our clustering technique is based on a deductive approach because the number and suitability of cluster variables are predefined and linked to theory (Ketchen and Shook 1996) and to the use of a two-step, nonhierarchical algorithm. The literature suggests (e.g., Hair et al. 2010; Ketchen and Shook 1996) that a two-step clustering procedure is the most suitable; during the first step, the variables and cluster centroids are defined; the results then form the basis for nonhierarchical clustering in the second step. This procedure does not have the pitfalls associated with other procedures and increases the validity of estimations.

3.3. Empirical results
In order to assess the results of price performance in the FMCG sector, price is regressed on brand equity, marketing investment, firm size, market share, company type and innovation type
in the PPM. The PPM has been described in a formal econometric manner with equation 1, in section 3.1. These results are reported in Table 3.

{TAKE IN TABLE 3}

We tested for multicollinearity using Stata regression collinearity diagnostic to test the VIFs. Our control has shown that multicollinearity is not likely to be a problem because all VIFs are less than 5.06. The literature suggests a threshold level of below 10, even though there are suggestions for more stringent thresholds of 5 or less (Hair et al. 2010).

We used Akaike’s information criterion (AIC) and the Bayesian information criterion (BIC) to compare the fit and complexity of competing models, following Akaike (1974) and Schwarz (1978). The underlying assumption is that competing models use the same data and likelihood of the null model. The model with the smallest value of the AIC and BIC will be considered to be a better fit. Our estimation reveals that AIC and BIC values are smallest for Model 3 (AIC 727; BIC 773; df=10), which is in line with our theoretical assumptions and intended focus on the importance of brand equity, and marketing investments, their interaction effect and innovation activities. This shows that Model 3 outperforms alternative models in model fit and provides theoretical justification for the approach under study.

We conducted Cohen’s power test (Cohen 1988; 1992) to estimate the statistical power of competing models, where a desirable power value is 0.8 because smaller values may incur a risk of a Type II error. Our results indicate that while Models 1a and 1b have smaller values than suggested (0.5037 and 0.4920, respectively), and Models 2 and 3 have the appropriate models power (0.8151 and 0.8505, respectively).
The crux of the matter in this study is *how* and *which* variables, if any, explain price performance in a branding context. The PPM results show that the following variables are statistically significant: marketing investment, brand equity, market share, firm size, company and innovation type. Only organic brands have no statistical significance on price. This finding corresponds with the cluster analysis conducted here, which showed that for the organic food brands there is no price premium compared to conventional brands, unlike functional brands that seem to draw a significant price premium. Thus, functional product innovation strategy seems to be more effective in generating price premium compared to organic product innovation strategy.

Table 3 presents the results estimating the likelihood of price performance. Models 1a and 1b are the baseline models that incorporate all control variables. The control variables in model M1 are significant at the 1% level, with the exception of the dummy for organic brands. Model 2 augments Model 1 by including the main effects for brand equity and marketing investments. The goodness-of-fit tests show that the $R^2$ value is 0.5868 and the adjusted $R^2$ value is 0.5822, which implies that M2 has a good explanatory power. Model 3 is expanded by the brand equity and marketing investment interaction term. Our estimations of Model 2 and Model 3 provide significant improvements over Models 1a and 1b, which implies that our independent models add predictive power to the control variables. The brand equity variable is positively related to price in Model 2, which is in line with H1. Marketing investment is positively related to a brand’s overall price performance in Model 2, as hypothesized by H2. The interaction effect between brand equity and marketing investment is negative and significant, which confirms H3.

To deal with the potential misspecification of the model due to the endogeneity effects, we have used the Hausman specification test to control for the difference between exogenous and
endogenous estimators in the PPM (Hausman 1978; Wooldridge 2001). Our estimations have shown that there is no statistical difference between estimators ($\chi^2_{df=7} = 61.94; p > .95$), that the model misspecification due to the endogeneity issues is not likely to be the problem, and that we can use the hypothesized regression approach in all our models.

The deductive approach in cluster analysis was taken in order to explain the relationship between quality independent variables and a dependent variable. The two-step clustering technique was applied: this is a scalable analysis method designed to handle large datasets and to produce results on data grouping. The price cluster profiles for the innovation type are presented in Table 5. This analysis shows that there are three clusters in the FMCG sector, which is presented in Table 4. The mean price is 3.96 €/kg; it is 4.06 €/kg in cluster 1; 2.94 €/kg in cluster 2 and 4.70 €/kg in cluster 3. These results suggest that cluster 3 takes the price premium in the market, and cluster 1 is almost equal to the average price.

{TAKE IN TABLE 4}

The price premium was obtained from the functional brands, which represent 39.2% of the brands in this market. The organic brands, which represent 29.7% of the market, have an average price in the market, whereas conventional FMCG brands have a below average price. This result may appear surprising because marketing and food science literature (e.g., Ngobo 2011; Bezawada and Pauwels 2013, Hamzaoui-Essoussi and Zahaf 2012) uniformly reports that organic food brands obtain the price premium.

{TAKE IN TABLE 5}
The price cluster profiles by company type are presented in Table 4 and reveal four clusters, which are presented in Table 6. The mean price is 3.95 €/kg; it is 1.85 €/kg in cluster 1; 5.13 €/kg in cluster 2 and 4.99 €/kg and 2.99 €/kg in clusters 3 and 4 respectively. This analysis shows that the price premium was obtained by cluster 2. It is noteworthy that cluster 3 has an above-average price. The below-average price in the enriched-food FMCG sector is in clusters 1 and 4. The price premium was acquired by 63.0% of the Italian SMEs, which represents 41.6% of the brands in this market. The above-average price was obtained by multinational brands, which represent 18.2% of the FMCG market. The below-average price was obtained by the private-label brands, which represent 15.8% of the market. The lowest price was found in cluster 1, which represents 37.0% of Italian SMEs and 24.0% of all brands in the enriched-food FMCG market. These results are presented in Table 6.

4. Discussion

With more knowledge of the forces that shape the branding paradigm in the FMCG brand performance context, managers can have a more in-depth understanding of their brand portfolio and make better decisions. This research brings together consumer, financial and marketing perspectives. Researchers and managers usually use only one approach in their decision-making process. Prior studies (e.g., Peterson and Jeong 2010; Barth 1998; Madden et al. 2006, etc.) have focused on public companies (i.e., companies that are listed on a stock-exchange); we avoid this theoretical and research limitation by using SMEs, international and multinational companies.
Managerial applicability of this study is based on the use of different theoretical and research perspectives within the mainstream industry and in a managerial-specific context.

The theory of industrial organization suggests that product (brand) differentiation has an important role in brand performance output; we have extended that view by employing (i) the importance of innovation activities based on technology and production standards and (ii) different brand properties (i.e., assets and expenditures), here operationalized by brand equity and marketing investments. We argue that a company can obtain higher prices by distinctive brand differentiation, which extends (simplified) theoretical assumptions and a general principle put forth by Schmalensee (1982). Our analysis expands limited knowledge on the role of value as a marketing phenomenon (brand equity) and financial phenomenon (marketing investments) operationalized through the brand performance output (i.e., price premium). This performance output is often used to determine a brand’s success and profitability (e.g., Shepherd 1972). We show that a brand framework influences the brand performance outputs of a company in the market. It is possible to obtain a price premium in FMCG market if a firm applies a brand strategy based on differentiated innovation.

The importance of financial factors on marketing phenomenon in the FMCG context is not widely discussed in the literature, and only a limited number of studies have contributed to the debate (e.g., Hanssens et al. 2009; Bharadway et al. 2011). This study sheds light on the role of marketing investment for the brand performance outputs. The empirical analysis has provided evidence that this variable is significant and positively related to the pricing strategy in a branding context. We have opened a new avenue to further explore the effects of marketing expenses in the context of brand performance outputs, which has been a neglected research area in the marketing literature.
The literature suggests (e.g., Slotegraaf and Pauwels 2008; Barth et al. 1998; Sriram et al. 2007; Suri et al. 2002) that the brand equity plays a central role in price performance. However, past research uses market-based (such as revenue-premium-based brand equity or brand value share prices) and not financially based measures, which are applicable to most brands in the market. Whereas prior research uses mono-brand firms for ease of exposition (e.g., Bharadway et al. 2011), we avoid this limitation because the two datasets were combined, and face-validation of the used brands has been conducted with data that is publicly available on the Internet.

Prior research suggests that brands with higher-value-driven properties (e.g., assets, actions, revenues, etc.) may have an influence on price (Srivastava et al. 1998; Peterson and Jeong 2010; Barth et al. 1998; Madden et al. 2006). Ours is the first study that theoretically conceptualizes and empirically tests interaction between brand equity and marketing investments in their influence on price performance. We found a significant interaction in our model as reflected by the AIC, BIC and power analysis, which opens new space for further research in marketing and finance studies. The results of the cluster analysis strongly support H4, which states that brand differentiation can be grouped according to different innovation traits.

Differentiation, based on market and technology innovation, drives the brand performance output (e.g., price premium). The study found that premium price was dominantly acquired by Italian SMEs. This result is not surprising if we take into account several social and consumption factors. Italian society is famous for its rich food culture, strong national sentiment and entrepreneurial tradition. The fact that no prior study appears to show these outcomes is surprising. Future research should study this effect in different cultural and entrepreneurial environments. The price of brands managed by multinational companies is positioned above the market average. Private-label brands and some Italian SME brands (37%) are positioned below
the average price in the market. The result for these SMEs came as a surprise and is in contrast to previous findings, already discussed above. We believe that this result shows that some SMEs cannot position themselves in the top-tier market segment and have to apply the low price strategy with retailers. The results of the model 1b are in line with this finding, because it shows that premium pricing is not a viable strategy for 37% of SMEs in the organic FMCG segment. Future research should study the nature of this strategy. Is it only a temporary effect because some SMEs have large stocks and / or a cash-flow shortage, or is it a long-term strategy which should allow them to acquire a bigger market share with low prices?

One of the major implications of this study for managers is that brands with the highest level of innovativeness (i.e., the functional food brands) are in market expansion because they are not limited by regulations and hard competition. We provide evidence that growth of the organic food brands market, which has a medium level of innovativeness, has reached its peak and there is little space for further enhancements from the point of view of pricing strategy. This result came as a surprise because contemporary marketing strategies and academic literature (e.g., Ngobo 2011; Bezawada and Pauwels 2013, Hamzaoui-Essoussi and Zahaf 2012) are based on the premise that organic foods always provide premium mark-up.

Why does the literature uniformly report the opposite findings? We believe that biased methodological reasons are the explanation. Previous studies took a dogmatic view that organic brands always obtain premium price ignoring new market developments such as functional food, premium private label brands, etc. Unlike the first two cases, the brands with the lowest level of innovativeness (i.e., the conventional brands) compete with low prices. The analysis suggests that this strategy does not obtain higher price markups.
5. Limitations and Future Research

Our research has a few limitations that future research may address. First, although we use a large and comprehensive dataset with multiple product categories, we only study one sector (i.e., FMCG) and focus on brand-level performance because of the complex data preparation required, in comparison to the standardized market data from marketing agencies. As a result, we could not study the differences among the three product categories included in this study (i.e., juice, milk and yoghurt). Hence, future research on other sectors (e.g., consumer durables) and across product categories would help test the generalizability of our findings.

Our estimates of price could have been more informative if we had been able to use confidential company-level data. For instance, more refined measures of advertising and brand equity would be beneficial to study different cost-related nuances and proprietary-related characteristics. Unfortunately, data of this type is dominantly proprietary and was not available for this study (Simon and Sullivan 1993). We did use official financial reports, but important marketing and financial nuances are hidden within them. For example, we cannot distinguish between type and structure of promotional expenditures, analyze the structure of marketing research expenditures (Simon and Sullivan 1993), or the quality of advertising investments; it is also impossible to allow for lag effects between the elements of marketing mix that may make reverse causality tests more robust. Due to the objective limitations of the study, we were not able to show that higher innovation activities may overcome consumer inertia and brand loyalty barriers. Future work should address this important problem in detail.

We provide empirical support for the theoretical development of the analytical model proposed by Schmalensee (1982). A future analytical model should show how to maximize brand performance outputs (such as price, market share, etc.) by maximizing the innovation activities,
and how this approach will influence brand entry barriers and first-/second-mover strategies. In line with this, the opportunity for future research is to show how different market players (SME, MNC, retailers) may benefit from this strategy. These limitations can be seen as providing new challenges and future advantages if marketers start producing more complex and informative datasets for firms’ decision makers. Finally, future research could focus on the dual role of market share as an endogenous variable due to its reverse causality properties, as a market performance measure and as a proxy for market power and/or size (Slotegraaf and Pauwels 2008; Madden et al. 2006), which could be especially important if the study utilizes the explanatory power of brand equity (Keller and Lehmann 2006).
REFERENCES


Table 1: Variables of the brand performance models

<table>
<thead>
<tr>
<th>Variable</th>
<th>Name</th>
<th>Description</th>
<th>Value</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
<td>PR</td>
<td>Amount of money that consumers have to pay to obtain the brand (€/kg).</td>
<td>n/l</td>
<td>Nielsen</td>
</tr>
<tr>
<td>brand equity</td>
<td>BEq</td>
<td>Asset that is constituted by advertising efforts, licenses, etc., allocated</td>
<td>n/l</td>
<td>AIDA</td>
</tr>
<tr>
<td></td>
<td></td>
<td>to the single brand in a company brand portfolio (position B. I –</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>intangible assets in the company balance sheets).</td>
<td></td>
<td></td>
</tr>
<tr>
<td>marketing</td>
<td>MI</td>
<td>Lagged service expenses that are intended to increase the quality and</td>
<td>n/l</td>
<td>AIDA</td>
</tr>
<tr>
<td>investment in a</td>
<td></td>
<td>reputation of the brand, allocated on a brand (position b7- services, in</td>
<td></td>
<td></td>
</tr>
<tr>
<td>brand</td>
<td></td>
<td>the company income statement).</td>
<td></td>
<td></td>
</tr>
<tr>
<td>market share</td>
<td>ms</td>
<td>A measure calculated as an overall market revenue multiplied by brand</td>
<td>n/l</td>
<td>Nielsen</td>
</tr>
<tr>
<td></td>
<td></td>
<td>share (following Ailawadi et al. 2003 and Slotegraaf and Pauwels 2008)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>firm size</td>
<td>fs</td>
<td>Parent firm sales as described in Slotegraaf and Pauwels (2008)</td>
<td>n/l</td>
<td>Nielsen</td>
</tr>
<tr>
<td>company type</td>
<td>co</td>
<td>Differences among private labeled brands (=1), brands owned by the Italian</td>
<td>1, 2,</td>
<td>QIV</td>
</tr>
<tr>
<td></td>
<td></td>
<td>SME producers (=2) and brands owned by MNC producers that have branches</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>in Italy (=3)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>innovation type</td>
<td>inn</td>
<td>Type of brands according to the applied technology: functional food (=3),</td>
<td>1, 2,</td>
<td>QIV</td>
</tr>
<tr>
<td></td>
<td></td>
<td>organic food (=2) and conventional food (=1)</td>
<td>3</td>
<td></td>
</tr>
</tbody>
</table>

Legend: AIDA – Company financial statements (balance sheet data), Nielsen – data from the ACNielsen research, QIV – Quality independent variable; n/l – Not limited
Table 2: Descriptive statistics

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>Standard deviation</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>price (log)</td>
<td>1.2127</td>
<td>.6221</td>
<td>-1.6013</td>
<td>2.4775</td>
</tr>
<tr>
<td>brand equity (log)</td>
<td>11.6249</td>
<td>2.5579</td>
<td>4.4641</td>
<td>19.4066</td>
</tr>
<tr>
<td>marketing investment (log)</td>
<td>13.2227</td>
<td>1.9725</td>
<td>7.8537</td>
<td>18.2651</td>
</tr>
<tr>
<td>firm size (log)</td>
<td>4.4577</td>
<td>2.2211</td>
<td>-.7989</td>
<td>9.9532</td>
</tr>
<tr>
<td>market share (log)</td>
<td>.0123</td>
<td>.0144</td>
<td>.0020</td>
<td>.1227</td>
</tr>
<tr>
<td>dummy innovation type – functional</td>
<td>.3917663</td>
<td>.4884694</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>dummy innovation type – organic</td>
<td>.2974768</td>
<td>.4574519</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>dummy innovation type – conventional</td>
<td>.310757</td>
<td>.4631111</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>dummy company type – Private label</td>
<td>.1580345</td>
<td>.3650158</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>dummy company type – SME</td>
<td>.6600266</td>
<td>.4740147</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>dummy company type – MNC</td>
<td>.1819389</td>
<td>.3860506</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>
Table 3: Estimations of the variables in the brand performance models

<table>
<thead>
<tr>
<th>Variables</th>
<th>Model 1a</th>
<th>Model 1b</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price (dependent)</td>
<td>0.1948***</td>
<td>0.2225***</td>
<td>0.1940***</td>
<td></td>
</tr>
<tr>
<td>dummy company type – SME</td>
<td>(4.52)</td>
<td>(5.00)</td>
<td>(4.31)</td>
<td></td>
</tr>
<tr>
<td>dummy company type – MNC</td>
<td>0.3384***</td>
<td>0.2832***</td>
<td>0.2454***</td>
<td></td>
</tr>
<tr>
<td>dummy innovation type – organic</td>
<td>-0.0710**</td>
<td>0.0178</td>
<td>0.0402</td>
<td></td>
</tr>
<tr>
<td>dummy innovation type – functional</td>
<td>0.3330***</td>
<td>0.3531***</td>
<td>0.3612***</td>
<td></td>
</tr>
<tr>
<td>market share (log)</td>
<td>0.0004***</td>
<td>0.0036***</td>
<td>0.0003***</td>
<td>0.0003***</td>
</tr>
<tr>
<td>firm size (log)</td>
<td>-0.3046***</td>
<td>-0.2885***</td>
<td>-0.2681***</td>
<td>-0.2677***</td>
</tr>
<tr>
<td>brand equity (log)</td>
<td>0.0197**</td>
<td>0.1464***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>marketing investment (log)</td>
<td>0.0230*</td>
<td>0.0720**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>brand equity x marketing investment (log)</td>
<td>-0.009***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.5274</td>
<td>0.5519</td>
<td>0.5868</td>
<td>0.5923</td>
</tr>
<tr>
<td>adjusted R²</td>
<td>0.5249</td>
<td>0.5496</td>
<td>0.5822</td>
<td>0.5873</td>
</tr>
<tr>
<td>Prob &gt; F</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>df</td>
<td>5</td>
<td>5</td>
<td>9</td>
<td>10</td>
</tr>
<tr>
<td>AIC</td>
<td>875</td>
<td>834</td>
<td>735</td>
<td>727</td>
</tr>
<tr>
<td>BIC</td>
<td>898</td>
<td>857</td>
<td>776</td>
<td>773</td>
</tr>
<tr>
<td>Cohen’s power</td>
<td>0.5037</td>
<td>0.4920</td>
<td>0.8151</td>
<td>0.8505</td>
</tr>
</tbody>
</table>

Note: N = 735; t-statistics appear in parenthesis; *** p < .01; ** p < .05; * p < .10
### Table 4: Price cluster profiles for the innovation and company type

<table>
<thead>
<tr>
<th>Cluster</th>
<th>Innovation Type</th>
<th>Company Type</th>
<th><strong>Centroids - price</strong></th>
<th><strong>Centroids - price</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Standard</td>
<td>Mean</td>
<td>Standard</td>
</tr>
<tr>
<td></td>
<td>Mean</td>
<td>deviation</td>
<td>Mean</td>
<td>deviation</td>
</tr>
<tr>
<td>1</td>
<td>4,060</td>
<td>1,8847</td>
<td>1,8417</td>
<td>0.6141</td>
</tr>
<tr>
<td>2</td>
<td>2,9378</td>
<td>1,9817</td>
<td>5,1337</td>
<td>1.2749</td>
</tr>
<tr>
<td>3</td>
<td>4,703</td>
<td>1,6938</td>
<td>4,9854</td>
<td>2.1756</td>
</tr>
<tr>
<td>4</td>
<td>---</td>
<td>---</td>
<td>2,9867</td>
<td>1.3859</td>
</tr>
<tr>
<td>Combined</td>
<td>3,9630</td>
<td>1,9840</td>
<td>3,9523</td>
<td>1,9839</td>
</tr>
</tbody>
</table>

### Table 5: Price frequencies for the innovation type

<table>
<thead>
<tr>
<th>Innovation type</th>
<th>Functional</th>
<th>Organic</th>
<th>Conventional</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cluster</td>
<td>Frequency</td>
<td>%</td>
<td>Frequency</td>
<td>%</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>0,0</td>
<td>224</td>
<td>100,0</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>0,0</td>
<td>0</td>
<td>0,0</td>
</tr>
<tr>
<td>3</td>
<td>295</td>
<td>100,0</td>
<td>0</td>
<td>0,0</td>
</tr>
<tr>
<td>Total</td>
<td>295</td>
<td>39,2</td>
<td>224</td>
<td>29,7</td>
</tr>
</tbody>
</table>

### Table 6: Price frequencies for the company type

<table>
<thead>
<tr>
<th>Company type</th>
<th>Private label</th>
<th>SME</th>
<th>MNC</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cluster</td>
<td>Frequency</td>
<td>%</td>
<td>Frequency</td>
<td>%</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>0,0</td>
<td>184</td>
<td>37,0</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>0,0</td>
<td>313</td>
<td>63,0</td>
</tr>
<tr>
<td>3</td>
<td>0</td>
<td>0,0</td>
<td>0</td>
<td>0,0</td>
</tr>
<tr>
<td>4</td>
<td>119</td>
<td>100,0</td>
<td>0</td>
<td>0,0</td>
</tr>
<tr>
<td>Total</td>
<td>119</td>
<td>15,8</td>
<td>497</td>
<td>65,6</td>
</tr>
</tbody>
</table>