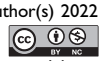
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Cross-National Differences in Market Response: Line-Length, Price, and Distribution Elasticities in 14 Indo-Pacific Rim Economies

Hannes Datta, Harald J. van Heerde, Marnik G. Dekimpe, and Jan-Benedict E.M. Steenkamp

Abstract

The field's knowledge of marketing-mix elasticities is largely restricted to developed countries in the North-Atlantic region, even though other parts of the world—especially the Indo-Pacific Rim region—have become economic powerhouses. To better allocate marketing budgets, firms need to have information about marketing-mix elasticities for countries outside the North-Atlantic region. The authors use data covering over 1,600 brands from 14 product categories collected in 7 developed and 7 emerging Indo-Pacific Rim countries across more than 10 years to estimate marketing elasticities for line length, price, and distribution and examine which brand, category, and country factors influence these elasticities. Averaged across brands, categories, and countries, line-length elasticity is .459, price elasticity is −.422, and distribution elasticity is .368, but with substantial variation across brands, categories, and countries. Contrary to what has been suggested in previous research, the authors find no systematic differences in marketing responsiveness between emerging and developed economies. Instead, the key country-level factor driving elasticities is societal stratification, with Hofstede's measure of power inequality (power distance) as its cultural manifestation and income inequality as its economic manifestation. As the effects of virtually all brand, category, and country factors differ across the three marketing-mix instruments, the field needs new theorizing that is contingent on the marketing-mix instrument studied.

Keywords

marketing-mix elasticities, emerging economies, emerging markets, culture, empirical generalizations, product, pricing, distribution

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Each year, firms in the United States and other countries spend hundreds of billions of dollars on marketing activities to support their brands. Many of these firms generate a significant share of their revenues in overseas markets. In the past, overseas revenues were earned mainly in the developed world, in particular the North-Atlantic region (North America and Western Europe). In recent decades, other regions, and especially emerging economies in the Indo-Pacific Rim region (e.g., China, India, Vietnam, Indonesia), have become increasingly important for Western firms. However, we know very little about how strongly consumers in countries outside the North-Atlantic region respond to marketing activities. To better allocate marketing budgets, firms need to have information about marketing-mix elasticities on an international basis (Fischer et al. 2011; Peers, Van Heerde, and Dekimpe 2017), including the marketing-mix elasticities for line length, price, and distribution, which collectively tap into three of the 4 Ps.[1]

An impressive amount of work has quantified price elasticities of demand in previous decades, much of which is summarized in the meta-analysis of Bijmolt, Van Heerde, and Pieters (2005). However, 96% of the price elasticities in this meta-analysis are derived from the North-Atlantic region. The remaining 4% are based on the developed Indo-Pacific Rim countries of Australia, New Zealand, and Japan, which are lumped together because of a dearth of elasticities for each country. Yet without empirical evidence, there is no a priori reason to assume that, say, Japan and New Zealand respond equally to price. More generally, we do not know whether price elasticities differ between countries or whether there is a systematic difference in price elasticity between developed

[1] Apart from two countries, we do not have advertising data. In one of the robustness checks, we examine advertising elasticities and whether including advertising spend in our model affects our focal estimates for line length, price, and distribution in one developed economy (Hong Kong) and one emerging economy (China) for which we were able to purchase advertising data.

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and emerging economies, as has recently been suggested by, among others, Kozlenkova et al. (2021).

While price has attracted a massive amount of research attention, distribution (tapping into the P of place) and line-length (tapping into the P of product) elasticities have been studied in only a handful of papers. Still, existing evidence (albeit often from a consumer packaged goods [CPG] setting) suggests that both marketing instruments have an appreciable effect on sales (e.g., Ataman, Mela, and Van Heerde 2008; Ataman, Van Heerde, and Mela 2010). We know next to nothing about cross-national differences or similarities for these two marketing-mix instruments, whether they differ between emerging and developed economies, or about brand- or category-related differences in these two elasticities.

These observations motivated the present study. We aim to address the following four research questions, using data from the Indo-Pacific Rim. First, what are the effects of line length, price, and distribution on brand sales? Second, are there systematic cross-national differences in line-length, price, and distribution elasticities, and if so, what is their magnitude? Third, which brand, category, and country factors influence the variation in line-length, price, and distribution elasticities? Fourth, controlling for brand and category factors, are there systematic differences in marketing responsiveness between emerging and developed economies?

Prior research could not empirically study these questions due to a lack of suitable data, especially for emerging economies. We analyze data that span a diverse set of emerging and developed countries. The data are collected in a uniform way, cover comparable products across the same time period, across multiple and diverse product categories and brands, and we analyze them with a unified modeling approach to ensure empirical generalizability and rule out alternative methodological explanations (Bijmolt, Van Heerde, and Pieters 2005). We break new empirical ground by using data spanning 14 Indo-Pacific Rim countries, including 7 emerging economies (China, India, Indonesia, Malaysia, the Philippines, Thailand, and Vietnam) and 7 developed economies (Australia, Hong Kong, Japan, New Zealand, Singapore, South Korea, and Taiwan). These countries jointly represent nearly 50% of the world's population but have nevertheless received little attention from market-response modelers. To put this data coverage into perspective, we note that the United States represents about 4.5% of the world population. The Indo-Pacific Rim region also leads the world in consumer spending and growth in most of the categories we study (Edge by Ascential 2019). The global market research agency GfK provided monthly national data on sales and marketing activities for over 1,600 brands in 14 electronics and appliance categories over a time period of up to 11 years (2004–2014). This enables us to draw broad empirical generalizations on line-length, price, and distribution elasticities and their drivers.

The remainder of the article is organized as follows. We first introduce our study framework. Next, we describe the data and motivate our two-stage approach to model and subsequently explain marketing-mix response. Then, we present the results, along with various robustness tests. We conclude with a discussion and suggestions for future research.

Study Framework

The focus of this study is on quantifying line-length, price, and distribution elasticities to arrive at empirical generalizations, and to consider determinants of these marketing elasticities. Figure 1 provides a schematic overview of the framework that guided our study. We distinguish between three classes of factors that can potentially influence the observed marketing-mix elasticities: brand factors, category factors, and country characteristics. In this research we adopt an inductive, ETET (empirical → theory) approach (Bass 1995). Our study framework incorporates 48 possible effects (16 drivers for 3 elasticities). Following previous theory and empirical research, we could have developed hypotheses for some, mostly price-related, effects.[2] Our inductive approach allows us to use the richness of our data to cast a wide net while still allowing us to discuss the findings in light of existing prior work, where applicable. In true ETET fashion, our findings can guide future research on which factors to prioritize in follow-up studies aimed at better understanding the theoretical mechanisms at the consumer, firm, and/or country level.

Brand Factors

We consider two factors anchored in the brand: brand equity, which has emerged as a key brand characteristic in the literature (Keller and Lehmann 2006), and the brand's country of origin, a factor of particular interest in cross-national research (Verlegh and Steenkamp 1999). We further consider the level of marketing support given to the brand (Gatignon 1993).

Brand equity. Brand equity is the value of a branded product compared with the same product without the brand name (Keller and Lehmann 2006). Brands that possess high equity have a strong appeal to consumers that goes beyond their observable attributes and marketing variables. In other words, a high-equity brand will experience higher demand than a low-equity brand, keeping everything else constant. Brand equity not only implies differential preferences and demand due to carrying the brand name, but also differential responses to marketing variables (Keller 1998). While high brand equity means that a brand has a strong intrinsic appeal to customers, this does not necessarily mean that its effect on marketing-mix effectiveness is uniform across instruments (Datta, Ailawadi, and Van Heerde 2017).

[2] For example, Narasimhan, Neslin, and Sen (1996) found a smaller price (promotion) response in less concentrated CPG markets (even though they also abstained from any hypothesis given the opposing theories that could be put forward). Chandon, Wansink, and Laurent (2000), in turn, found in two choice experiments that promotional price changes are more effective for more utilitarian products.

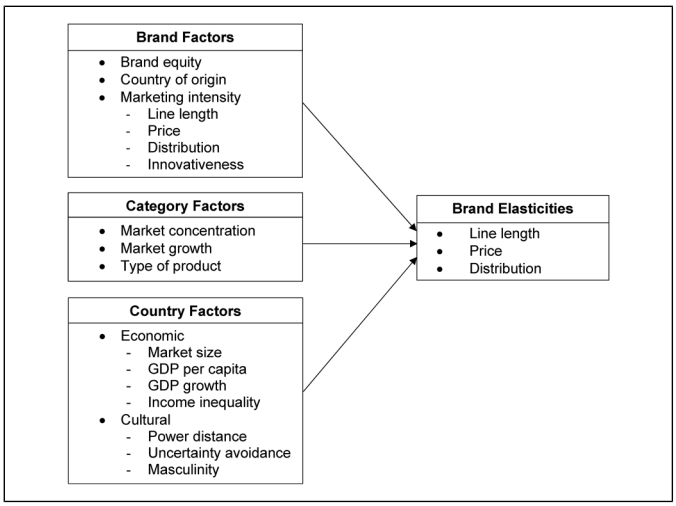


Figure 1. Study framework for factors influencing observed line-length, price, and distribution elasticities.

Country of origin. Certain countries, most notably the United States, Japan, Germany, Switzerland, and Sweden, have an almost universal positive country-of-origin image (Steenkamp 2017). Previous research has documented the impact of the brand's country of origin on consumer evaluations of quality and purchase intention (Verlegh and Steenkamp 1999). However, this research is mainly experimental or survey-based. The extent to which country of origin actually affects marketing-mix elasticities is unclear.

Marketing intensity. Marketing-mix elasticities may also be affected by the level of marketing support for the brand (Gatignon 1993). We consider the average level of the three focal marketing-mix instruments—line length, price, and distribution—and the brand's innovativeness, which we define as the extent to which a brand's product line includes newly introduced items. Russell and Bolton (1988), for example, discuss how a brand's price level can influence the size of submarket expansion effects (switching from brands in one price tier to another and vice versa; see also Karande and Kumar 1995). Similarly, brands with a deep assortment may already target most needs and wants of their heterogeneous customer base, which might dampen the demand-expansion effects of further line extensions (Bayus and Putsis 1999). At the same time, higher levels in one marketing variable may unlock or strengthen the effect of another marketing activity. In other instances, marketing instruments may act as substitutes (rather than complements) of one another (Gatignon 1993).

Category Factors

In industrial economics, market concentration and growth of the category have been identified as important category factors to consider (Scherer and Ross 1990). In marketing, there is a long-standing tradition to distinguish between brown goods (electronics) and white goods (appliances) (see, e.g., Tellis, Stremersch, and Yin 2003). Therefore, we also consider the type of product.

Market concentration. Concentration is often used to characterize the competitive structure of a category. More concentrated categories are seen as less competitive, though what impact this will have on marketing effectiveness is not clear. More concentrated categories have been argued to be more price elastic because consumer search costs will be lower (Pagoulatos and Sorensen 1986). However, others have argued (see, e.g., Ferguson 1974) that demand elasticity can decrease with concentration, because tacit or explicit collusion could restrict price competition in order to prevent substitution in the market. The effect of market concentration on the effectiveness of line length and distribution is equally unclear.

Market growth. In consumer durables, the two key drivers of category growth are reduction in interpurchase time among existing consumers and entry of new consumers. The second factor particularly contributes to strongly growing markets being in a greater state of flux. Preferences of new consumers are likely to be less stable due to the lack of direct usage experience. This provides more opportunities for firms to influence purchase decisions with their marketing mix.

Type of product. We distinguish between household appliances ("white goods") and electronics ("brown goods"). Household appliances are primarily bought for utilitarian reasons, whereas electronics have a more pronounced experiential component. This suggests differences in information processing between these two types of products (Holbrook and Hirschman 1982), which might affect various marketing-mix elasticities.

Country Factors

A logical point of departure for studying cross-national differences in market-response parameters is to examine macroeconomic factors (Farley and Lehmann 1994). Moreover, market-response parameters are the results of decisions made by individual consumers, and it is well established that consumer attitudes and behavior are affected by the national-cultural context (Hofstede 2001; Steenkamp and De Jong 2010; Tellis, Stremersch, and Yin 2003).

Economic factors. We cast a fairly comprehensive net to capture economic factors. First, we include the country's population, as this reflects the overall potential market size. The economic resources that consumers have at their disposal are captured in three factors. Gross domestic product (GDP) per capita reflects the average level of economic resources per person in a country. Income inequality captures how these economic resources are distributed across the population and reflects whether consumers have, broadly speaking, the same amount of resources at their disposal, or, alternatively, whether these economic resources are unevenly distributed. The third factor, GDP growth, adds a dynamic component. Do economic resources change over time and by how much? There are vast differences in GDP growth between countries, with emerging economies such as China or India growing at a much faster

rate than mature economies such as Japan or New Zealand. This, too, could affect how strongly consumers respond to marketing activities.

Cultural factors. Hofstede (2001) identified four major dimensions of national culture: power distance, uncertainty avoidance, masculinity, and individualism. We use the first three dimensions because of the well-known collinearity problems between power distance and individualism (Hofstede 2001; Smith, Dugan, and Trompenaars 1996).[3] Power distance describes the extent to which a culture condones norms of inequality. Cultures high in power distance tend to emphasize the importance of prestige and wealth in shaping boundaries or vertical relationships between social and economic classes such as rich and poor, and superiors and subordinates (Roth 1995). In high-power-distance cultures, people aim to maintain and increase their power as a source of satisfaction. Social consciousness is high, and consumption behavior is relatively more motivated by the need to maintain and signal social distinctions.

Uncertainty avoidance refers to the degree to which societies tend to feel threatened by uncertain, risky, ambiguous, or undefined situations, and the extent to which they try to avoid such situations by adopting strict codes of behavior. In countries where uncertainty avoidance is high, consumers are resistant to change from established patterns and will be focused on risk avoidance and reduction. In low-uncertainty-avoidance societies, the feeling would rather be "what is different, is curious" and worth exploring (Hofstede 1991, p. 119).

Masculinity is defined as the degree to which a society is characterized by assertiveness versus nurturance. More "masculine" societies place greater emphasis on wealth, success, ambition, material things, and achievement, whereas more "feminine" societies place greater value on people, helping others, preserving the environment, and equality (Hofstede 2001).[4]

Each of these economic and cultural factors is meaningful in its own right, but they are also indicators for three broader societal strands: stratification, appetite for risk, and success.[5] Societal stratification refers to a society's categorization of its people into groups based on socioeconomic factors. Income inequality is the economic expression of societal stratification, while power distance is its cultural manifestation. Higher GDP per capita allows people to take more risks in their purchases because the financial loss of potential product failure weighs less heavily, while uncertainty avoidance is the cultural representation of societal (lack of) appetite for risk. High economic growth is an economic measure of societal success, while masculinity captures how much success is valued culturally.

Developed versus emerging economies. Another way to consider country factors is to classify countries as either developed or emerging economies. Although this classification is cruder than considering specific economic and cultural factors as we have done previously, it holds considerable appeal among marketing academics (Burgess and Steenkamp 2006; Roberts, Kayande, and Srivastava 2015; Sheth 2011), marketing practitioners (McKinsey & Company 2019), investors (e.g., Vanguard, Fidelity, and others all have emerging-economy funds) and (international) organizations such as the United Nations. We will consider whether the use of this simpler country classification leads to interesting insights.

Data and Measures

Data Sources

The global market research agency GfK provided national monthly data from its retail panel across 14 countries, 14 product categories, and 1,600 + brands over a time period of up to 11 years (2004–2014).[6] The 14 countries in the sample are from the Indo-Pacific Rim region and cover the world's two emerging economic giants (China and India); more established Asian powerhouses (Japan and South Korea); rapidly developing emerging economies (e.g., Vietnam, Malaysia); and smaller, highly developed economies (e.g., Singapore, Hong Kong). The data also include two established Western countries (Australia and New Zealand). Table 1 provides an overview of the countries in the sample. The data include seven developed economies (Australia, Hong Kong, Japan, New Zealand, Singapore, South Korea, and Taiwan) and seven emerging economies (China, India, Indonesia, Malaysia, the Philippines, Thailand, and Vietnam). Collectively, these countries have 3.4 billion inhabitants, nearly half of the world's population.

Sample

Category selection. The product categories in the data cover a wide range of electronic goods: tablets, smartphones, regular

[3] Hofstede (2001, p. 216) reported a correlation of −.68 between power distance and individualism across 53 countries and regions. We observed a similarly high correlation of −.66 for the 14 countries in our study.

[4] Hofstede used traditional gender-role descriptions to label this dimension. However, gender roles have changed substantially since this dimension was introduced, suggesting that these labels may eventually be replaced by descriptions that are not linked to gender-role stereotypes.

[5] The exception is population size. It is nevertheless important to include this variable in cross-national econometric studies to control for the total size of the market.

[6] GfK reports sales, price, and distribution coverage at the stockkeeping unit (SKU) level. Its data for a representative sample of stores is obtained using electronic point of sale technology and/or field audits. To obtain a representative sample, the store universe in each country is divided into homogeneous subuniverses (based on several factors, including distribution channel and turnover class), followed by disproportional quota sampling, so that larger stores are sampled more. The sample information is extrapolated to the subuniverse level (and then summed across subuniverses), with the inverse of the sampling fraction in each cell as the extrapolation factor. A uniform measurement approach is used globally to ensure comparability and consistency, with regular checks at both the category and brand levels (involving, e.g., comparisons with manufacturer-to-trade data provided by cooperating manufacturers).

Table 1. Economic and Cultural Indicators for Countries in Sample.

Country	Market Size (Mil.)	GDP per Capita ($)	GDP Growth (%)	Income Inequality	Power Distance	Uncertainty Avoidance	Masculinity
Australia	21.77	42,025	2.75	34.70	38	51	61
China	1,333.94	8,970	8.80	42.20	80	30	66
Hong Kong	6.98	47,502	3.34	53.70	68	29	57
India	1,212.78	3,847	9.20	35.10	77	40	56
Indonesia	238.64	6,814	10.58	39.50	78	48	46
Japan	127.12	34,725	.48	32.10	54	92	95
Malaysia	27.64	19,333	6.36	43.90	104	36	50
New Zealand	4.31	31,240	2.70	34.90	22	49	58
Philippines	91.77	5,196	6.29	46.00	94	44	64
Singapore	4.96	64,543	7.76	47.90	74	8	48
South Korea	48.76	31,096	3.37	32.00	60	85	39
Taiwan	23.05	38,977	2.81	33.60	58	69	45
Thailand	66.61	12,031	5.06	39.40	64	64	34
Vietnam	87.66	3,970	8.45	39.30	70	30	40

Notes: Countries are shown in alphabetical order. Market size is a country's population (in millions). GDP per capita is a country's expenditure-side real GDP at chained purchasing power parities (PPPs; expressed in 2011 USD), divided by a country's market size. GDP growth is computed as the annual percentage change in expenditure-side real GDP at chained PPPs. Measures are obtained from the Penn World Tables 9.0 (Feenstra, Inklaar, and Timmer 2015) and reported as an average over the observation period (2004–2014). Income inequality is expressed as the Gini coefficient, which is extracted from the CIA World Factbook (Philippines, Taiwan, Hong Kong, and Singapore), Organisation for Economic Co-operation and Development (New Zealand) and the World Bank (all remaining countries; symbol: SI.POV.GINI). The metric is not consistently available for all years and all countries, and the closest available observation to 2010 has been used. Power distance, uncertainty avoidance, and masculinity (reported in the last three columns) are based on Hofstede, Hofstede, and Minkov (2010) and extracted from https://geerthofstede.com/research-and-vsm/dimension-data-matrix/.

mobile phones, compact cameras ("point and shoot"), SLR cameras (catering to more professional photographers), desktop computers, laptop computers, DVD players and recorders, LCD TVs, plasma TVs, and CRT TVs (i.e., old, "bulky" TVs), as well as appliances: microwave ovens, refrigerators, and washing machines. The categories cover both novel products, such as tablets and smartphones, and more mature products, such as washing machines and microwaves.

In total, there are 196 potential markets defined by the combination of 14 countries and 14 product categories. Data in four markets were unavailable to us (microwaves in Japan; refrigerators, desktop PCs, and washing machines in New Zealand). In six more markets, we did not have sufficient data (e.g., less than four years of data), so we excluded these markets: compact cameras and SLR cameras in India; CRT TV in Japan; and tablets in India, Vietnam, and the Philippines. Finally, we exclude four more markets, because an inspection of the category's sales volume revealed implausible breaks between two consecutive calendar years (laptops and desktop PCs in India and China). Thus, in total, we have $196 - 4 - 6 - 4 = 182$ category-country combinations, or 182 markets for short.

Brand selection. Many of the markets we study are highly fragmented (i.e., have many brands with a small to negligible market share). For example, there are more than 100 brands selling tablets in Hong Kong, while the top two brands Apple and Samsung have more than 80% of the market. To arrive at a feasible set of brands for estimation that also guarantees a sufficient number of monthly observations with nonzero sales and nonmissing marketing-mix instruments, we selected all brands in a market that obtain at least 1% unit share over a consecutive period of five years (four years for tablets, which is the newest category in our sample). To avoid the very small sales volumes that are sometimes observed in the initial months before take-off or the final months preceding a brand's demise, we exclude observations from months when sales are less than 5% of the brand's maximal monthly sales level and include those brands for which at least four consecutive years of data remained available. This resulted in 1,619 category-country-brand time series (or 1,619 brands for short) that capture 86% of the total unit sales. Because the same brand may operate in different countries and categories (e.g., Samsung operates in all 14 countries and 14 categories in the sample), the total number of *unique* brands is lower, 329 to be precise. The other, smaller brands (with less than 1% share) are included as a composite category- and country-specific "rest" brand.[7] Table A1 in Web Appendix A provides a list of all brands and information on the brands' country of origin. Most brands in the sample are from China (50), Japan (42), and the United States (36).

Table 2 provides an overview of the categories, their coverage across countries, the number of brands, and the top-three-selling brands. The top brands include well-known giants such as Apple, Canon, LG, Samsung, and Sony. In Table A2 in the Web Appendix, we cross-tabulate countries with categories and give details about the number of included brands per category/country combination.

[7] Although we do not estimate elasticities for the composite rest brands, we account for them in the operationalization of the competitor marketing-mix variables.

Table 2. Category Overview.

Category	Category Type	Number of Countries with Data	Number of Brands	Top Three Brands
Compact cameras	Electronics	13	21	Canon, Sony, Samsung
CRT TVs	Electronics	13	65	Sampo, Samsung, LG
Desktop computers	Electronics	11	27	Samsung, NEC, Fujitsu
DVD players and recorders	Electronics	14	129	Arirang, AJ, California
Laptop computers	Electronics	12	20	NEC, Acer, LG
LCD TVs	Electronics	14	47	Samsung, LG, Sony
Microwaves	Appliances	13	51	Galanz, Sampo, American Home
Mobile phones	Electronics	14	55	Nokia, Samsung, Sharp
Plasma TVs	Electronics	14	46	Samsung, LG, Sony
Refrigerators	Appliances	13	54	Zipel, Dios, Westinghouse
SLR cameras	Electronics	13	5	Canon, Nikon, Sony
Smartphones	Electronics	14	13	Samsung, Sharp, Apple
Tablets	Electronics	11	3	Samsung, Apple, Taiwan Mobile
Washing machines	Appliances	13	67	Tromm, Simpson, LG

Notes: Categories are shown in alphabetical order. We determined the top three brands on the basis of their average volume share across countries and listed them in decreasing order of their market share.

Variable Operationalization and Summary Statistics

First-stage variables. The GfK data include monthly SKU sales for all brands in each market. Some product categories feature more than 1,000 SKUs. Some SKUs have a relatively high sales volume, while others are only sold every few months. Because we are interested in analyzing the performance of *brands* across countries and product categories, the logical unit of analysis is at the brand level. Modeling sales at the SKU level would be almost impossible given the short, erratic time series variation that is available for the tens of thousands of SKUs underlying the 1,600+ brands in the data, whereas sales at the brand level are much more stable and more informative on how the brand is performing as a whole in a product category. Moreover, our research questions are at the brand level rather than at the SKU level.

Therefore, we aggregate the data to the brand level and note that the estimated elasticities apply to brands rather than SKUs. We use as dependent variable a brand's monthly volume (i.e., unit) sales and weigh all independent variables observed at the SKU level with the SKUs' sales in the previous three months. By focusing on sales as dependent variable—rather than market share—we retain sales variation due to primary-demand growth that can vary substantially across categories and countries, and which may be related to how effective a brand's marketing-mix instruments are.

Table 3, Panel A, provides details about the operationalization of the variables. The price variable represents the actual price paid. Importantly, we note that pricing for electronics and appliances tends to follow a common pattern. When a new SKU is released, it comes with a recommended retail price, which is often heavily discounted around certain times of the year—such as Diwali in India, Lunar New Year in many East Asian countries, or Boxing Day in Australia and New Zealand—or, depending on the product category, around certain specific events (e.g., Mother's Day, Father's Day). Similarly, discounts are often used to clear inventories of certain items. Thus, the price variation observed in these data tends to be predominantly based on price discounting/promotion and as such, we interpret the price elasticity as a measure of price-discounting effectiveness.

Further inspection of the data reveals that some observations are missing (e.g., a brand's average price), and we linearly interpolate up to two months of missing intermediate observations in a given data series. If brands have more than two subsequent missing observations (e.g., minor brands with few sales that can easily "fall off the radar"), we select those time periods for which most observations for the focal variables are available consecutively.

The data set that we use for estimation includes, as indicated before, 1,619 brands. This data set constitutes the final data set that we use for estimating marketing elasticities, and we provide summary statistics in Table A3 in Web Appendix A. In Figures A1–A3 in Web Appendix A, we provide plots that show the range and level of the marketing-mix variables across categories and countries, underscoring their substantial variation.

Control variables. In the model, we account for competitor marketing-mix effects by including the marketing mix of a brand's average competitor within each category and country, operationalized as the mean of all other brands' marketing-mix activities in the same period, weighted by a brand's sales in the previous three months.[8] We control for seasonality through brand-specific quarterly dummies. We further control for national holidays in a country using the count of the number of public holidays in a given month of a year. Finally, we

[8] Our metric for competition includes *all* remaining brands, which include the category- and country-specific composite brand, brands for which we cannot verify their country of origin (see also footnote 9), and observations for brands in their early (or late) life cycle stages.

Table 3. Variable Operationalization.

A: Variables in First-Stage Sales-Response Model

Variable	Operationalization
$Sales_{kcb,t}$	Unit sales for brand b in country k and category c in period t.
$LineLength_{kcb,t}$	Number of unique SKUs sold by brand b in country k and category c in period t.
$Price_{kcb,t}$	Price of brand b in country k and category c in period t, computed as a sales-weighted average across its SKUs sold in period t, expressed in local currency and adjusted by a country's consumer price index.[a,b]
$Distribution_{kcb,t}$	Distribution of brand b in country k and category c in period t, computed as a sales-weighted average across its SKUs' store-weighted distribution in period t (0 = no market coverage, 100 = full market coverage).[a]
$CompLineLength_{kcb,t}$	Sales-weighted average of brands b's competing brands' ($\neq$b) number of unique SKUs sold in country k and category c in period t.[c]
$CompPrice_{kcb,t}$	Sales-weighted average of brands b's competing brands' ($\neq$b) average price in country k and category c in period t.[c]
$CompDistribution_{kcb,t}$	Sales-weighted average of brands b's competing brands' ($\neq$b) average distribution in country k and category c in period t.[c]
$Trend_t$	Linear trend variable in period t.
$Quarter_{q,t}$	Quarterly dummy for quarter q ($Quarter_{q,t}$ = 1 if period t is in quarter q, and 0 otherwise) to account for seasonality; quarter 4 is the base category.
$Holiday_{k,t}$	Number of national holidays in country k in period t.[d]

B: Variables in Second-Stage Regression[e]

Variable	Operationalization
η^m_{kcb}	Elasticity for marketing-mix instrument m (m = 1 for line length, m = 2 for price, m = 3 for distribution) of brand b in country k and category c, derived from the first-stage sales-response model.
$BrandEquity_{kcb}$	Sales-based brand equity of brand b in country k and category c, standardized by country k and category c.[f]
$CountryOfOriginImage_b$	Dummy variable, equaling 1 if brand b's headquarter is located in the U.S., Japan, Germany, Switzerland or Sweden, 0 if not.
$AvgLineLength_{kcb}$	Line length of brand b in country k and category c, divided by the sales-weighted average of the line length of all brands in country k and category c.[g,h]
$AvgPrice_{kcb}$	Price of brand b in country k and category c, divided by the sales-weighted average of the price of all brands in country k and category c.[g,h]
$AvgDistribution_{kcb}$	Distribution of brand b in country k and category c, divided by the sales-weighted average of distribution of all brands in country k and category c.[g,h]
$AvgInnovativeness_{kcb}$	Number of SKUs introduced by brand b in country k and category c, expressed as a share of total unique SKUs sold by brand b in country k and category c, divided by the sales-weighted average of that measure for all brands in country k and category c.[g,h]
$MarketConc_{kc}$	Herfindahl index in country k and category c, calculated as the sum of squared brand market shares over the time period for which category c in country k has been observed in the data.
$MarketGrowth_{kc}$	Average growth rate (expressed in annual percent) in country k and category c, averaged over the time period for which category c in country k has been observed in the data.[i]
Appliances (versus electronics)$_c$	Dummy variable, equaling 1 if category c consists of appliances (washing machines, microwaves and refrigerators), 0 for all other categories.
$MarketSize_{kc}$	Population (in millions) in country k, averaged over the time period for which category c in country k has been observed in the data.[j]
$GDPperCapita_{kc}$	GDP per capita in country k, averaged over the time period for which category c in country k has been observed in the data.[j]
$GDPGrowth_{kc}$	GDP growth (expressed in annual percent) for country k, averaged over the time period for which category c in country k has been observed in the data.[j]
$IncomeInequality_k$	Gini index in country k.[k]
PDI_k	Power distance for country k.[l]
UAI_k	Uncertainty avoidance for country k.[l]
MAS_k	Masculinity for country k.[l]

[a]Weights equal to an SKU's unit sales in the most recent quarter (periods t − 3, t − 2, t − 1).
[b]Consumer price indices obtained from Thomson Reuters Datastream.
[c]Weights equal to a brand's unit sales in the most recent quarter (periods t − 3, t − 1, t − 1).
[d]Retrieved from https://holidayapi.com.
[e]Continuous explanatory variables only taking on nonnegative values are logged before model estimation (except brand equity, which is standardized).
[f]Obtained from a market-share attraction model (Datta, Ailawadi, and Van Heerde 2017). For details on the technical implementation, see Web Appendix C.
[g]Weights equal to a brand's unit sales in the most recent quarter (periods t − 3, t − 1, t − 1).
[h]Averages values of marketing mix instruments computed over the estimation period for brand b's elasticities.
[i]Annual growth rate of the total number of unit sales in a market (category/country combination) computed across all consecutive years with 12 months of data (i.e., dropping potentially incomplete first or last years), and averaged over the observation period of category c and country k.
[j]GDP per capita is a country's expenditure-side real GDP at chained PPPs (expressed in 2011 USD), divided by a country's market size. GDP growth is computed as the annual percentage change in expenditure-side real GDP at chained PPPs. Measures obtained from the Penn World Tables 9.0 (Feenstra, Inklaar, and Timmer 2015), and averaged over the observation period of category c and country k.
[k]Measure of the inequality of income distribution, extracted from the CIA World Factbook (Philippines, Taiwan, Hong Kong, Singapore), OECD (New Zealand) and the World Bank (all remaining countries; symbol: SI.POV.GINI) for the year 2010. The metric is not consistently available for all years and all countries, and the closest available observation to 2010 has been used.
[l]Measures based on Hofstede, Hofstede, and Minkov (2010) and extracted from https://geerthofstede.com/research-and-vsm/dimension-data-matrix/.

include a brand-specific linear trend to capture underlying increases or decreases in demand.

Second-stage variables. After the first-stage estimates the marketing elasticities, the second-stage analysis studies how these elasticities differ systematically and predictably between brands, categories, and countries. Table 3, Panel B, provides details about the operationalization of the variables used in the second stage. As for two of the 1,619 brands there are missing values on some of their characteristics, we report summary statistics on those 1,617 brands for which these characteristics are available.[9] Table A4 in Web Appendix A shows the correlation between the second-stage variables. Multicollinearity is not a concern, as the highest variance inflation factor is just 5.36.

Method

Our goal is to estimate and explain market response to line length, price, and distribution. In line with an established tradition in the marketing literature (e.g., Nijs et al. 2001; Srinivasan et al. 2004), we first estimate marketing-mix responsiveness for all 1,600+ brands in the data using sales-response models. We then estimate a regression to investigate the drivers of marketing-mix response across brands, categories and countries, using weighted least squares to account for the uncertainty of the elasticity estimates from the first stage.

Sales-Response Model Specification

We want to estimate marketing-mix elasticities in a uniform way across a wide set of brands, categories, and countries. The model must satisfy four criteria. First, it should be able to handle a wide variety of sales patterns, including strong growth (e.g., in relatively new product categories such as smartphones), stable markets (mature categories such as microwaves), and strong declines (such as traditional mobile phones without touchscreens). Second, it should capture not only the short-term effects of marketing activities on sales but also their long-term effects. Third, it should account for the potential endogeneity of marketing activities, and, finally, it should accommodate competitor effects.

To satisfy these four criteria, we adopt an error-correction specification (for marketing applications, see, e.g., Fok et al. 2006; Pauwels, Srinivasan, and Franses 2007; Van Heerde, Srinivasan, and Dekimpe 2010; Van Heerde et al. 2013). The model for brand b in country k and category c is

$$\begin{aligned}\Delta Sales_{kcb,t} &= \alpha_{0kcb} + \alpha_{1kcb}\Delta LineLength_{kcb,t} + \alpha_{2kcb}\Delta Price_{kcb,t} \\ &+ \alpha_{3kcb}\Delta Distribution_{kcb,t} + \alpha_{4kcb}\Delta CompLineLength_{kcb,t} \\ &+ \alpha_{5kcb}\Delta CompPrice_{kcb,t} + \alpha_{6kcb}\Delta CompDistribution_{kcb,t} \\ &+ \gamma_{kcb}[Sales_{kcb,t-1} - \beta_{1kcb}LineLength_{kcb,t-1} \\ &-\beta_{2kcb}Price_{kcb,t-1} - \beta_{3kcb}Distribution_{kcb,t-1}] \\ &+ \alpha_{7kcb}Trend_t + \sum_{q=1}^{3}\alpha_{7+q,kcb}Quarter_{q,t} + \alpha_{11kcb}Holiday_{k,t} \\ &+ \sum_{m=1}^{3}\alpha_{11+m,kcb}Copula^{m}_{kcb,t} + \varepsilon_{kcb,t}, \end{aligned} \quad (1)$$

where $\Delta X_t = X_t - X_{t-1}$ is the first difference. All variables are defined in Table 3, Panel A. We use a linear model to avoid the aggregation bias that would occur when working with, for example, a log-log specification (Christen et al. 1997).[10]

Error-correction Model 1 can capture a wide variety of both stable and trending sales patterns. In Model 1, the short-term marketing effects for line length, price, and distribution are captured by α_{1kcb}, α_{2kcb}, and α_{3kcb}, respectively, whereas the corresponding long-term parameters are β_{1kcb}, β_{2kcb}, and β_{3kcb}. From the latter parameters, in line with Srinivasan et al. (2004) and Van Heerde, Helsen, and Dekimpe (2007), we compute the long-term elasticities at the mean as $\eta^{m}_{kcb} = \beta_{mkcb} \times (\bar{X}^{m}_{kcb}/\overline{Sales}_{kcb})$, where $\bar{X}^{m}_{kcb}$ is the mean of a brand's marketing-mix instrument m (m = 1, 2, 3 for line length, price, and distribution, respectively) for brand b in category c and country k, and $\overline{Sales}_{kcb}$ is a brand's mean sales in category c and country k, computed over the estimation period for that brand. We obtain corresponding standard errors using the delta method (Greene 2003). Our focus (also in the second-stage regression) is on the long-term elasticities, because they capture the full dynamic impact of a 1% change in the focal marketing variable. For example, if a price reduction increases sales in month t, followed by a postpromotion dip (Van Heerde, Leeflang, and Wittink 2000) in subsequent months, the long-term price elasticity captures the net sales effect.

Accounting for Endogeneity

Brand managers may be strategic in setting the levels of the marketing variables for their brands based on unobserved demand shocks. One potential source of these demand shocks is cross-sectional (e.g., brands setting higher prices in wealthier

[9] Specifically, from the DVD player category, we exclude two brands ("Super" sold in Hong Kong and "Amazon" sold in Indonesia; we have verified that the latter is not U.S.-based Amazon.com).

[10] As alternative specifications, we considered a linear partial-adjustment model (Leeflang et al. 2000, p. 488) and an error-correction specification with a log-transformed (rather than linear) trend, advocating our chosen model on the basis of the root mean square error (both within- and out-of-sample), and out-of-sample symmetric mean absolute percentage error (Armstrong and Collopy 1992; the differences with regard to the within-sample fit in symmetric mean absolute percentage error were negligibly small). Details are provided in Web Appendix A, Table A5.

countries). To safeguard against this potential endogeneity concern, we only use within-market longitudinal variation for estimation. That is, Model 1 is specified for each brand in each country and category separately, eliminating concerns about cross-sectional endogeneity issues.

However, there is also a potential longitudinal endogeneity issue: brands may adjust their marketing mix based on unobserved demand shocks over time, such as higher demand due to seasonality. As a first safeguard, Model 1 controls for seasonality, holiday effects, lagged brand sales, competitor marketing variables, and a trend. This rich data approach (through observed covariates; see Germann, Ebbes, and Grewal 2015) is a first line of defense against longitudinal endogeneity.

However, it is still conceivable that there are other longitudinal demand shocks the model does not account for, such as idiosyncratic changes in consumer preferences for brands. To help safeguard the model against this potential endogeneity issue, we have to isolate exogenous from endogenous variation in the regressors. Many papers adopt an instrumental variable approach. In our setting, this would mean identifying brand-specific instrumental variables (for 1,600+ brands) that can meaningfully explain variation in line length, price, and distribution across 14 countries, 14 categories, and up to 11 years of data. As this is not feasible, we decided to adopt Gaussian copulas, an instrument-free approach. Therefore, we augment Equation 1 with Gaussian copula terms that absorb the correlation between potentially endogenous marketing-mix variables and the normally distributed error term (Park and Gupta 2012). The copula method, which was recently used in, for example, Datta, Foubert, and Van Heerde (2015) and Gielens et al. (2018), does not require instrumental variables and thus is particularly useful when valid instruments are hard to find (Rossi 2014).

The Gaussian copula for marketing instrument $X^m_{kcb,t}$ is obtained as $Copula^m_{kcb,t} = \Phi^{-1}[H(X^m_{kcb,t})]$, where Φ^{-1} is the inverse distribution function of the standard normal, and $H(\cdot)$ is the empirical cumulative distribution function of X^m_{kcb}. Web Appendix B reports on a simulation analysis for data similar to our empirical setting that shows that Gaussian copulas allow us to recover the true parameters well in the presence of endogeneity.

With a normally distributed error term, an identification requirement for the Gaussian-copula method is that the endogenous regressors are not normally distributed. In our application, Shapiro–Wilk tests at $p < .10$ confirm this for 91% of the cases. Rather than including all copula terms at once, we follow Mathys, Burmester, and Clement (2016) and first test for the presence of endogeneity per regressor. Specifically, we first estimate brand-specific models including a Gaussian copula correction term for only one particular marketing-mix variable, one at a time. We subsequently retain copula terms that were significant at $p < .10$ in the first step (18.08% of all copula terms).

Model estimation. The model for the B_{kc} brands operating in country k and category c is a system of B_{kc} brand equations (Equation 1). We allow for correlated errors across brands because it is quite likely that there are category-/country-specific unobserved exogenous shocks. For example, the rollout of a 5G network in China may lead to an increase in demand for higher-end smartphones in China at the expense of lower-end models. To capture such shocks flexibly, we correlate the error terms for brands operating in the same country and category using a seemingly unrelated regression specification and estimate this system of seemingly unrelated equations for each category-country combination using feasible generalized least squares.

Brand equity. We adopt sales-based brand equity as our measure of brand equity, which captures the intrinsic appeal of brand b net of its marketing mix and a wide range of physical attributes. We use the intercept estimates from a market-share model, similar to Datta, Ailawadi, and Van Heerde (2017). For details, see Web Appendix C.

Second-stage regression. The study framework specifies that line-length, price, and distribution elasticities could vary systematically and predictably in function of brand characteristics, category characteristics, and/or country characteristics. Thus, we estimate the following regression model for each of the three long-term marketing elasticities η^m_{kcb} for marketing variable m (m = 1 for line length, m = 2 for price, m = 3 for distribution), country k, category c, and brand b:

$$\begin{aligned}\eta^m_{kcb} = {} & \delta_{0,m} + \delta_{1,m}\text{BrandEquity}_{kcb} \\ & + \delta_{2,m}\text{CountryOfOriginImage}_b \\ & + \delta_{3,m}\log(\text{AvgLineLength}_{kcb}) + \delta_{4,m}\log(\text{AvgPrice}_{kcb}) \\ & + \delta_{5,m}\log(\text{AvgDistribition}_{kcb}) \\ & + \delta_{6,m}\log(\text{Innovativeness}_{kcb}) + \delta_{7,m}\log(\text{MarketConc}_{kc}) \\ & + \delta_{8,m}\log(\text{MarketGrowth}_{kc}) + \delta_{9,m}\text{Appliances}_c \\ & + \delta_{10,m}\log(\text{MarketSize}_{kc}) + \delta_{11,m}\log(\text{GDPperCapita}_{kc}) \\ & + \delta_{12,m}\log(\text{GDPGrowth}_{kc}) + \delta_{13,m}\log(\text{IncomeInequality}_k) \\ & + \delta_{14,m}\log(\text{PDI}_k) + \delta_{15,m}\log(\text{UAI}_k) \\ & + \delta_{16,m}\log(\text{MAS}_k) + u_{m,kbc}, \end{aligned} \quad (2)$$

where the variables are defined in Table 3, Panel B. To account for the uncertainty in the elasticity estimates, we estimate Equation 2 with weights equal to the inverse standard errors of the elasticity estimates (Van Heerde et al. 2013). We use robust standard errors using three-way clustered errors for brands, categories, and countries.

Results

Descriptive Results

Figure 2 visualizes the model fit for selected brands and categories in the various countries. The combined evidence across all 1,600+ brands provides strong evidence that each of the three marketing-mix instruments plays a significant role in explaining a brand's over-time sales performance. Comparing the model fit of our full model (across all brands, categories, and countries) with a more restricted specification in which one of the marketing-mix instruments was consistently omitted (in terms

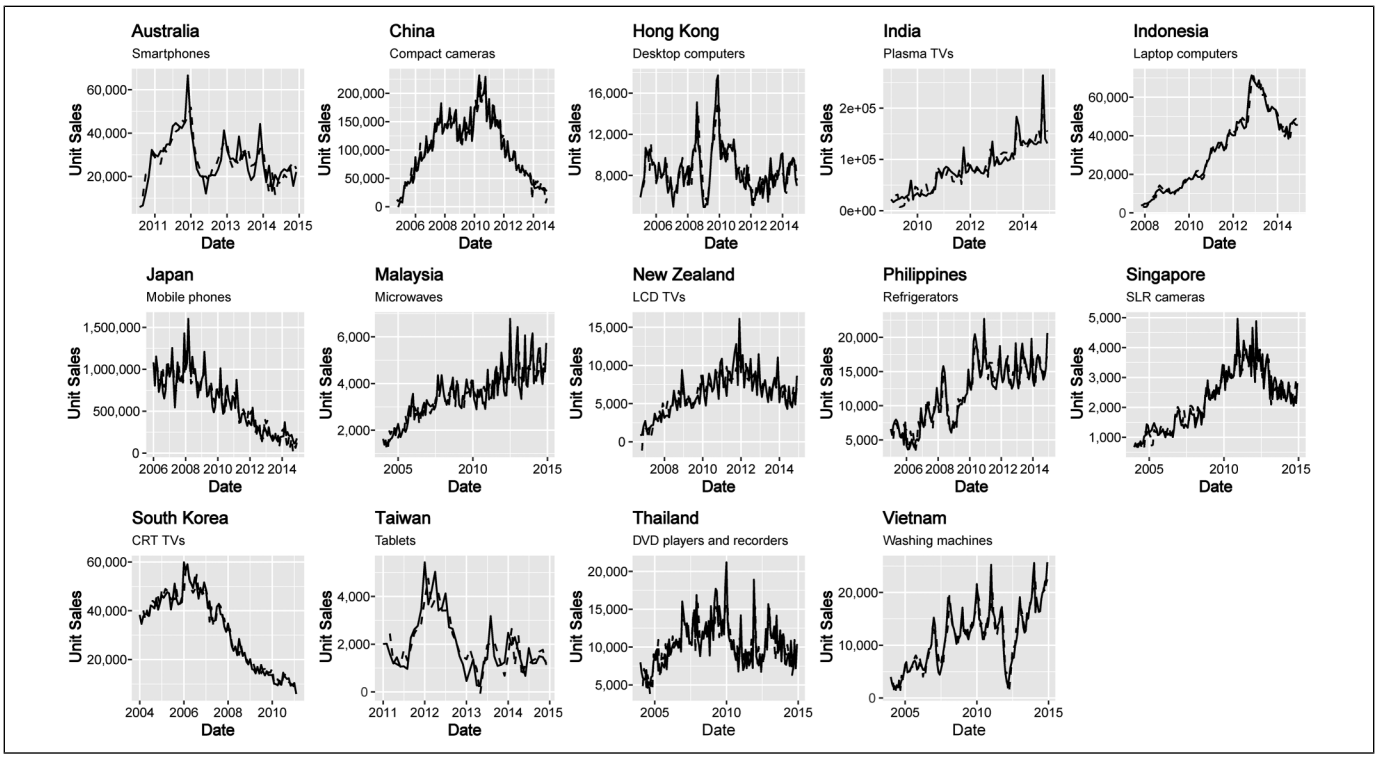


Figure 2. Model fit for brand sales for a random sample of top five brands in 14 selected categories and countries.
Notes: Model fit shown for randomly chosen brands (out of the top five best-selling brands in a market (category/country combination), as determined by their average volume share, cf. Table 3) in 14 selected countries and categories. Categories and countries have been chosen so that each of the 14 countries and categories are displayed. Solid lines represent observed brand sales and dashed lines represent predicted brand sales.

of own short-term and long-term effects, as well as competitive cross-effects), we find a highly significant difference (nested model F-test $p < .001$) in each instance. We reach a similar conclusion when comparing the most restricted model without any marketing-mix instrument with more extended models where one of the three marketing-mix instruments is added each time (nested model F-test $p < .001$ in each instance).[11]

Table 4 shows the mean long-term elasticities for the three marketing variables for each country in the sample, along with the percentages of estimates in three groupings: positive and significant ($p < .10$), negative and significant ($p < .10$), and nonsignificant ($p \geq .10$). All mean values have the expected sign: negative for price elasticity, and positive for distribution and line-length elasticity. We first focus on the last row, which provides long-term elasticities for the entire data set used in the second-stage regression.[12] The average line-length elasticity is .459 ($p < .01$), indicating that a 1% longer line length lifts sales by .459% on average. The average price elasticity is −.422 ($p < .01$), which means demand is relatively inelastic to price discounts. This average is also low compared with the mean price elasticity (−2.62) reported by Bijmolt, Van Heerde, and Pieters (2005). We return to this difference in the final section of the article. The mean distribution elasticity is .368 ($p < .01$), implying that 1% more distribution increases sales by .368% on average. Thus, in terms of the long-term elasticities, we find that, on average, line length (distribution) appears to be most (least) effective. However, as we discuss in more detail subsequently, these averages conceal considerable heterogeneity.

Table 4 further shows the mean long-term elasticities for each country in the sample. Given the considerable cross-country heterogeneity in the respective elasticities, a first key takeaway is that broad aggregations across country groupings (e.g., Bijmolt, Van Heerde, and Pieters 2005) are less appropriate.

Table 5 provides long-term elasticities averaged per category across countries, underscoring that brand elasticities vary substantially across categories as well. For example, line length elasticities are strongest for smartphones (.882) and weakest for microwaves (.225). The coefficient of variation calculated on the 1,600+ elasticities is 2.841 for line length, and even more pronounced for price (−5.760) and distribution (4.962). To better understand this variability, we now turn to our second-stage regression, where we explore the potential

[11] To allow for a fair comparison (given that the number of retained copula terms may differ), we compared the model fit without adding any of the Gaussian copula terms.

[12] For each elasticity, the mean and median are very similar, suggesting fairly symmetrical distributions (line length: mean = .459, median = .486; price: mean = −.422, median = −.404; distribution: mean = .368, median = .367). Given their similarity, we focus on the means rather than the medians from now on.

Table 4. Long-Term Elasticities by Country.

		Line Length				Price				Distribution			
Country	**N**	**Mean[a]**	**% Pos**	**% Neg**	**% n.s.**	**Mean[a]**	**% Pos**	**% Neg**	**% n.s.**	**Mean[a]**	**% Pos**	**% Neg**	**% n.s.**
Australia	146	.315***	44	16	40	−.352***	13	40	47	.419***	40	11	49
China	134	.420***	49	8	43	−.605***	11	52	37	.383***	54	9	37
Hong Kong	133	.471***	52	11	37	−.468***	13	43	44	.411***	51	9	40
India	80	.273***	41	10	49	−.321***	16	33	51	.137***	50	14	36
Indonesia	122	.732***	54	5	41	−.767***	7	40	53	.371***	52	11	37
Japan	98	.261***	30	11	59	−.262***	12	40	48	.305***	31	12	57
Malaysia	127	.510***	57	6	37	−.406***	10	32	58	.441***	63	5	32
New Zealand	79	.405***	51	14	35	−.483***	5	42	53	.624***	49	12	39
Philippines	129	.448***	50	7	43	−.161***	16	24	60	.400***	51	6	43
Singapore	118	.588***	62	5	33	−.400***	9	48	43	.457***	56	10	34
South Korea	70	.440***	58	6	36	−.559***	7	41	52	.294***	53	3	44
Taiwan	149	.552***	58	5	37	−.377***	12	39	49	.255***	44	13	43
Thailand	125	.472***	46	5	49	−.531***	9	47	44	.441***	51	6	43
Vietnam	107	.513***	43	11	46	−.217***	11	25	64	.414***	52	13	35
Total	1,617	.459***	50	9	41	−.422***	11	39	50	.368***	50	9	41

***$p < .01$.

[a]Two-sided tests of significance. Elasticities are weighted by inverse standard errors. Significance tested using meta-analytic p-value (method of added Zs).

Notes: Countries are shown in alphabetical order. The number of line-length estimates for Malaysia is 126 (rather than 127), as one brand in one category did not have sufficient variation on that variable. Share of significant effects reported at $p < .10$. The column "% Pos" ("% Neg") shows the percentage of estimated elasticities that are significant and positive (negative) in magnitude. The column "% n.s." reports the share of estimated elasticities that is not significantly different from zero ($p \geq .10$).

Table 5. Long-Term Elasticities by Category

		Line Length				Price				Distribution			
Category	**N**	**Mean[a]**	**% Pos**	**% Neg**	**% n.s.**	**Mean[a]**	**% Pos**	**% Neg**	**% n.s.**	**Mean[a]**	**% Pos**	**% Neg**	**% n.s.**
Compact cameras	130	.540***	46	7	47	−.473***	6	46	48	.527***	55	9	36
CRT TVs	139	.531***	55	7	38	−.620***	11	38	51	.351***	50	8	42
Desktop computers	72	.607***	58	6	36	−.346***	10	29	61	.231***	47	10	43
DVD players and recorders	216	.428***	49	11	40	−.364***	14	36	50	.321***	44	12	44
Laptop computers	119	.463***	56	9	35	−.490***	9	44	47	.296***	51	9	40
LCD TVs	141	.494***	53	10	37	−.473***	6	52	42	.379***	48	11	41
Microwaves	113	.225***	39	12	49	−.592***	5	47	48	.273***	50	12	38
Mobile phones	113	.676***	48	10	42	−.070**	20	19	61	.514***	48	8	44
Plasma TVs	141	.474 ***	51	9	40	−.444***	6	52	42	.385***	50	11	39
Refrigerators	139	.309***	43	7	50	−.332***	14	37	49	.383***	59	6	35
SLR cameras	54	.653***	65	5	30	−.244***	13	30	57	.620***	56	7	37
Smartphones	73	.882***	49	7	44	−.650***	15	40	45	.748***	48	5	47
Tablets	14	.807***	43	0	57	−1.082***	14	36	50	−.013	14	0	86
Washing machines	153	.349***	49	9	42	−.340***	16	31	53	.328***	52	9	39
Total	1,617	.459***	50	9	41	−.422***	11	39	50	.368***	50	9	41

**$p < .05$.

***$p < .01$.

[a]Two-sided tests of significance. Elasticities are weighted by inverse standard errors. Significance tested using meta-analytic p-value (method of added Zs).

Notes: Categories are shown in alphabetical order. The number of line-length estimates for DVD players and recorders is 215 (rather than 216), as one brand in one country did not have sufficient variation on that variable. Share of significant effects tested at $p < .10$. The column "% Pos" ("% Neg") shows the percentage of estimated elasticities that are significant and positive (negative) in magnitude. The column "% n.s." reports the share of estimated elasticities that is not significantly different from zero ($p \geq .10$).

impact of various brand-, category-, and country-level drivers. While not the central focus of our analysis, we provide short-term elasticities by category and country in Web Appendix A, Tables A6–A7.

Second-Stage Regression

The results of the second-stage regression (Equation 2) are reported in Table 6. For expositional purposes, we replace the index m with the corresponding variable labels (1 = line

Table 6. Regression of Long-Term Elasticities on Predictors.

	Line-Length Elasticity	Price Elasticity	Distribution Elasticity
BrandEquity (δ_1)	−.028	−.145***	−.018
	(.022)	(.043)	(.020)
CountryOfOriginImage (δ_2)	.049	−.075	.031
	(.045)	(.083)	(.041)
Log AvgLineLength (δ_3)	−.010	.020	−.071**
	(.040)	(.034)	(.031)
Log AvgPrice (δ_4)	−.055	.016	.023
	(.056)	(.070)	(.047)
Log AvgDistribution (δ_5)	−.056	.023	.010
	(.035)	(.047)	(.032)
Log AvgInnovativeness (δ_6)	.058	.207	.111*
	(.058)	(.177)	(.059)
Log MarketConc (δ_7)	.116*	.033	.025
	(.064)	(.108)	(.063)
Log MarketGrowth (δ_8)	.011	−.106	.147***
	(.113)	(.145)	(.047)
Appliances (versus electronics) (δ_9)	−.234***	−.001	−.019
	(.054)	(.113)	(.052)
Log MarketSize (δ_{10})	−.020	−.121***	−.023
	(.021)	(.021)	(.027)
Log GDPperCapita (δ_{11})	.047	−.199***	−.028
	(.035)	(.032)	(.027)
Log GDPGrowth (δ_{12})	.094***	−.076	.006
	(.030)	(.051)	(.028)
Log IncomeInequality (δ_{13})	.020	−.769***	.419
	(.324)	(.180)	(.277)
Log PDI (δ_{14}) (power distance)	.147**	.257***	−.175**
	(.075)	(.078)	(.076)
Log UAI (δ_{15}) (uncertainty avoidance)	.043	−.102	−.013
	(.039)	(.063)	(.035)
Log MAS (δ_{16}) (masculinity)	−.071	.353**	−.005
	(.070)	(.138)	(.094)
Constant	.509***	−.376***	.371***
	(.039)	(.064)	(.039)
Log-likelihood	−1,908.85	−2,507.69	−1,715.11
Observations	1,616	1,617	1,617

*$p < .10$.
**$p < .05$.
***$p < .01$.

Notes: Two-sided tests of significance. Elasticities are Winsorized at the 1% and 99% levels and weighted by inverse standard errors. There are 1,616 elasticities for line length and 1,617 elasticities for price and distribution. The number of observations differs slightly for line length, as one brand in one market (category/country combination) did not have sufficient variation on that variable. We take the logarithm of all continuous variables that only take on nonnegative values. Brand equity is standardized, as explained in Table 3 and Web Appendix C.

length, 2 = price, 3 = distribution) when discussing parameter estimates in the empirical results section.

Brand characteristics. We observe that higher brand equity is associated with a stronger (more negative) price elasticity ($\delta_{1,\text{price}} = -.145$, $p < .01$), which is consistent with the argument that stronger brands benefit more from price discounting (Blattberg and Wisniewski 1989; Sethuraman 1996). Brands with shorter product lines benefit more from additional distribution coverage ($\delta_{3,\text{distribution}} = -.071$, $p < .05$), as it may compensate for their reduced in-store visibility compared to brands with longer product lines. Distribution also becomes more effective when the brand's product line contains (compared with its competitors) a higher number of novel SKUs ($\delta_{6,\text{distribution}} = .111$, $p < .10$). Innovativeness creates a variety effect (Hausman and Leonard 2002) that is valued by both retailers and consumers, enhancing the marginal sales effect of additional distribution.

Category characteristics. Categories with more concentrated demand are associated with a stronger line-length elasticity ($\delta_{7,\text{price}} = .116$, $p < .10$). A concentrated market means that a few brands control a large part of the market. To target heterogeneous consumer preferences, each of those brands has to offer an extensive set of items, increasing the marginal sales effect of additional line length. Conversely, in less concentrated

markets, a broad set of players can cater to different consumer preferences, each offering a shallower assortment.

High-growth categories have a higher distribution elasticity ($\delta_{8,\text{distribution}} = .147$, $p < .01$). Strongly growing categories will require more consumer touchpoints to satisfy demand, and this can be created through more distribution points. Finally, appliances have a lower line-length elasticity ($\delta_{9,\text{linelength}} = -.234$, $p < .01$) than electronics. Product differentiation and the availability of novel products may be less important for utilitarian products such as appliances than for more hedonic electronics products such as tablets and smartphones (Chandrasekaran and Tellis 2008).

Country characteristics. Turning to the effect of country-level factors, we find that price elasticity is stronger (more negative) in larger markets ($\delta_{10,\text{price}} = -.121$, $p < .01$). Markets with a larger population support a larger variety of goods, resulting in a more crowded product space, which raises the price elasticity of demand (Barron, Umbeck, and Waddell 2008; Desmet and Parente 2010). The responsiveness to line length is greater in countries characterized by high GDP growth ($\delta_{12,\text{linelength}} = .094$, $p < .01$). High GDP growth creates new demand for new products, making broader product lines more effective. Income inequality, in turn, makes consumers more sensitive to price changes ($\delta_{13,\text{price}} = -.769$, $p < .01$). In countries with considerable income differences, many consumers experience little asset ownership, making them more price sensitive (Kozlenkova et al. 2021).

Consumers in richer countries per capita ($\delta_{11,\text{price}} = -.199$, $p < .01$) respond more strongly to price reductions. One explanation is that consumers in these countries have the financial means to purchase relatively expensive products (electronics and appliances in this case) when they are price discounted, whereas these products—even when discounted—may stay out of reach for consumers in poorer countries. We elaborate more on this finding in the "Discussion" section.

Importantly, we find that national culture affects marketing-mix effectiveness over and above macroeconomic factors. Sensitivity to line length is higher in countries high on power distance ($\delta_{14,\text{linelength}} = .147$, $p < .05$), while their price ($\delta_{14,\text{price}} = .257$, $p < .01$) and distribution ($\delta_{14,\text{distribution}} = -.175$, $p < .05$) elasticity is lower. High-power-distance societies (e.g., Malaysia, the Philippines; see Table 1) have been found to be more materialistic because the acquisition and possession of goods is one important way to signal one's social position (Ogden and Cheng 2011; Xiao and Tessema 2019). Consumers in these societies respond more strongly to product assortments, and a wide assortment is more valued because demand is more heterogeneous along socially stratified lines. Stronger focus on status consumption is associated with reduced price sensitivity (Lee, Lalwani, and Wang 2020). The greater importance of material goods suggests that people may be more involved with this consumer activity (Goldsmith, Flynn, and Kim 2010) and more willing to exert effort to acquire the product, which explains the lower sensitivity to distribution in high-power-distance countries. The systematic and significant effect of power distance on all three marketing elasticities is one of the most salient findings of this article. We also find that price sensitivity is considerably lower in masculine countries such as Japan ($\delta_{16,\text{price}} = .353$, $p < .05$). In these countries, the ability to afford high prices, as a measure of success and achievement (Veblen 1899), is relatively more pronounced.

Emerging Versus Developed Economies

With the rapid rise of countries such as China, India, and Vietnam, there is an interest among marketing academics and practitioners as to whether there are significant differences in market-response parameters between emerging and developed economies (Burgess and Steenkamp 2006; Roberts, Kayande, and Srivastava 2015; Sheth 2011). To examine this important issue, we constructed an emerging-economy indicator, with the lower- and middle-income countries China, India, Indonesia, Malaysia, the Philippines, Thailand, and Vietnam being classified as emerging economies and the other (high-income) countries as developed economies, based on the World Bank Analytical Classification using gross national income per capita in USD (2014). We reestimated our second-stage model, replacing the economic and cultural factors with the emerging-economy indicator. Across the three marketing-mix elasticities, the emerging-economy indicator had no significant impact. Thus, we find no evidence for a generalized emerging- versus developed-economies effect. Country factors matter, but the picture is more nuanced than the distinction between emerging and developed economies. The economic and cultural factors that we discussed previously offer more insight into how elasticities differ between countries.

Model Extensions

Advertising. The lack of advertising data may lead to an omitted-variable bias in the parameter estimates of the other marketing elasticities. To study the seriousness of this concern, we purchased advertising spend data from Kantar for one emerging economy (China) and one developed economy (Hong Kong).[13] Web Appendix A (Table A8) compares the results of our focal model with sales models that include advertising spend. Two key conclusions emerge. First, the average advertising elasticities are small (.031, $p < .01$), in line with much recent work (e.g., Sethuraman, Tellis, and Briesch 2011; Shapiro, Hitsch, and Tuchman 2021; Van Ewijk, Gijsbrechts, and Steenkamp 2021; Van Ewijk et al.2021; Van Heerde et al. 2013). Second, the estimates for the elasticities of line length, price, and distribution when advertising is included do not differ ($p > .10$) from the estimates obtained when advertising is excluded. Thus, while it would be interesting to estimate

[13] The high costs (several tens of thousands of U.S. dollars for these two countries alone) precluded us from also obtaining similar data on the other countries.

advertising elasticities, the unavailability of advertising in the models does not necessarily lead to an omitted-variable bias.

Inclusion of physical search attributes. We account for a broad range of category-specific physical search attributes in the derivation of our sales-based brand-equity measure. We refer to Web Appendix A (Table A9) for a complete listing of these attributes and Web Appendix C for technical details on the brand-equity derivation. As a robustness check, we considered their addition to the error-correction specification as well. The resulting elasticity estimates were not significantly different from the ones obtained in our main model, as detailed in Web Appendix A (Table A10).

Inclusion of long-term competitive marketing-mix effects. Our focal model specification controls (through the parameters α_{4kcb} to α_{6kcb}) for the short-term effects of competitor line-length, price, and distribution elasticities. As a third model extension, we also control for any long-term effects of these activities by adding the lagged levels of the corresponding variables. Again, the resulting own-elasticity estimates are not significantly different from those obtained in our main model, as described in Web Appendix A (Table A11).

Nonconstant response parameters. We assumed constant response parameters over time. However, it is possible that marketing-mix effectiveness varies over time, especially in emerging countries that go through a phase of rapid economic change. To test whether we are justified in assuming constant response parameters, we reestimate our focal model on a split data set (early vs. late in our observation period) and compare the estimated elasticities. As shown in Web Appendix A (Table A12), we find that elasticities are stable (i.e., they do not statistically differ across the two time windows for any of the three marketing-mix instruments; $p \geq .10$).

Discussion

This article uses a large-scale, consistently collected data set covering 14 durable goods categories in 14 Indo-Pacific Rim countries and applies a unified modeling approach to estimate line-length, price, and distribution elasticities for over 1,600 brands. We summarize our findings using the four research questions introduced previously.

Our first objective was to report on the magnitude of the estimated elasticities. We find that, averaged across brands, categories, and countries, line-length elasticity is .459, price elasticity is −.422, and distribution elasticity is .368. However, these means should be regarded with caution, given that their standard deviation is about three to six times the mean value. Indeed, our findings point more toward substantial heterogeneity across brands, categories, and countries.

Our second research question was whether there are systematic cross-national differences in line-length, price, and distribution elasticities, and if so, what is their magnitude? We do find substantial differences between countries. For example, the average line-length elasticity in Indonesia is three times that of India, and Indonesia is nearly three times as price sensitive as Japan. We also find that total sensitivity to marketing activity (operationalized as the sum of the [absolute] three marketing-mix elasticities) exhibits considerable differences between countries. For example, total sensitivity to marketing in China is about twice that in India.

Regarding the third research question regarding how brand, category, and country factors influence marketing elasticities, we find that line-length elasticities are higher in more concentrated categories and for electronics (vs. appliances). They are also higher in strongly growing countries and countries whose culture is characterized by high power distance. Brand sales change more strongly due to price reductions (1) for higher-equity brands, (2) in richer and larger countries with more income inequality, and (3) in countries that are lower on power distance and masculinity. Distribution elasticity is higher for brands with a smaller and more innovative assortment, in strongly growing categories, and in low-power-distance countries (e.g., New Zealand). Finally, we find no systematic, generalizable difference in responsiveness to marketing activities between developed and emerging economies, addressing the fourth research question.

Implications for Marketing Theory

Following the ETET philosophy of our article, our empirical findings point to several areas in need of further theoretical exploration. First, marketing scholars have become increasingly interested in emerging economies and contrast them with developed economies. This is an important step in broadening the scope of scholarly work to non-Western settings. There are indeed important differences between developed and emerging economies on metrics such as income per capita. However, we find no systematic differences between emerging and developed economies on market responsiveness. The absence of a systematic emerging-market effect on price sensitivity is particularly interesting, as it has often been claimed that emerging markets are more price sensitive (e.g., Kozlenkova et al. 2021). Our findings suggest a more nuanced picture. For example, emerging economies have lower per capita income and tend to have higher income inequality, both of which increase price sensitivity, but they are also higher on power distance, which decrease price sensitivity.[14] Thus, in future conceptual and empirical work, academics are advised to go beyond the developed–emerging economy dichotomy and take the specific economic and cultural context into account.

[14] In our study, the correlation between emerging-economy status and power distance is .68. The association between power distance and emerging-economy status is not unique to our sample. We considered power distance for 66 countries (http://clearlycultural.com/geert-hofstede-cultural-dimensions/power-distance-index/), including 35 developed (high-income) economies and 31 emerging (lower- and middle-income) economies, using a median split. Only 26% of the developed economies scored above the median on power distance, versus 65% of developed economies, a difference that is highly significant ($p < .001$).

Second, we find that societal stratification emerges as the most pertinent phenomenon when considering cross-national differences in marketing-mix elasticities. Aggregated over the three marketing-mix instruments, half of the significant effects are found for economic (income inequality) and cultural (power distance) manifestations of societal stratification. Future research should delve deeper into mechanisms through which societal stratification affects how people respond to marketing activities. It is particularly noteworthy how important power distance is—it is the only factor in our research framework that has a significant effect on all three marketing-mix elasticities. All three effects are in line with a strong focus on displaying status through product ownership in high-power-distance countries, in that higher prices and lower distribution become less of a barrier to interested buyers, and line-length extensions are more likely to find interested buyers. How cultural power distance affects individual purchase decisions clearly deserves further research attention.

Third, except for power distance, the effects of the various factors considered in Figure 1 are specific to a particular marketing-mix instrument. This suggests that when and why a marketing instrument is effective depends on the instrument considered. In other words, our findings suggest the need for new theorizing on each marketing-mix activity (especially for line length and distribution, which have received much less attention in marketing than price). In particular, researchers may study how marketing-mix instruments unfold in consumer decision making and investigate which factors moderate the effect of the marketing mix on purchase decisions, in which direction, and why.

Fourth, we find some elasticities that are not "typical" (i.e., positive for price and negative for distribution and line length). In addition, a relatively high proportion of estimates is nonsignificant (see Tables 4 and 5). Although we are not the first to report atypical and nonsignificant estimates (e.g., Datta, Ailawadi, and Van Heerde 2017; Nijs et al. 2001; Van Heerde et al. 2013), one could argue that this calls for using priors for parameter estimates. Yet we are cautious to advocate such an approach. In our view, nontypical and nonsignificant estimates are the empirical reality if one estimates a large number of elasticities (in our case: $3 \times 1{,}617$ brands $= 4{,}851$ elasticities) across a wide variety of countries and categories. We believe it is important to document this openly, as it offers empirical researchers a realistic benchmark, especially considering recent concerns about the replicability of empirical findings. Moreover, there are scenarios where atypical estimates can convey important market information. A positive price elasticity may be caused by a strong price–quality effect (Scitovszky 1944) or by the Veblen effect of conspicuous consumption. A negative distribution elasticity might occur if the best retail outlets already carry the brand and new outlets are of lower quality (e.g., do not provide the same service, store atmosphere, and quality of product display). Finally, there is experimental evidence that increasing a product assortment might decrease consumer demand (Iyengar and Lepper 2000). Future research should investigate what we can learn from these atypical and nonsignificant cases and evaluate whether free or constrained estimation is preferable.

Fifth, the average price elasticity in our study is −.422, which is much lower than the mean price elasticity of −2.62 reported in Bijmolt, Van Heerde, and Pieters's (2005) meta-analysis. There may be multiple reasons for this difference. Our price elasticities are estimated at the national level, while the typical study in Bijmolt, Van Heerde, and Pieters (2005) estimates price elasticities at the chain or store level. National-level elasticities are likely lower than chain-level ones, given that they are not affected by within-brand store switching. Arguably, retailers are more interested in chain-level elasticities, while national-level elasticities are more informative to manufacturers. Another reason could be publication bias; studies with nonsignificant or mixed price elasticities may be underrepresented in published work. Third, it is noteworthy that several more recent studies (published after Bijmolt, Van Heerde, and Pieters 2005) that analyze large numbers of categories find considerably lower price elasticities. For example, Van Heerde et al. (2013) report a mean long-term price elasticity of −.838 for the United Kingdom across 150 brands in 36 product categories, Ataman, Van Heerde, and Mela (2010) find a mean total price promotion elasticity of .04 across 70 brands in 25 categories in France, and Van Ewijk, Gijsbrechts, and Steenkamp (2021) report an average price elasticity of −.612 for China across 391 brands in 62 categories. Fourth, 86% of the price elasticities in Bijmolt, Van Heerde, and Pieters (2005) are based on North American data. Might the United States respond more strongly to price than the Indo-Pacific Rim countries? Consider in this respect the low price elasticity for China (−.612) found by Van Ewijk, Gijsbrechts, and Steenkamp (2021). Future research could update the meta-analysis of Bijmolt, Van Heerde, and Pieters with more recent and more geographically diverse findings and explore the differences between national-level and store-level price elasticities.

We finally highlight three specific findings that we believe are among the most pertinent in informing future theorizing and research. We find that consumer response to price reductions is stronger in more affluent than in less affluent countries. One explanation we offered is that richer consumers have the financial means to act on price discounts, whereas poorer consumers do not. Another explanation can be found in the dual role of price in purchase decisions as a cost factor and an indicator of quality (Zeithaml 1988; Zielke and Komor 2015). If consumers believe that price is strongly associated with quality, they are more likely to evoke a price–quality schema (Peterson and Wilson 1985). Steenkamp, Van Heerde, and Geyskens (2010) report that if consumers more strongly believe that higher prices indicate higher quality, they are less price sensitive in that they have a higher willingness to pay a price premium. If countries with a lower income per capita on average hold a stronger price–quality schema (as argued in Zielke and Komor 2015), this can also explain the negative effect we observe in our study. To explore this idea, at least initially, we correlated the country average on price–quality schema for 28 countries reported by Van Ewijk, Gijsbrechts, and Steenkamp (2021) with GDP per capita (for the year

2010, following the operationalization of GDP per capita as reported in Table 1). The correlation is −.82. So, it appears that consumers in poorer countries are more prone to employ price–quality schema, which may dampen the effect of price reductions in these countries compared with more affluent countries. Future research could study this in more depth because this analysis is only indicative (e.g., country means are based on CPG categories), yet our results suggest the importance of including mindset metrics such as price–quality schema in econometric modeling (Srinivasan, Vanhuele, and Pauwels 2010). In addition, future research could test the rival explanation based on the financial means to act on price discounts, along with further contingency factors on the relative importance of both explanations.

We find that a favorable country of origin does not impact the effectiveness of marketing.[15] This result raises intriguing issues for future research. One issue is whether brand equity already incorporates, and therefore eliminates, country-of-origin effects. In an additional analysis, we find that country-of-origin effects remain nonsignificant even when we omit brand equity as a predictor. This triggers the follow-up question whether the strong country-of-origin effects observed in surveys and experiments (Verlegh and Steenkamp 1999) could be an artifact of the methods chosen. If not, how can these findings be reconciled with our findings? Are consumers thinking about country of origin when purchasing a brand? Are they actually aware of the brand's country of origin? Or does it matter more in which country the brand was manufactured? Very often, electronics and appliances have a Western country of origin (e.g., Miele washing machines from Germany) but are made in low-cost countries.

Finally, in previous meta-analyses, countries were often grouped based on geographic proximity. Our findings caution against this practice, as our research documents that market-response parameters can be quite different, even for countries that are neighbors. One avenue to pursue is whether a grouping of countries on the broader construct psychic proximity (Dinner, Kushwaha, and Steenkamp 2019) is justified.

Managerial Implications

A vexing question in global marketing management is to what extent market-response parameters are transnational and context-free (Steenkamp 2017). There are three main positions on this issue (Farley and Lehmann 1994; Grewal, Chandrashekaran, and Robert Dwyer 2008; Steenkamp and Geyskens 2014). A first position is "everything is the same": this assumes universality of parameters, perhaps with some inconsequential random error. This view appeals to global brand managers operating from headquarters. A second position is "everything is different": country contexts are so different that managers can learn nothing from knowledge development in other countries. Managers working in local markets often embrace this view, for understandable reasons; after all, differences between countries are the raison d'être for their jobs. The third position is "it depends": country contexts are different, but knowledge of these differences is associated with predictable cross-national differences in market-response parameters. The results of our second-stage analysis provide support for this third position.

Country managers can use the parameter estimates reported in Table 6 to adjust insights on market-response parameters to their own market. Our study framework and econometric model not only incorporate cross-national differences in economic and cultural factors but also allow for brand and category factors to vary across countries, allowing for the possibility that, say, the equity of Samsung or Apple in tablets is not necessarily the same in different countries (which will affect their price elasticity in these markets) and that there are cross-national differences in the growth of the market (which will affect the impact of changes in distribution coverage). To illustrate, we use the parameter estimates and scores on the various factors for one of the world's leading smartphone brands, along with the characteristics of the smartphone category in different countries, to predict the corresponding marketing-mix elasticities in its markets (Figure 3). The results show that market-response elasticities can, and do, vary substantially across countries, even for the same brand within the same product category.

The country-specific brand elasticities can be used to inform managers in their cross-national budget allocation (Fischer et al. 2011; Peers, Van Heerde, and Dekimpe 2017). One often-used heuristic is to allocate the budget according to country sales, which is essentially the well-known percentage-of-sales rule common in advertising (Deleersnyder et al. 2009). A second approach is to allocate budgets across countries proportional to their market-response parameter, in line with the Dorfman–Steiner rule (Hanssens, Parsons, and Schultz 2001). However, Fischer et al. (2011) show that the allocation rule should take not only market responsiveness into account but also the size of the countries' profit contribution (last year's sales × profit contribution) and their growth potential over a given planning horizon. They show how the optimal allocation can be approximated well through the following allocation rule:

$$\%\ \text{allocated to country k for brand b} = \frac{\text{sales}_{kb} \times \hat{\eta}^{m}_{kb} \times \text{margin}_{kb} \times \text{growth}_{kb}}{\sum_{j \in k} \text{sales}_{jb} \times \hat{\eta}^{m}_{jb} \times \text{margin}_{jb} \times \text{growth}_{jb}} \times 100\%, \quad (3)$$

where sales_{kb} is equal to a brand's average monthly sales in country k in the last year, $\hat{\eta}^{m}_{kb}$ is brand b's predicted market responsiveness for marketing-mix instrument m in country k, margin_{kb} is brand b's profit margin in country k, and growth_{kb} is brand b's expected (unit) growth rate.

For illustrative purposes, we consider one of the leading brands in the washing machine category and assume that the firm has an overall budget for expenditure on distribution for the 14 Indo-Pacific Rim countries. How should that budget be allocated across the countries? The results for each allocation

[15] An alternative specification using Western brands vs. non-Western brands did not have a significant effect either.

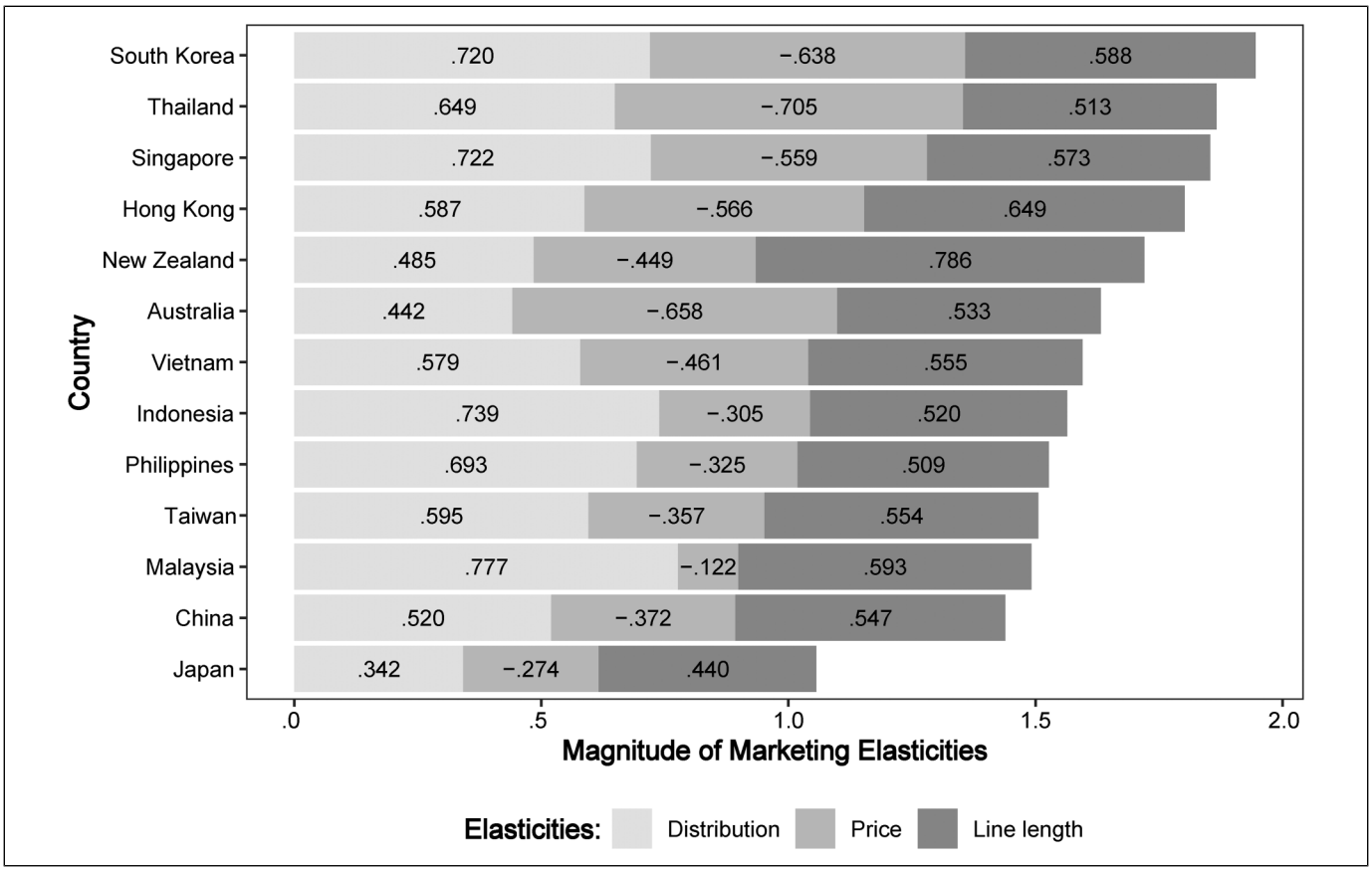


Figure 3. Predicted elasticities for a leading smartphone brand.
Notes: Countries shown in decreasing order of total marketing-mix responsiveness, defined as the sum of the absolute predicted marketing-mix responsiveness in a country using the parameter estimates from Table 6.

Table 7. Allocation of Expenditure on Distribution

Country	Unit Sales	Distribution Elasticity	Expected Brand Growth Index	Allocation Rule		
				Unit Sales (%)	Distribution Elasticity (%)	"Optimal" (%)
Australia	10,282	.346	1.095	4.7	9.7	6.3
China	25,008	.337	1.153	11.4	9.4	15.6
Hong Kong	1,297	.472	1.064	.6	13.2	1.0
India	82,089	.206	1.049	37.6	5.7	28.5
Indonesia	19,174	.301	1.177	8.8	8.4	10.9
Malaysia	8,994	.280	1.136	4.1	7.8	4.6
Philippines	3,424	.411	1.213	1.6	11.5	2.7
Singapore	3,787	.381	.993	1.7	10.6	2.3
South Korea	31,448	.224	1.006	14.4	6.2	11.4
Thailand	25,929	.299	.971	11.9	8.3	12.1
Vietnam	7,125	.331	1.218	3.3	9.2	4.6

Notes: Countries are shown in alphabetical order. Predicted distribution elasticities shown for a leading brand in the washing machines category. Unit sales are a brand's average monthly unit sales in the data, scaled by a constant to preserve the anonymity of the brand. The expected brand growth index is computed as the annual percentage change in unit sales for the chosen brand, averaged over the last three years in the data. The "optimal" allocation is based on the decision rule developed in Fischer et al. (2011).

rule are reported in Table 7. Because we do not have cost (to realize a given increase in distribution coverage) or profit-margin data (although obviously, the brand manager would have both), we assume these to be the same across countries and use the brand's historic growth rate in a country averaged over the last three years as an estimate for growth in the next year. While the results should be regarded as approximate, when we compare the optimal rule with the two most often-used

heuristics, we find some pertinent differences, especially for China, India, Indonesia, and South Korea. For example, according to its contribution to total unit sales, India should receive about 37.6% of the total budget. Its optimal budget—taking into account India's relatively low distribution elasticity and moderate expected growth—corresponds to 28.5%. This translates into a sizeable difference of 9.1 percentage points. We further illustrate in Web Appendix D how firms can use our findings to better allocate budgets *within* a given country across the different categories they are operating in.

Finally, we find no evidence that brands from the West get more bang for the marketing buck—marketing-mix elasticities are not stronger for brands from countries with a favorable country of origin. This is an important and encouraging finding for managers of emerging-economy firms, who are often concerned about their unfavorable country-of-origin image (Kumar and Steenkamp 2013).

Limitations

Our results are based on consumer electronics and appliances in the Indo-Pacific Rim. Future research should extend, generalize, or modify our findings to other product categories and other parts of the world. Extant research is notably silent on marketing effectiveness in Africa and Latin America, both important growth regions for companies. Future research should also consider other marketing-mix instruments such as advertising. We performed a robustness analysis for two countries for which we were able to secure advertising data, China and Hong Kong. We found that the advertising elasticity was small and that accounting for advertising did not lead to a significant change in the other marketing-mix elasticities. Still, given the importance of advertising in brand marketing, it is important to investigate advertising elasticities and their drivers on an international basis. Finally, our data are at the national level. Future research should investigate market-response parameters at the channel level or even the chain level and/or account for regional within-country differences in responsiveness.

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