### **Singapore Management University**

# Institutional Knowledge at Singapore Management University

Research Collection Lee Kong Chian School Of Business

Lee Kong Chian School of Business

3-2023

# The future of private label markets: A global convergence approach

Katrijn GIELENS University of North Carolina at Chapel Hill

Marnik G. DEKIMPE *Tilburg University* 

Anirban MUKHERJEE Katholieke Universiteit Leuven

Kapil R. TULI Singapore Management University, kapilrtuli@smu.edu.sg

Follow this and additional works at: https://ink.library.smu.edu.sg/lkcsb\_research

Part of the Marketing Commons

### Citation

GIELENS, Katrijn; DEKIMPE, Marnik G.; MUKHERJEE, Anirban; and TULI, Kapil R.. The future of private label markets: A global convergence approach. (2023). *International Journal of Research in Marketing.* 40, (1), 248-267.

Available at: https://ink.library.smu.edu.sg/lkcsb\_research/7152

This Journal Article is brought to you for free and open access by the Lee Kong Chian School of Business at Institutional Knowledge at Singapore Management University. It has been accepted for inclusion in Research Collection Lee Kong Chian School Of Business by an authorized administrator of Institutional Knowledge at Singapore Management University. For more information, please email cherylds@smu.edu.sg.

International Journal of Research in Marketing xxx (xxxx) xxx



Contents lists available at ScienceDirect

## International Journal of Research in Marketing

journal homepage: www.elsevier.com/locate/ijresmar

# The future of private-label markets: A global convergence approach

Katrijn Gielens<sup>a,\*</sup>, Marnik G. Dekimpe<sup>b,c</sup>, Anirban Mukherjee<sup>d</sup>, Kapil Tuli<sup>e</sup>

<sup>a</sup> Professor of Marketing and Sarah Kenan Graham Scholar at the University of North Carolina at Chapel Hill, USA

<sup>b</sup> Research Professor of marketing department at Tilburg University, the Netherlands

<sup>c</sup> Professor of Marketing at KU Leuven, Belgium

<sup>d</sup> Fellow at the Emerging Markets Institute, INSEAD, Singapore

<sup>e</sup> Lee Kong Chian Professor of Marketing, and Director of Retail Centre of Excellence, at the Lee Kong Chian School of Business, Singapore Management University, Singapore

#### ARTICLE INFO

Article history: Received 15 January 2019 Available online xxxx

Keywords: Private labels International marketing Adaptive foresight

#### ABSTRACT

Private-label (PL) shares are characterized by considerable heterogeneity across both countries and categories, not only in their current level, but also in the rate at which they are growing. This creates ambiguity about their remaining growth potential. To offer insights into the likely long-run PL shares, we take a forward-looking perspective by means of a convergence model. We apply the model to two unique datasets that together span more than 50 countries, both emerging and developed, across more than70 CPG categories. We find evidence of partial PL convergence: even though PL shares will become more similar, part of the currently observed heterogeneity will persist. The future evolution in two key marketing instruments, *new-product introductions* by both NB manufacturers and retailers and the NB-PL *price gap*, is found to play a substantial role in shaping the global PL landscape of the future. This impact is not uniform, however, but depends on the category, and varies with the retail, economic and cultural context. In addition, the long-run impact of both marketing drivers differs from what is currently observed, suggesting that managers should not adhere too strongly to earlier practices when planning for the future. © 2022 Published by Elsevier B.V.

#### 1. Introduction

"Where do you see yourself in five years?" is a typical interview question. If you were to ask private label brands the same question, they would likely say, "everywhere".

#### Thompson (2017).

"Now is not the time for retailers to rest on their Private Brand laurels. No matter where a retailer or brand stands today, continued success always depends on having an eye towards the future."

Michael Taylor, President of Daymon, Daymon (2020).

https://doi.org/10.1016/j.ijresmar.2022.07.006 0167-8116/© 2022 Published by Elsevier B.V.

Please cite this article as: K. Gielens, M.G. Dekimpe, A. Mukherjee et al., The future of private-label markets: A global convergence approach, International Journal of Research in Marketing, https://doi.org/10.1016/j.ijresmar.2022.07.006

<sup>\*</sup> Corresponding author at: University of North Carolina at Chapel Hill, Campus Box 3490, McColl Building, Chapel Hill, NC 27599-3490, U.S. Te.I: +1-919-962 90 89.

*E-mail addresses:* katrijn\_gielens@unc.edu (K. Gielens), M.G.Dekimpe@uvt.nl (M.G. Dekimpe), anirban.mukherjee@insead.edu (A. Mukherjee), kapilrtuli@ smu.edu.sg (K. Tuli).

#### K. Gielens, M.G. Dekimpe, A. Mukherjee et al.

Over the past decades, private labels (PLs), also known as store brands, own labels, or distributor-owned brands (Pauwels and Srinivasan 2009),<sup>1</sup> have become mainstream in most CPG (Consumer Packaged Goods) markets. This trend is observed in many categories, countries, and retail environments. By offering products that are not available elsewhere, retailers differentiate themselves from their competitors, and hope to build loyalty to their chain (Ailawadi et al. 2008). PLs typically offer retailers higher (percentage) margins than national brands (NBs) and strengthen retailers' negotiation power vis-à-vis NB manufacturers (ter Braak et al. 2013). Their growing sales "pose significant challenges for national brands (NBs) *around the world*" (Steenkamp et al. 2010, p., p. 1011, italics added), not only because of the lost sales levels that they represent for NBs, but also because of the pressure they put on NB manufacturers to lower their prices (Pauwels and Srinivasan 2004). Moreover, increasing PL success shows risk-averse consumers that many others have tried and liked PLs, which may create a positive performance feedback loop.

In 2019, PLs in the CPG market had already reached a global value share of 21.6% (Nielsen 2021). Such aggregate number is impressive, and (not surprisingly) often cited. Still, one can wonder to what extent this truly reflects a *global* PL threat. While PL shares in Western Europe (over 30%) continue to be larger than in the US (around 20%), both levels vastly exceed the shares currently observed in most developing countries (often not exceeding the 10% mark). Furthermore, double-digit growth rates have recently been observed in several Eastern European (e.g., Romania), African (e.g., South Africa), and Latin American (e.g., Mexico) countries, while countries such as Russia, Brazil, and China experience only modest growth.<sup>2</sup>

Given these level and growth differences, it should come as no surprise that there is little consensus about what global PL landscape to expect in the coming years. Almost ten years ago, Rabobank analysts (2013, p. 1), predicted that by 2030 the main Asian grocery markets, India and China, would reach PL shares as seen in Europe, whereas around the same time Euromonitor (2014, p. 6) expected PLs to "only make gradual, if any, inroads into emerging markets". Unfortunately, the rationale for such far-reaching statements, irrespective of the position taken, is often anecdotal and not very informative of the specific long-term levels that can be expected. Within Europe, for example, current PL levels differ considerably (with a 2020 level of 49.7% in Spain, versus 22.6% in Italy; PLMA 2021), which makes broad predictions that global levels will be similar to what is currently observed in Europe ambiguous at best. To complicate matters, the categories where PL shares are stronger, and/or growing the fastest, vary dramatically by country (Sethuraman 2018). Still, knowing what PL levels to expect in various markets is of high strategic relevance to NB manufacturers and retailers alike (see Table 1).

In the spirit of Zeithaml et al. (2006, p. 168), we argue that to adequately plan their international position, managers should develop "*adaptive foresight*" to better predict the expected *future* state of affairs, which may be very different from the current position. In doing so, they should not only take the anticipated changes in the business environment into account, but also the expected evolution in marketing-support activities that could attenuate (manufacturers) or amplify (retailers) a potential target market's long-run PL position.

Building on these ideas, we contribute to the PL literature along several dimensions: we (i) take a forward-looking perspective, (ii) considerably expand the geographic scope of the insights, and (iii) consider how the effectiveness of two key marketing tools in the manufacturers' and retailers' arsenal, their innovativeness and price positioning, depends on a broad set of contingency factors and changes as PL markets mature.

#### 1.1. Forward, rather than backward, looking

Foremost, we present the first systematic empirical study that adopts a *forward-looking* perspective towards understanding the future evolution of PL shares. Most cross-country PL research to date has taken either a backward-looking view (which Zeithaml et al. 2006 call a rear-view mirror approach) to assess where currently observed differences in PL success originated, or described the then-present situation (see, e.g., Steenkamp et al. 2010 or Steenkamp and Geyskens 2014). Prior studies, therefore, do not account for differences in growth dynamics between different regions in the world and/or between different product categories.

We draw upon the economic convergence literature to establish an empirical specification that measures and formally tests whether, and to what extent, lagging (lower-share) PL markets will catch up (or even surpass) currently leading (higher-share) PL markets. Markets are, in this respect, referring to specific category/country combinations, such as the detergent market in Spain or the toilet-tissue market in China.

The adopted specification allows us to derive for each market its likely long-term position, even when these markets are in very different stages of their life cycle (mature in some versus rapidly growing in others). In so doing, we capitalize not only on over-time patterns *within* the individual PL series, but also take advantage of similarities/differences in these patterns *across* markets. Conceptually, our approach can be compared to prior cross-national diffusion studies (Dekimpe et al. 2000; Talukdar et al. 2002). However, in contrast to these studies, the convergence approach does not require matched (Dekimpe et al. 1998) nor known (Jiang et al. 2006) times of origin, making the approach well suited to the left-censored series that characterize our setting.

<sup>&</sup>lt;sup>1</sup> PLs can carry either the retailer's name or a separate brand name created by the retailer (Keller et al. 2016).

<sup>&</sup>lt;sup>2</sup> Information derived from Euromonitor International's Passport GMID.

International Journal of Research in Marketing xxx (xxxx) xxx

#### Table 1

Geographic COVERAGE.

	Continent <sup>a</sup>	Developed Countries <sup>b,c</sup>	Emerging Countries <sup>b,c</sup>
Study 1	Africa (2)		Morocco (22), South Africa (50)
	America (10)	Canada (51), USA (51)	Argentina (44), Brazil (48), Chile (44), Colombia (45),
			Dominican Republic (23), Guatemala (22), Mexico (44), Peru (28)
	Asia (13)	Israel (48), Japan (46), Singapore (45), South Korea (31), Taiwan (38), United Arab Emirates (25)	China (13), India (24), Malaysia (33), Philippines (25), Saudi Arabia (31), Thailand (40), Turkey (47)
	Europe (29)	Austria (52), Belgium (52), Denmark (51), Finland (52),	Bulgaria (51), Croatia (45), Czech Republic (52), Estonia
		France (52), Germany (52), Greece (51), Ireland (52),	(39), Hungary (52), Latvia (45), Lithuania (43), Poland
		Italy (50), The Netherlands (52), Norway (51), Portugal	(52), Russia (44), Serbia (40), Slovakia (52), Slovenia
	o · (n)	(51), Spain (51), Sweden (51), Switzerland (52), UK (52)	(50), Ukraine (47)
	Oceania (2)	Australia (50), New Zealand (47)	
Study 2	America (6)	USA (71)	Argentina (57), Brazil (41), Chile (42), Mexico (47), Peru (38)
	Asia (2)		China (42), India (7)
	Europe (12)	Austria (61), Belgium (76), Denmark (72), France (68), Germany (74), Italy (63), NL (74), Sweden (65), Spain (54), UK (52)	Hungary (69), Poland (73), Russia (74)

(a): The number in parentheses is the number of countries on which data is available in the continent; (b) The number in parentheses is the number of categories on which data is available in the country; (c) We classify a country as emerging if the World Bank classified the country (on the basis of its per-capita Gross National Income) as Low, Low-Medium, or Upper-Medium income in any year of our data (2003–2015). All other countries are classified as developed.

While still probabilistic, the predicted long-run patterns have a high probability of materializing (see Inglehart and Baker 2000 for a similar argumentation). In the same spirit, Bass (1969, p. 215) acknowledged that while long-range forecasting will always remain to some extent a guessing game, some developments can be made easier to guess than others.

#### 1.2. A global rather than developed-market perspective

Second, we adopt a global perspective by analyzing data on the evolution of PL shares from over 50 countries across all inhabited continents. As such, we extend the prior literature on PL success that has focused almost exclusively on the developed markets of the United States and Western Europe (Sethuraman and Gielens 2014). Importantly, this global focus allows us to study in detail emerging economies that have become increasingly important but differ from developed countries on several fundamental dimensions (Sheth 2011). By looking at this evolution across a broad cross-section of categories, we accommodate that categories' PL success may continue to vary dramatically by country (Sethuraman 2018) and exploit that the observed variations are partly systematic and (to some extent) predictable (Steenkamp and Geyskens 2014).

#### 1.3. Key drivers of the long-run PL scape

To better understand the likely PL evolution, we not only consider expected changes in the business environment (such as the growing popularity of the discount and online channel), but also the anticipated evolution in two key marketing instruments, the introduction of new products by both channel parties (Gielens 2012) and the NB-PL price gap (Pauwels and Srinivasan 2009). Moreover, we investigate, along the lines suggested by Sethuraman and Gielens (2014, p. 150) and Steenkamp et al. (2010, p. 1014), to what extent their impact increases or diminishes as PLs gain traction, and consider a broad set of category-related, retail-context, economic and cultural contingency factors for these instruments' long-term effectiveness.

Our findings support the idea that the end of PL growth is not yet in sight, and even though current differences in PL success will become smaller over time, they are unlikely to fully disappear. Remarkably, the remaining country-level differences will not follow the classic divide between developed and developing markets. Future PL levels will continue to depend not only on market-structure (importance of the discount channel and of independent retailing), economic (GDP per capita and level of urbanization) and cultural factors but will also (and increasingly so) depend on strategic levers under retailers' and manufacturers' control. From the retailers' perspective, more PL growth can be expected when the price differential relative to the leading national brands is narrowed and (when operating in affluent societies and less self-expressive cultures) by playing the innovation card. Manufacturers, in turn, should maintain their innovation focus to keep further PL growth at bay. However, the relative impact of several drivers will change over time, making an automatic reliance on old success recipes precarious.

#### 2. Conceptual motivation

Gaining insight into the future potential of global PL markets is not an easy feat, especially since not all PL markets are in the same stage of their product life cycle (PLC). Furthermore, key marketing-mix instruments supporting PLs as well as the business environment in which they operate are also undergoing a rapid, not necessarily homogeneous, evolution. We first discuss the heterogeneity in these PLCs and business drivers, before discussing the differences in data availability in different markets.

#### 2.1. Heterogeneity in PLCs of PLs

PLs require extensive learning, not only on the part of consumers to ascertain their quality and develop sufficient trust, but also on the part of retailers on how best to support them, and on the part of NB manufacturers on how best to fight them (Steenkamp et al. 2010). Hence, very diverse introduction times may explain, in part, the currently observed heterogeneity in PL stages. In some markets, the PL environment can be considered mature (Steenkamp et al. 2010), in that the PLs have been a major presence for many decades, with little (if any) growth in recent years. Industry observers have therefore concluded that, in those markets, PL shares "have hit a proverbial glass ceiling" (IRI 2012), which is supported by academic research that has found that there is a certain level beyond which PLs are unlikely to grow without undermining a retailer's profitability (Ailawadi et al. 2008). In other markets, PLs are a much more recent phenomenon, and still in their growth, or even introduction, stage. At the country level, PLs were introduced much later in the developing economies of Latin America, Eastern Europe, and the Asia-Pacific region than in the developed economies of Western Europe and Northern America. At the category level, PLs were introduced first, and quickly obtained a sizable presence, in undifferentiated commodity categories, such as milk and bread. They subsequently expanded into categories where retailers could offer acceptable-quality alternatives at a lower price, such as snacks. Lately, PLs have also been introduced in variety-enhancing or fill-in categories with higher functional risk, and even in categories with lower price sensitivity (Gielens et al. 2021), like spirits or special spices. By now, they are present in most, if not all, CPG categories.

#### 2.2. Heterogeneity in PLs' and NBs' marketing-mix evolution

Traditionally, the price positioning relative to NBs has been discussed as the main tool to support and build PLs. Whereas in less mature PL markets, the mostly generic PLs are priced 50 to 70% below the typical prices of NBs, these differences usually become smaller as PLs mature. Partly due to an increasing PL quality, typical NB-PL price differentials are now reported to be between 15 and 50 percent (Gielens et al. 2021), while also price differentials close to zero have been observed (Pauwels and Srinivasan 2009). Prior research has shown that consumers' willingness to pay a price premium for NBs varies considerably and depends (among other factors) on their involvement with the category (Pauwels and Srinivasan 2009), and a country's economic wealth and culture (Steenkamp and Geyskens 2014). Importantly, Steenkamp et al. (2010) found that consumers' willingness to pay a price premium for NBs becomes smaller as PL markets mature. Hand in hand with these evolutions in price positioning, the focus is also shifting towards innovativeness to support PLs and build stronger PL quality perceptions. Whereas prior work has mainly emphasized the role of new-product activities by NBs as a defense mechanism against further PL growth (Gielens 2012), recent work (see, e.g., Gielens et al. 2021) emphasizes the increasing role of retail-ers' PL innovations to build PL share.

#### 2.3. Heterogeneity in the evolution of retail and business environment

PL success has often been described as a supply-driven phenomenon (Sethuraman and Gielens 2014) in that PL shares tend to be higher in markets where retailers are strong. Thus far, unorganized retailing remains much more prevalent in emerging countries, even though organized retailing is on the rise (Bronnenberg and Ellickson 2015). However, different retail conditions exist not only *between* developed and emerging markets, but also *within* those groups. Discounter success is often seen as key impetus to further PL acceptance, but discounter presence is still in a nascent phase in countries like Italy, while in a mature stage in others, like Germany and Norway (BCG 2017). Even though the expected roll-out of the discount format in lagging countries is likely to positively influence their future PL position, it remains unclear when, and to what extent, this will happen. Moreover, within a given country, discounter shares vary considerably across categories (Steenkamp and Sloot 2018).

Similarly, as e-commerce develops globally, both traditional and pure-play retailers have started to actively push their private brands online; yet, not only do online-shopping penetration and evolution vary considerably across both categories and countries, the extent to which they impact PL preference evolves over time as well (Gielens and Steenkamp 2019). Online channels may be more nurturing to NBs, as any opportunity to interact physically with the product disappears. This intangible nature forces consumers to pay more attention to other quality indicators such as the brand (González-Benito et al. 2015), so that NB loyalty may be higher online (Chu et al. 2010). Nevertheless, this preference may alter as consumers become more apt at shopping online. At the same time, making use of unique information, recommendation and review tools, online retailers become more experienced in pushing their PLs.

#### K. Gielens, M.G. Dekimpe, A. Mukherjee et al.

#### 2.4. Heterogeneity in data availability

Available data sets do not cover the early years for every market. On a global basis, it is impossible to assess in a reliable way how long PLs have been offered in all category/country combinations, making inferences about PL stages and consumer and retailer/manufacturer learning hard (see also Steenkamp et al. 2010, p. 1023 for a similar observation). This data issue creates a left-censoring problem with unknown starting date (Jiang et al. 2006), which makes valid cross-market comparisons even more difficult.

International PLC theory (Kotabe and Helsen 2004) suggests that by comparing markets on key dimensions, managers should be able to make better informed estimates about the future situation in markets with a more limited history (Steenkamp et al. 2010). Bass (2004) and Jiang et al. (2006) refer to this idea, which has also been put forward in prior international diffusion studies, as "forecasting (guessing) by analogy". However, apart from the clear need to adequately deal with this left-censoring issue, we argue that one should not just look at the *current* level in those "leading" markets (as done, for example, in (Steenkamp and Geyskens, 2014) or Steenkamp et al. 2010), but also take their *future* evolution into account.

In sum, to obtain long-term insights in PL shares, we will exploit the heterogeneity in PL patterns over time and between markets. We will subsequently explore the differences in these long-run shares by relating them to the long-term values of key marketing-mix instruments: the number of new-product introductions by PLs and NBs and the PL price positioning relative to NBs. We will allow the effect of these instruments to depend on (i) the retail-format preferences in a given market, as well as (ii) more general category, cultural and economic factors. The latter will include the consumers' involvement with the product and their perception on the hedonic vs. utilitarian nature of the category, along with the economic (GDP/Capita and urbanization level) and cultural (secular-rational and self-expression) context of the country.

We note upfront, given our broad market coverage along both the country and category dimension, that our choice of covariates can by no means be exhaustive.<sup>3</sup> Still, they will cover multiple market-structure and marketing-conduct variables that have been identified as key drivers in the (international) PL literature. While our choice of variables is informed by prior studies on the historical impact of these drivers, we will refrain from making formal hypotheses on their likely future impact. Instead, in the ET (Empirics leading to Theoretical insights) tradition advocated by Bass (1995) and (Alba, 2012), we will let the data speak.

#### 3. Modeling framework

To accommodate the challenges caused by the nature of the data, we propose a convergence approach, which can (i) handle left-censored data with unknown starting points (and thereby accommodate that PL markets may be at different stages of their life cycle), (ii) take into account similarities and differences in the over-time evolution of (iii) both PL shares and several key drivers (and thereby make use of systematic and predictable cross-sectional and longitudinal variation to improve our "guessing by analogy"). For ease of explanation, we use PL share as the focal variable to explain the intuition of our approach, but the same procedure is used for the other time-varying variables as well.

Intuitively, we combine the information observed in another market, i.e., a reference market that has already obtained its steady-state level, with the growth evolution observed in the focal market. Specifically, we assess to what extent the latter moves towards (converges to) the reference market. By combining the estimated convergence rate with the steady-state level of the reference market, insights in the long-term state of the focal market can be derived. Importantly, the approach does not require the lagging market to fully converge to the reference market. Steady-state levels in the focal market can be below, at par, or above the long-term state observed in the reference market.

In a nutshell, our modeling framework requires three steps. First, we assess whether the PL market in the reference country has indeed stabilized. Maturity does not preclude temporary up- and-downs, nor does it imply that PL shares have stabilized at the same level in all categories. As such, we compute for each product category in the reference country the long-run equilibrium around which PL levels can temporarily fluctuate.

Second, we assess whether a category's PL share in each other country will settle at the same (or different) level than in the reference country. To do so, we introduce the notion of  $\beta$ -convergence (Islam 2003).<sup>4</sup>  $\beta$ -convergence requires share differences vis-à-vis the reference country to become smaller over time (Islam 2003). In case of absolute convergence, the mean difference between the LR equilibrium level of a category in other countries relative to the reference country becomes zero. In case of partial convergence, the difference between the equilibrium share in other countries relative to the reference country does not fully disappear, but becomes (apart from temporary disturbances) constant over time. The combination of the convergence rate between the focal and reference country and the asymptotic share in the reference country allows us to compute the long-term shares in the focal country.

Finally, we explore underlying drivers for the heterogeneity (if any) in the levels at which the various markets (category/country combinations) stabilize. We summarize the various steps, along with the various statistical issues involved, in Table 2.

<sup>&</sup>lt;sup>3</sup> A similar observation has been made in several prior studies with a more global focus (e.g., Sebri and Zaccour 2017, p. 125; Talukdar et al. 2002, p. 102). <sup>4</sup> Initially, β-convergence was used primarily in the macro-economics field (see, for example, Islam 2003 for a review). More recently, the application domain

has expanded considerably with, among others, studies on the convergence of car prices (Goldberg and Verboven 2005), retail gasoline prices (Suvankulov et al. 2012), retail payment methods (Martikainen et al. 2015), or consumers' revealed preferences for car attributes (Silver 2010).

#### K. Gielens, M.G. Dekimpe, A. Mukherjee et al.

International Journal of Research in Marketing xxx (xxxx) xxx

#### Table 2

Overview of econometric and time-series techniques.

Research question	Methodological issues	<b>Relevant tests/metrics</b>	Relevant literature
Step 1: Derive long-run PL levels in reference country	у		
	Panel unit-root (UR) test across categories		Levin et al. (2002); Pesaran (2004, 2007)
Has the reference country stabilized?	If needed, account for cross-sectional dependencies	Eq (1): $\beta_{Ref} < 0$ ?	
What is the long-run PL level of category p in the	Apply small_sample bias	$\left(-\gamma_{-1}/\beta_{-1}\right)$	Dekimpe & Hanssens (1995) Dekimpe & Hanssens (1995); Nickell (1981);
rejerence country?	correction	Eq (2): $PL_{p,Ref}^{\infty} = e^{(-\alpha_{p,Ref}/p_{Ref})}$	Nickell (1981),
Chan D. Davis Lawrence Dr. Lawle in Atlantation			Gaulier et al. (1999)
Step 2: Derive long-run PL levels in other countries	Panel UR test per category		Levin et al. (2002); Pesaran (2004, 2007)
Is there global PL convergence?		$F_{0}(3): \beta < 0?$	
	If needed, account for cross-sectional dependencies	$Lq(5).p_p < 0.$	
What is the long-run PL differential in category p of country c relative to category p in the reference		( * /8)	Cecchetti et al. (2002); Goldberg & Verboven (2005); Nickell (1981);
country?	Apply small-sample bias correction	Eq (4): $\Delta PL_{p,c}^{\infty} = e^{(-\alpha_{p,c}/\beta_p)}$	(Nickell, 1981) Gaulier et al. (1999)
What is the long-run PL level in category p of country c?		$PL_{p,c}^{\infty} = e^{\left(-\alpha_{p,Ref}/\beta_{Ref}\right)}e^{\left(-\alpha_{p,c}/\beta_{p}\right)}$	
Step 3: Explain heterogeneity in long-run PL levels	Cross-sectional	E.	
	regression		Park & Gupta (2012);
what arivers help explain the heterogeneity in long-run PL levels across markets (category-country combinations)?	Endog. correction: Copulas		Papies et al. (2017)
	Bootstrapped standard errors		

#### 3.1. Step 1: Derivation of the long-run PL levels in the reference country

To establish that the PL market in the reference country has stabilized, we employ unit-roots tests to determine whether the PL series in that country are mean reverting. Univariate unit-root tests of the type pioneered by Dickey and Fuller (1979), and used in (among others), Dekimpe and Hanssens (1995) and Nijs et al. (2007), are known to have low power when the time series is rather short. This makes it difficult to reject the unit-root null hypothesis when it is false. One way to enhance the efficiency of the unit-root test is to exploit the panel dimension of the data. Panel unit-root tests allow for group-wise (in this case, across all categories in the reference country) testing, and have the advantage of providing considerably higher power through the pooling of information across categories (Baltagi 2013). We apply the popular Levin et al. (2002) test, with the following test equation:<sup>5,6</sup>

$$\Delta \log \left( PL_{p,Ref,t} \right) = \alpha_{p,Ref} + \beta_{Ref} \log \left( PL_{p,Ref,t-1} \right) + \sum_{l=1}^{L} \eta_{l,Ref} \Delta \log(PL_{p,Ref,t-l}) + \varepsilon_{p,Ref,t}$$
(1)

with  $\Delta$  the first-difference operator. When  $\beta_{Ref}$  is significantly smaller than zero, the unit-root null-hypothesis is rejected, and year-to-year fluctuations in product category *p*'s PL share are just temporary deviations from a stable long-run equilibrium value  $PL_{p,Ref}^{\infty}$ , given by (Dekimpe and Hanssens 1995):

$$PL_{p,Ref}^{\infty} = e^{-\alpha_{p,Ref}/\beta_{Ref}}.$$
(2)

<sup>&</sup>lt;sup>5</sup> For a recent marketing application see, for example, Colicev et al. (2018).

<sup>&</sup>lt;sup>6</sup> We are not aware of any panel UR test that explicitly accounts for the range constraint that is inherent to market- share data. In each of the 4 countries that we use as reference country, the PL share at the 90th percentile across all categories considered was below 75%, while the maximum share observed in our data never exceeded 90%. As such, while theoretically relevant, the logical-consistency constraint was not a practical issue in our data.



Fig. 1. Absolute versus partial convergence. Country A depicts absolute convergence. Countries B and C depict partial convergence to different long-term levels.

Through the inclusion of category-specific fixed effects ( $\alpha_{p,Ref}$ ) in Eq. (1), the equilibrium value is allowed to differ between categories. As is common in the unit-root literature, additional lags of the dependent variable are included to account for potential serial correlation, with the number of lags determined through the AIC.<sup>7</sup>

If the data only covers a limited number of time periods, estimates of  $\beta_{Ref}$  are known to be biased downward. To this extent, we implement Nickell's (1981) small-sample adjustment to all parameters in Eq. (1).<sup>8</sup> Imputing the adjusted parameters,  $\beta_{Ref}^{adj}$  and  $\alpha_{p,Ref}^{adj}$ , into Eq. (2) gives the adjusted long-run equilibria.

#### 3.2. Step 2: Derivation of the long-run PL levels in the other countries

Besides the long-term share in the reference country, we need to gain insight in the extent to which a focal market evolves towards (convergences to) the reference market. Underlying the convergence idea is the notion that the difference between a category's PL share in country *p* and the corresponding PL share in the reference country becomes smaller over time. If that difference disappears completely (apart from some temporary deviations), the convergence is complete (or absolute). If a fraction of that difference persists, the convergence is partial. These scenarios are depicted visually in Fig. 1, with absolute convergence for country A, and partial convergence for countries B and C. Even when convergence is partial, insight in the extent to which the focal country converges to the reference country, as expressed by the asymptotic differential in their shares, will allow us to gain insight in the focal country's long-term share.

To determine whether the various countries converge (fully or partially) to the level observed for the category in the reference country, we use, in line with Goldberg and Verboven (2005) and Cecchetti et al. (2002), the Levin et al. (2002) panel unit-root test to assess the significance of  $\beta_p$  in Equation (3):<sup>9</sup>

$$\Delta log\left(\frac{PL_{p,c,t}}{PL_{p,Ref,t}}\right) = \alpha_{p,c} + \beta_p log\left(\frac{PL_{p,c,t-1}}{PL_{p,Ref,t-1}}\right) + \sum_{l=1}^{L} \eta_l \Delta log\left(\frac{PL_{p,c,t-l}}{PL_{p,Ref,t-l}}\right) + \varepsilon_{p,c,t}$$
(3)

<sup>&</sup>lt;sup>7</sup> Panel UR tests can provide spurious support for stationarity if there is a significant degree of ignored positive cross-sectional error dependence (O'Connell 1998). Such cross-sectional dependence could arise between complementary or substitute categories. Still, if the cross-sectional dependence is not high, a loss of power may result if tests that allow for cross-sectional dependence are used. To balance these two considerations, we follow Pesaran (2007) and first apply the cross-sectional dependence test of Pesaran (2004). Based on the outcome, we apply the "original" Levin et al. (2002) test, which assumes i.i.d. disturbances, or the "cross-sectionally de-meaned" version, which controls for cross-sectional dependence (Pesaran 2007).

<sup>&</sup>lt;sup>8</sup> We refer to Cecchetti et al. (2002) and Gaulier et al. (1999) for a detailed derivation.

<sup>&</sup>lt;sup>9</sup> In this equation, homogeneity (across countries) in  $\beta_p$  is assumed (i.e.,  $\beta_{p,c} = \beta_p$  for all c), which is relaxed in the Im et al. (2003) test. The null hypothesis in both the Levin et al. (2002) and the Im et al. (2003) procedure is the same, in that each series is assumed to contain a unit root. Where the two tests differ is in their treatment of  $\beta_{p,c}$  under the alternative hypothesis. In the Levin et al. test, the alternative is  $H_a$ :  $\beta_{p,c} = \beta_p < 0$  (hence, for all countries), whereas in the Im et al. (2003) test the alternative permits heterogeneity over the countries, with Ha:  $\beta_{p,c} < 0$  for at least one country c (Cechetti et al. 2000, p. 1087). We opt for the Levin et al. (2002) test for three reasons. First, allowing for heterogeneity in the growth parameter, as implied by Im et al., conceptually makes the notion of convergence a trivial construct as for the cross-country dimension is concerned (Islam 1998, p. 326). Moreover, the Levin et al. test is more conservative, as it is less likely that the behavior of one or two countries leads to rejecting the unit-root hypothesis (Goldberg and Verboven 2005). Finally, unlike Im et al., the Levin et al. test gives a direct panel estimate of  $\beta_p$  (Cechetti et al. 2002).

#### K. Gielens, M.G. Dekimpe, A. Mukherjee et al.

Note that the dependent variable in Eq. (3) is the first difference ( $\Delta$ ) in the log of the PL share in country *c* (for a given product category *p*) in year *t* relative to the corresponding PL share in the reference country (*Ref*). By taking the log-transform of the ratio of the two market-shares, the variable to which the unit-root test is applied is no longer range-constrained. To improve the power of the test, we pool information across the different countries. Given that there may be cross-sectional dependence in this case as well (for example between countries that are geographically close or which are culturally and/or economically similar), we again apply the aforementioned procedure advocated by Pesaran (2004, 2007).

The parameter of interest is the convergence rate,  $\beta_p$ . If  $\beta_p$  is significantly lower than zero, share differences relative to the reference country become smaller over time, and the hypothesis of no convergence is rejected. We apply this test to each of the different categories to allow convergence to occur for some categories but not for others. The joint significance of the country-specific fixed effects  $\alpha_{p,c}$  allows us to distinguish absolute from partial convergence.

Once convergence is established, we use the estimated values of  $\beta_p$  and  $\alpha_{p,c}$  to derive the the ratio between the long-run PL share in country *c* and the reference country, which we call the long-run share differential. This is given by (Goldberg and Verboven 2005):

$$\Delta_{\infty} P L_{p,c} = e^{-\frac{\alpha_{p,c}}{\beta_p}} \tag{4}$$

The long-run share differential expresses to what percentage of the reference country's long-term PL share in that category the focal country will converge. To obtain the long-term PL share in the country, we still need to multiply this differential with the long-term share in the reference country. For example, if the reference country's equilibrium share is 40% and the long-term differential ( $\Delta_{\infty}PL$ ) is 0.75, the focal country's PL share will converge to 30% ( $PL^{LR} = 0.75 * 40\%$ ). Generally,

$$PL_{p,c}^{\infty} = e^{-\alpha_{p,Ref}/\beta_{Ref}} * e^{-\alpha_{p,c}/\beta_p}$$
(5)

whereby a Nickel's small-sample adjustment is made to  $\alpha_{p,c}$  and  $\beta_p$  prior to their substitution in Equations (4) and (5).

When  $\alpha_{p,c}$  is not significantly different from zero, the long-run differential becomes 1, in which case the focal country converges to 100% of the reference country and absolute convergence is obtained. Note that  $\Delta_{\infty}PL$  is not restricted to be smaller than one. When values larger than one are obtained, the country's PL share will converge to a value higher than the corresponding value in the reference country.<sup>10</sup>

#### 3.3. Step 3: Explore drivers of the heterogeneity in long-run PL levels

We test whether, and to what extent, the long-term PL shares in the different markets (or category-country combinations) are systematically and predictably linked to the expected future level of the drivers denoted in Fig. 1. It is important to emphasize that we link bias-adjusted long-run PL levels to bias-adjusted long-run values in the various drivers, rather than to their currently observed levels. Like the PL shares, most drivers are expected to evolve over time. Two exceptions are the cultural variables (which are known to only change very gradually, if at all; see, e.g., Breugelsdijk et al. 2015) and the consumer perception variables, as the historical values of these variables were not available.

A linear model is used to link the various drivers to the long-term PL levels, in which we allow for a category random effect on the intercept. To account for the possible endogeneity of the marketing-mix variables, we implement a Gaussian copula correction (see, e.g., Datta et al. 2017 for a marketing application). In contrast to classical methods to deal with endogeneity, this approach does not require instrumental variables to partial out the exogenous variation in the endogenous regressors (Park and Gupta 2012). Specifically, for each potentially endogenous variable (IV), we add the following regressors to the equation:  $IV^* = \emptyset^{-1}[(H_I (IV_i)]]$ , where  $\emptyset^{-1}$  is the inverse of the cumulative normal distribution function, and where  $H_I (.)$  denotes the empirical distribution function. For identification, the potentially endogenous regressors must be non-normally distributed, which was confirmed through the Shapiro-Wilk test (p < .05). Standard errors for the parameter estimates are obtained using the bootstrapping approach of Papies et al. (2017, Eq. 18.22), with 2,000 repetitions to ensure stability and reliability of the standard-error estimates. Following Papies et al. (2017), we focus our interpretation on the more efficient model where only significant correction terms are included.

#### 4. Data

We use international PL data from two sources: Euromonitor International's Passport GMID and AiMark's BG20 project. The Euromonitor data offer the opportunity to study the role of new-product introductions; however, they do not contain information on the price positioning in the markets covered. The BG20 data base, in contrast, contains that price information, but does not contain information on the new-product introductions. A similar quandary was encountered in Nijs et al. (2007). In line with the approach adopted in that study, we capitalize on the collective strength of both data sources to max-

<sup>&</sup>lt;sup>10</sup> In Germany, for example, the 2018 PL share surpassed the UK level in several categories, such as bath and shower (18.9 vs. 11.2) and coffee (20.9 vs. 10.0). A similar situation can be expected to happen in the long-run.



1: features in Study 1, 2: features in Study 2



imize the number of insights that we can derive. Fig. 2 presents a schematic overview of the effects that are tested in this step of our analyses, where the superscripts indicate in which study the respective variables are considered.<sup>11</sup>

Below, we first detail the market coverage of the two databases. Next, we motivate our choice of the UK as benchmark country and describe the data sources on the other variables.

#### 4.1. Euromonitor data: market coverage

In a first data set, we use Euromonitor International's Passport GMID to obtain PL value-share information for 16 years (2003–2018). Euromonitor data have been used repeatedly in durable-goods studies (see, e.g., Tellis et al. 2003). Within a CPG setting, Euromonitor data were used in Bronnenberg and Ellickson (2015) and Ozturk et al. (2021). Given its "integrated and consistent methodology in defining, operationalizing and collecting metrics," this database is widely considered to be a credible source for cross-national marketing research (Ozturk et al. 2021, p. 109; see also Kotabe 2002).<sup>12</sup>

Annual data are available across 52 CPG categories and 56 countries coming from five different continents. This resulted in 2,399 country/category time series.<sup>13</sup> The full list of countries is presented in Table 2, along with the number of categories covered in each country. The categories involve a broad range of CPG products, such as beauty & personal care (e.g., bath & shower), beverages (e.g., coffee), processed foods (e.g., cereals), home care (e.g., dishwashing and laundry care), and tissue & hygiene (e.g., kitchen towels). Of the countries represented in our data, 29 can be classified as emerging markets and 27 as developed.<sup>14</sup> In total, about 50% of all market/category combinations pertain to emerging markets.

The 56 countries represent around two-thirds of the world's population in the final year of our data collection, and about 90% of the world's GDP.<sup>15</sup> Using the same data source, we compile the number of new SKUs launched in each category and country by the top 5 retailers and the top 5 competing national brands. The latter are determined based on their worldwide revenue shares per category, averaged over the observation window. The data allow us to investigate the role of both channel parties' innovations in shaping the long-run PL landscape. However, it does not have information on the PL price positioning.

<sup>&</sup>lt;sup>11</sup> Given the smaller number of countries in the BG20 data, resulting in fewer degrees of freedom along that dimension, we do not include cultural variables in the second study; we do so after testing and finding that they are not significant when adding them on a one-by-one basis. The perceptual measures (involvement and hedonistic) in turn, were only available for the categories as defined in the BG20 data.

<sup>&</sup>lt;sup>12</sup> For more details on the data collection by Euromonitor, see https://www.euromonitor.com/research-methodology.

<sup>&</sup>lt;sup>13</sup> This reflects 82% of the maximum number of 2,912 (52 x 56) market/category combinations, indicating that while occasionally missing a few categories in some countries, our sample is reasonably balanced.

<sup>&</sup>lt;sup>14</sup> This dichotomous classification is used for illustrative purposes. In our analyses, we use time-varying GDP/Capita as a continuous measure of economic development.

<sup>&</sup>lt;sup>15</sup> Based on population data from the 2019 Revision of World Population Prospects, United Nations (https://data.un.org) and GDP data from the World Bank (https://data.worldbank.org).

#### K. Gielens, M.G. Dekimpe, A. Mukherjee et al.

#### 4.2. AiMark's BG20 project: market coverage

As a second data set, we obtained through AiMark information on the PL shares in 18 countries (10 developed, 8 emerging; see Table 2 for details) in (up to) 76 categories. Depending on the country, the data were obtained from the consumer panels of GfK or Kantar. Similar data have been used repeatedly in prior PL studies, such as Geyskens et al. (2010) or Ailawadi et al. (2008). On average, 11 years are available and 903 country-category combinations are covered. The product categories were defined differently than in the Euromonitor data, precluding both a one-on-one comparison and a derivation of new-SKU measures. However, unlike the Euromonitor data, the data contain information on the PL price positioning, which is captured by the price gap between PLs and NBs in the market.

#### 4.3. Choice of benchmark country

To evaluate convergence, the UK is chosen as benchmark. The UK is widely seen as one of the most sophisticated retail markets (Gielens 2012). It also has a PL market that is among the most mature and stable in the world over the last years, which we formally test using a panel unit-root test. Importantly, UK data are available for all categories. In subsequent robustness checks, also other countries (i.c., France, Germany and the US) are used as benchmark country.

In Web Appendix A, we graphically present some of the PL share series, both for the UK (our focal reference country) and (for the same categories) for some other countries (the Czech Republic, Mexico, South Africa and Turkey) from different continents.

#### 4.4. Other variables

Apart from the focal information on PL shares, new-product introductions and PL price positioning, we also obtained information on a range of category and country characteristics from several data sources. For example, the relative importance of various store formats (discounters, the internet channel and independent retailers) is captured by the share of grocery purchases made through that format in each market, which we obtained from Euromonitor International's Passport GMID. Information on a country's GDP/Capita, level of urbanization and cultural values was obtained from, among others, Edge by Ascential and Inglehart et al. (2020), while information on consumers' involvement level was obtained through an Mturk survey. A detailed description on all operationalizations and data sources, along with relevant summary statistics, is given in Web Appendix B.

#### 5. Empirical findings

Before providing insight in the long-term PL shares and their drivers, we discuss the extent to which global PL convergence is achieved and whether the reference market is stabilized.

#### 5.1. Global convergence

Has the reference country stabilized? The Levin et al. (2002) test given in Eq. (1), applied across the 52 categories covered in the Euromonitor data and the 76 categories covered in the BG20 data firmly rejected (p <.05 in both instances) the unit-root hypothesis, confirming that the PL market in the UK has indeed stabilized.

*Is there global convergence*? We subsequently applied the global convergence test described in Eq. (3) to each of the 128 (52 + 76) categories.<sup>16</sup> The test statistic rejected the divergence hypothesis (with *p*-values ranging between 0.000 and 0.043), in all but two instances (laundry care and fruit/vegetable juice in the Euromonitor data). The combined evidence therefore offers the clear empirical generalization that PL shares are globally converging.

Absolute or partial convergence? No evidence of absolute convergence was obtained in the 116 converged categories, as the fixed-effect terms, i.e. the  $\alpha_{p,c}$  in Eq. (3), were each time *jointly* significant. Hence, while the long-run differential relative to the stabilized UK values is mean-reverting in all but two categories, this mean is each time different from zero for at least a subset of countries. This implies that heterogeneity will remain in the global PL market, and that not all markets will settle at the same level as the category levels of the UK. Looking at the *individual*  $\alpha_{p,c}$  values, 74% of estimates were significantly (p <.10) different from zero. In Web Appendix C, we present the frequency distribution of the t-values of the 128 estimated

 $\beta_p^{adj}$  values, the 2,399 estimated  $\alpha_{p,c}^{adj}$  values, and the 2,399 derived  $e^{-\frac{\sigma_{p,c}^{u,j}}{\rho_p^{adj}}}$  values.

<sup>&</sup>lt;sup>16</sup> In all unit-root tests, the number of lagged dependent-variable terms (determined on the basis of the AIC) was zero or one. The fit of these test equations was very good, with a squared correlation between observed and predicted PL levels consistently above 0.89.

#### K. Gielens, M.G. Dekimpe, A. Mukherjee et al.

#### 5.2. Long-run PL shares

Table 3 summarizes the estimated long-run share levels (averaged across the different categories in each country) and contrasts them with the 2018 observed shares. We do so for the Euromonitor data, given its broader geographic coverage. In both developed and emerging economies, further growth is still expected, with an anticipated change (on average) of, respectively, 2.89 and 4.28 share points. However, also in several developed Southern (e.g., Portugal, Spain) and Northern (e.g., Denmark) European countries, gains of over 4.0 share points are still expected. As such, in quite a number of developed economies, the "end of the PL party" is not yet in sight. In other countries (like New Zealand, Canada and Japan), a much moderate (if any) growth can be expected, which underscores the danger of broad generalizations.

In several emerging economies, especially in Eastern Europe, significant growth is still to come, with double-digit sharepoint gains in Poland, the Czech Republic and Latvia, and gains of 7 to 9 share points in other countries (e.g., Hungary, Slovakia). These findings suggest that most Eastern-European countries will converge to share levels as seen in leading Western European countries. For several countries, this may even be a too conservative estimate, as the long-run share is set to surpass the UK in several categories. However, this scenario will not unfold uniformly across all Eastern European markets, as the expected growth in, for example, Bulgaria is predicted to be a more limited 2.8 share points.

In the Asian emerging markets, growth predictions are equally mixed, with Middle-Eastern markets like Turkey expecting a 7 percentage-point increase in PL shares, whereas in Far-Eastern markets like Thailand and the Philippines the increase is expected to be only in the 2 to 3 percentage point range. The latter is also what can be expected in important retail hubs such as South-Africa. By far the lowest growth in emerging markets is expected in Latin America, where an almost status quo is expected in countries like Argentina and Guatemala.

Overall, it is fair to state that, globally, the end of PL growth is not in sight. Yet, this does not imply a uniform UK scenario across the globe. Interestingly, the remaining geographic divide will not follow the classic lines between developing and developed markets, calling for a further exploration of other systematic drivers.

Moreover, the geographic divide does not tell the entire story, as considerable variation exists across product categories as well. In Web Appendix D, we depict the expected growth (by contrasting 2018 and predicted long-run values) for the more hedonic product class beauty & personal care and the more utilitarian product class home care. Not only do the long-term levels and growth potential between these two product classes differ, within the same country PL patterns vary substantially. For example, in the Ukraine, the home care category is expected to grow with 0.9% share points to achieve a relatively modest share of 5.3%, whereas PLs in Beauty and Personal Care will see a surge of 16 percent points and achieve a long-term share of 23.4%.

Developed Markets	Emerging Markets						
Country	Share in 2018	Long-Run Share	Difference	Country	Share in 2018	Long-Run Share	Difference
Portugal	28.08	38.10	10.02	Poland	20.45	37.97	17.51
Spain	32.49	39.91	7.42	Latvia	9.41	22.37	12.96
Denmark	23.91	29.83	5.92	Czech Republic	18.29	29.03	10.73
Israel	7.21	12.23	5.02	Slovakia	17.27	26.99	9.72
Finland	19.00	22.76	3.76	Hungary	21.58	29.90	8.33
Sweden	16.67	20.24	3.57	Turkey	15.51	22.57	7.06
Greece	15.73	19.10	3.36	Estonia	6.35	12.34	5.99
Slovenia	18.32	21.51	3.20	Russia	6.61	12.55	5.94
The Netherlands	27.18	29.96	2.78	Dominican Rep.	8.55	14.21	5.66
Switzerland	36.28	38.97	2.69	Serbia	6.19	11.69	5.49
United Arab Emirates	5.41	8.00	2.59	Lithuania	11.67	16.66	4.98
France	21.24	23.74	2.51	Ukraine	5.12	9.84	4.72
Germany	31.50	33.89	2.40	Croatia	12.83	15.88	3.05
Belgium	29.38	31.72	2.34	Philippines	5.20	8.02	2.83
Italy	15.63	17.88	2.25	Bulgaria	3.81	6.61	2.80
Singapore	6.75	8.99	2.24	South Africa	15.08	17.45	2.37
Japan	6.85	9.04	2.19	Malaysia	3.46	5.47	2.01
Norway	13.91	16.08	2.17	Mexico	4.17	5.92	1.76
Ireland	20.34	22.24	1.91	Thailand	5.11	6.47	1.36
USA	15.62	17.22	1.60	China	1.55	2.88	1.34
South Korea	6.44	7.97	1.54	Chile	6.48	7.35	0.88
Australia	14.47	16.00	1.53	Peru	4.36	5.03	0.67
Canada	9.91	11.30	1.39	Brazil	2.13	2.67	0.54
Taiwan	5.76	6.82	1.06	Colombia	5.95	6.46	0.51
Austria	22.33	23.34	1.01	Morocco	3.74	3.93	0.19
New Zealand	9.20	10.16	0.96	Argentina	6.46	6.64	0.18
Saudi Arabia	2.44	3.12	0.69	India	1.87	2.02	0.15
				Guatemala	5.73	5.76	0.04
Average	17.11	20.01	2.89	Average	8.39	12.67	4.28

## Table 32018 and long-run share.



Fig. 3. Model-free evidence of convergence: sigma convergence.<sup>a</sup>

#### 5.3. Robustness checks

*Testing for sigma convergence.* To provide some model-free support for our partial-convergence finding, we check whether the dispersion in observed PL shares across different countries decreases over time, as should be the case when PLs converge. In Fig. 3, the evolution in the coefficient of variation between countries' PL share is depicted. The downward pattern, which is often referred to as sigma convergence (Janssen et al. 2016; Monfort 2008), reflects a clear reduction in the cross-market dispersion (in line with the convergence idea). Moreover, with the pattern moving towards a non-zero asymptote, partial convergence is also supported. To better visualize this pattern, a smooth regression line was plotted through the various data points.

Sensitivity to estimation method. Different estimation methods have been proposed to test for beta convergence. In our main analysis, we used the estimates from Levin et al.' (2002) panel unit root test. An alternative approach that has gained wide acceptance (e.g., Cavenaile and Dubois 2011; Martikainen et al. 2015) is Arrellano and Bond (1991)''s GMM approach, also because of its suitability for panels with a relatively short time dimension. In all but two of the 128 (52 + 76) analyses, evidence of convergence (p < .10) was found. In those two instances (which involved the same two categories as in our main analyses), the corresponding p-values were 0.11 and 0.12, respectively.

Sensitivity to functional form. The adopted functional form where we regress  $\Delta log\left(\frac{PL_{p.c.t.}}{PL_{p.Ref.t.}}\right)$  on  $log\left(\frac{PL_{p.c.t-1}}{PL_{p.Ref.t.}}\right)$  assumes that dif-

ferences relative to the reference country become smaller at an exponential rate. This assumption is often made in the convergence literature, irrespective of the application domain (see, e.g., several of the studies in footnote 4) and (ii) appears to be supported by the model-free evidence in Fig. 3. Still, we also applied our convergence tests on non-log-transformed series, where we again applied both the Levin et al. (2002) test and Arrellano and Bond (1991)'s GMM estimator. In both instances, we again found strong evidence of convergence.<sup>17</sup>

Sensitivity of right censoring. To truly validate long-run estimates, one should wait many years, and then compare the estimates with the level at which the PL shares settle. Absent the practical feasibility to do so, we adopted the approach used in Dekimpe et al. (1998) and assess the robustness of the estimates when derived from a reduced time window. Our long-run estimates were found to be very robust. When dropping the last, last two and last three years of every series, very similar results are obtained. Similar to Nijs et al. (2001), we computed the correlations between the long-run levels obtained on the full series and the ones obtained with the shorter series, and found this correlation to be very high (>0.98 in all instances). Moreover, the median absolute deviation (MAD) was smaller than 0.40 in all three instances.

Sensitivity to left censoring. This is also the case when dropping the first one, two and three years of the observation window (all correlations > 0.93 l; MAD < 0.45), which confirmed the robustness to increasing levels of *left censoring*.

Sensitivity to choice of reference country. In our main analysis, we used the UK as reference country. We considered three alternative reference countries (France, Germany and the US), and found very similar results: all correlations were higher than > 0.95, and the MAD varied between 0.37 (Germany) and 0.51 (US).

<sup>&</sup>lt;sup>17</sup> Detailed results are available from the first author upon request.

#### 5.4. Drivers of heterogeneity in long-run PL levels

*Main-effects analyses.* In Table 4, we report insights on the impact of long-run new product activity by both PLs and NBs (using the Euromonitor data) and in Table 5 we focus on the role of PL price positioning (using the BG20 data). All continuous independent variables are mean centered for the ease of interpretation. The maximum VIFs (3.60 and 1.09, respectively) are below 10, indicating that multi-collinearity is not a concern. All three mix drivers are endogenous, as evidenced by the significant Gaussian copulas (*p* <.05).

Most of the main effects are significant, with a sign that attests to the face validity of the insights. For example, consistent with conventional wisdom (e.g., Steenkamp and Sloot 2018), a higher long-run discounter share will continue to contribute to a higher PL share ( $\beta = 0.001$ ; p <.01), while a continued popularity of independent small-scale retailing will attenuate that level ( $\beta = -0.001$ ; p <.05). Similarly, long-term PL share will thrive in more concentrated retail environments ( $\beta = 0.004$ ; p <.01) and will continue to reach higher acceptance in richer countries ( $\beta = 0.005$ ; p <.05). As for the cultural variables, the positive effects for traditional ( $\beta = 0.336$ ; p <.01) and self-expression ( $\beta = 0.153$ ; p <.01) cultures are consistent with the effects hypothesized in Steenkamp and Geykens (2014, p. 10). Also, the variables that appear in both studies (GDP/Capita, urbanization and retail concentration) have a similar impact in both analyses. In both instances, a negative effect is found for

#### Table 4

New product drivers of global private-label success evolution over time.

	Long Run		2018		2011	
	estimate	t-value	estimate	t-value	estimate	t-value
Intercept	-2.223***	-18.84	-2.665***	-19.87	-2.895***	-21.42
New product introductions by NBs New product introductions by PLs	-0.045 <sup>***</sup> 0.075	-2.63 0.80	-0.016 0.138*	-1.01 1.79	0.001 0.019	0.18 1.49
Importance discounter Importance internet Importance independent retailing	0.001 <sup>***</sup> 0.020 -0.0001 <sup>**</sup>	3.42 0.70 -2.54	0.030 <sup>***</sup> 0.024 <sup>**</sup> -0.120 <sup>***</sup>	1.28 2.06 -5.50	0.025 <sup>***</sup> -0.009 -0.007 <sup>***</sup>	7.39 -1.25 -3.64
Secular-rational culture Self-expression culture	0.336 <sup>***</sup> 0.153 <sup>***</sup>	9.64 3.34	0.115 <sup>***</sup> 0.207 <sup>***</sup>	3.19 4.34	0.003 -0.020	0.08 -0.41
GDP per capita Urbanisation	0.005 <sup>**</sup> -0.001 <sup>***</sup>	2.36 -6.56	0.011 <sup>***</sup> -0.002 <sup>***</sup>	3.54 -4.42	0.024 <sup>***</sup> -0.002 <sup>***</sup>	5.96 -3.38
Control variables Share of wallet Retail concentration	25.952*** 0.004***	2.62 2.82	-8.184 <sup>****</sup> 0.019 <sup>****</sup>	-2.74 8.52	-7.968*** 0.019***	-3.06 9.20
Copulas Copula New products NB Copula New products PL	-0.155*** 0.358***	-3.49 8.19	0.004 0.149*	1.05 1.93	-0.191*** 0.303***	-3.25 4.75

\*p <.1, "p <.05, ""p <.01 (two-sided); Corrected standard errors are obtained using the bootstrapping procedure described in Papies et al. (2017).

#### Table 5

Price-gap drivers of global private-label success evolution over time.

	Long Run		2018		2011	
	estimate	t-value	estimate	t-value	estimate	t-value
Intercept	-1.830***	-12.90	-2.035***	-14.11	-2.081***	-13.69
NB-PL Price Gap	-1.026***	-6.46	-0.559***	-3.23	-0.340**	-2.01
Hedonic	-0.032	-0.20	-0.004	-0.02	0.037	0.24
Involvement	-0.163	-0.57	-0.199	-0.69	-0.259	-0.94
GDP per capita	0.025***	9.01	0.036***	11.61	0.028***	7.48
Urbanisation	-0.003***	-11.38	-0.007***	-11.16	-0.007***	-7.43
Retail concentration	0.007***	5.12	0.004***	3.23	0.012**	2.53
Copulas						
	1.028***	6.54	0.482***	4.34	0.583***	3.12
Price Copula						

\*p <.1, "p <.05, "p <.01 (two-sided); Corrected standard errors are obtained using the bootstrapping procedure described in Papies et al. (2017).

urbanization, which is consistent with Sebri and Zaccour's (2017) analysis with a broader and more diverse (also non-European) set of countries. The positive association between share of wallet and long-run PL share in turn, is consistent with AC Nielsen's (2014, p. 8) observation that, across the globe, private-label sales and market share will especially flourish in commodity-driven, high-purchase categories.

Turning to the variables under managers' control, we observe that also in the long run, new-product introductions by NB manufacturers will remain essential to keep PLs at bay ( $\beta = -0.045$ ; p < .01). Even though recent industry reports (e.g., AC Nielsen 2018; Daymon 2020) have emphasized the growing importance of new PL introductions, no significant (main) effect was found (p > .10), an issue that we will explore in more detail in our subsequent contingency analyses. As for the price gap, we find higher long-run PL shares are obtained when the price gap vis-à-vis the NBs is smaller ( $\beta = -1.206$ ; p < .01). Combined, these findings support the contention in Pauwels and Srinivasan (2009, p. 277) that even though larger price gaps may yield more immediate success, smaller price gaps, accompanied by investments in PL quality will yield higher PL success in the long run.<sup>18</sup>

Evolution over time. We see that this price-gap effect was already observed around 2011 ( $\beta$  = -0.340; *p* <.05) but became more pronounced by 2018 ( $\beta$  = -0.559; *p* <.01). Our findings show that this will be even more so in the future ( $\beta$  = -1.026; *p* <.01). In line with the reasoning in Gielens et al. (2021), these results support the idea that maintaining low PL price points will become less and less appropriate for the smart PLs of the future. Interestingly, we also see that the price gap itself is expected to become lower in the long-run, moving, on average, from almost 1.9 in 2018 to 1.6 in the long-run. This indicates that NB and PL prices are moving closer to one another, which bears well for PLs' future.

Also, the impact of new product introductions changes over time. Whereas the competitive impact of NB introductions appears to become stronger over time, the supportive effect of PL innovation is rockier. Once again, this urges us to explore contingency factors for this mix element.

The over-time evolution in the role of the internet channel is note-worthy: while an (albeit insignificant) negative effect was observed in 2011 (consistent with the idea that NBs had a competitive advantage over PLs in the online channel), a significant positive impact ( $\beta = 0.024$ ; p < .05) materialized by 2018, in part because of the efforts of an increasing number of both traditional and pure-play retailers to actively push their PLs online (Gielens et al. 2021). Our findings suggest that in the future, as such online presence becomes more widespread, its differentiating effect will become smaller and eventually disappear ( $\beta = 0.020$ ; p > .05).

This over-time evolution in the main effects underscores the idea that, when planning for the future, managers should take the likely changes in the business environment into account.

#### 5.5. Contingency analyses

The long-run impact of the focal marketing-mix instruments is not homogeneous but varies with several contextual factors. Below, we focus on those instances where either a cross-over effect takes place, or the impact becomes insignificant for certain values of the moderating variable.

Contrary to the notion that retailers should take ownership of the innovation process as the best way to ensure long-run PL growth, we found no significant 'average' effect for PLs' new product activity ( $\beta = 0.075$ ; p > .05), which calls for an exploration of boundary effects across categories and countries. To gauge the underlying heterogeneity in this seemingly non-significant effect, we interacted the new-product variables with the various economic, cultural and retail-context variables (see Table 6). Importantly, we found a significant and positive interaction effect with (long-term) GDP/Capita. A simple-slope analysis (depicted in Fig. 4, Panel A) shows how in the highly developed markets (i.c., the top 35 percent) typically covered in industry studies, PL innovations are indeed an effective tool to create long-run share gains, and significantly so (p < .05). However, for the vast majority of countries, PL innovations have no effect, and for the bottom 5% they are even counter-effective. Table 7.

Similarly, PL innovations are effective when introduced in societies that score lower on the self-expression dimension (Fig. 4, Panel B). In those societies, typical branding activities (such a differentiating innovations) are valued more (Steen-kamp and Geyskens 2014), offering private labels an incentive to take ownership of the new-product development process, and position themselves as innovators (Daymon 2020). Especially societies in the bottom 45% of the self-expression scale are found to be fertile ground for PL innovations. On the other hand, in countries with high self-expression values (the top 25%), PL innovations damage the PL share. In those societies, post-materialist priorities (with a reduced emphasis on branding) get more prominence, and PLs should avoid presenting themselves too much as yet another brand in their own right.

Turning to the impact of NB innovations, we find that NB innovations will be less effective in markets where the discount channel converges to a high level (i.c., above the 85% percentile of discounter share in the market; Fig. 4, Panel C), even though they still are an effective defense tool in a majority of the markets. Because of the growing acceptance of discounters, over time NBs will have a harder time to convince the consumer of the added value of their products, making incremental investments in innovations less effective in fighting PLs.

<sup>&</sup>lt;sup>18</sup> In a similar vein, Sayman and Raju (2007, p. 137) discuss how within a given category "an increase in a brand's relative price in the short term would naturally decrease its share. And store brand is no different in this respect." However, *across* categories, stronger store brands (i.e., with a higher market share and better quality) will be characterized by higher equilibrium prices.

#### K. Gielens, M.G. Dekimpe, A. Mukherjee et al.

#### Table 6

New product drivers of global-pl success: contingency analyses.

	Base Model estimate	Extended Model t-value	estimate	t-value
Intercent	estimate	t-value	connuc	t-value
Intercept	<b>ว</b> ววว***	10.04	2 262***	10 60
Now ND Droducto	-2.225	-10.04	-2.205	-16.06
* Importance discounter	-0.045	-2.05	-0.127	-2.00
* Importance internet			0.178	1.02
* Importance independent retailing			0.092	1.01
			-0.024	-2.51
* Self evenession evenue			-0.034	-1.38
* CDD registering			-	-
GDP per capita			-	-
Vidanisation	0.075	0.90	0.046	1.11
New PL Products	0.075	0.80	0.192	0.87
* Importance discounter			—	_
* Importance index on dont noteiling				- 1.20
* Crawley article independent retaining			-0.031	-1.29
* Secular-rational culture			-0.277	-0.99
* CDD regression culture			-0.947*	-1.82
GDP per capita			0.047	1.97
Urbanisation	0.000***	2.42	-0.280	-1.52
Importance discounter	0.096	3.42	0.168	3.43
Importance internet	0.021	0.70	0.008	0.24
Importance independent retailing	-0.001	-2.54	-0.017	-2.49
Secular-rational culture	0.336	9.64	0.299	7.28
Self-expression culture	0.153	3.34	0.086	1.39
GDP per capita	0.005	2.36	0.005	2.94
Urbanisation	-0.146	-6.56	-0.147	-5.76
Control variables	***			
Share of Wallet	25.952	2.62	27.064	2.88
Retail concentration	0.004	2.82	0.004	2.55
Copulas				
Copula NB new products	-0.155	-3.49	-0.152	-3.29
Copula PL new products	0.358	8.19	0.341	7.68
AIC	7,749.4	7,683.3		
*p <.1, "p <.05, "p <.01 (two-sided); Corrected standard errors are obtained using the				

bootstrapping procedure described in Papies et al. (2017). Interaction terms with |t| < 1 in a

full model (i.e., with all interactions) were omitted.

Finally, we also explored whether there are certain categories where the price gap plays a more/less prominent role. Overall, we see that the impact of the price gap remains negative and significant over almost all values of the significant attenuating moderators, i.e. retail concentration and urbanization (only for values above the 99th percentile the effect becomes insignificant). As for the reinforcing moderators, we find that smaller price gaps will be even more effective in more hedonic categories. Hedonic product categories typically bear more social risk than more functional categories, as they are often consumed in the company of others (Loebnitz et al. 2020). Because of that, higher price gaps may raise further doubts whether the desired quality can be reached in a consistent manner.

#### 6. Discussion

Industry experts as well as academic researchers agree that PLs are here to stay and expect that they will continue to grow. Nevertheless, considerable ambiguity exists about their future growth potential. This poses a formidable challenge to both NB manufacturers and retailers. To do so, a forward-looking approach is called for, which we achieve by means of a convergence modeling approach to benchmark how a country's PL market will evolve relative to an established (and stabilized) reference country, viz. the UK. This approach was applied to two unique datasets with a very broad geographic scope. This allowed us to glean insights in important, yet typically overlooked, emerging markets, even though some of these markets are currently in the early development or growth stage of their life cycle. By covering a broad array of CPG categories, we could track differences in PL success not just across geographic boundaries, but also acknowledge the different roles categories play in different countries. While commonalities exist, the categories where PLs will reach their highest acceptance level vary dramatically across countries. Based upon our results, we propose the following key takeaways, which are summarized in Table 8.

Globally, further PL growth is expected. In many countries and categories, the proverbial glass ceiling has not yet been reached. Importantly, this holds not only in emerging, but also in several developed markets. Given that a status quo has





Fig. 4. Moderating effects on the impact of new products.<sup>a</sup>

not yet been obtained in the global PL market, both NB manufacturers and retailers have to prepare for a changing long-term reality.

A uniform PL market remains unlikely. Predictions that all markets will gravitate towards the Western European model are widely off the mark. Uniformity will not even be the case within Western Europe. Even though many Eastern and Western European markets are growing to similar, elevated PL levels, in many other markets, both in and outside Europe, the overall PL share will remain considerably lower. Importantly, we find no support for the contention of some business analysts that

#### K. Gielens, M.G. Dekimpe, A. Mukherjee et al.

#### Table 7

Price gap drivers of global-pl success: contingency analyses.

	Base Model		Extended Model	
	estimate	t-value	estimate	t-value
Intercept	-1.830****	-12.90	$-1.846^{***}$	-12.94
NB-PL Price Gap	-1.026***	-6.46	$-1.114^{***}$	-6.41
* Hedonic			-0.184**	-2.30
* Involvement			0.171	1.34
* GDP per capita			_	_
* Urbanisation			0.056***	3.17
* Retail concentration			0.007**	2.46
Hedonic	-0.032	-0.20	-0.020	-0.13
Involvement	-0.163	-0.57	-0.140	-0.49
GDP per capita	0.025***	9.01	0.024***	8.71
Urbanisation	-0.307***	-11.38	-0.283***	-1.30
Retail concentration	0.007***	5.12	0.003	1.45
Copulas				
Price-gap copula	1.028***	6.540	1.082***	6.53
AIC	2870.0			
			2863.1	

\**p* <.1, "*p* <.05, "*p* <.01 (*two-sided*); Corrected standard errors are obtained using the bootstrapping procedure described in Papies et al. (2017). Interaction terms with |*t*| < 1 are omitted from the model.

#### Table 8

Key take-aways.

Issue	Finding
Is the end of PL growth in sight?	No: across 2,000 + markets (country/category combinations), an average growth of 16.9 share points is expected.
Will a uniform global PL scene emerge?	
Across countries	No
Across categories within a country	No
Will currently observed differences in PL share become smaller?	Yes
Will remaining geographic differences follow the classic divide between emerging and developed economies?	No: in both groups, markets with a high and low remaining growth potential are present.
Will channel preferences continue to play a role?	Yes: PL share will remain higher (lower) in markets where hard discounters (independent retailers) are more popular.
Will economic context continue to play a role?	Yes: PL share will remain higher in more affluent and less urbanized societies.
Will cultural context continue to play a role?	Yes: PL share will remain higher in more secular-rational and more self- expressive cultures.
Will category characteristics continue to play a role?	Yes: The impact of a smaller NB-PL price gap will be higher in hedonic categories.
Will the NB-PL price differential continue to play a role?	Yes: Especially in hedonic categories, PL levels will benefit from a lower price differential.
Will NB innovations continue to play a role?	Yes: NB innovations will remain a significant antidote to further PL growth.
Will PL innovations continue to play a role?	Yes, but only in the more affluent countries and among the least self- expressive cultures.
Will old success recipes continue to work?	No: the impact of most drivers becomes more (less) pronounced.

countries like India and China will soon reach PL shares currently observed in Western Europe. NB losses will therefore be relatively modest in these important economies. Still, the lines between emerging and developed PL markets are blurring, as witnessed by more pronounced PL inroads in the Dominican Republic, South Africa, and Turkey. A simple 'flock into emerging markets' strategy to avoid the PL threat is therefore not uniformly the best strategy to pursue. Similarly, important differences between categories will prevail, differences that will continue to be region (country) specific.

*Strategic weapons are available.* Even though preparing for a fairly distant future is difficult, we can offer some actionable guidelines. Foremost, innovation is key! But, not everywhere, or to same extent... Retailers can play the innovation card to stimulate further PL growth, although important boundary conditions exist across countries, but not so much across categories. Relying on innovation to further grow the PL is a strategy that only works in the most affluent countries and in cultures that score lower on self-expression. NB manufacturers, on the other hand, should fully play the innovation card to effectively keep PLs at bay. Although some manufacturers may be hesitant to keep on investing in R&D for fear of quickly

#### K. Gielens, M.G. Dekimpe, A. Mukherjee et al.

being copied by their PL rivals, NB innovations remain a powerful antidote to further PL growth. Still, it is important to make one proviso, in that in heavily discounter-dominated markets the effectiveness of NB innovations is reduced. Given that discounters still have a substantial anticipated growth margin in several markets, brand manufacturers cannot afford to lose track of the price positioning of PLs. This is all the more so given that retailers have an interest in reducing the price gap with NBs. Unlike PLs' early days, retailers no longer steer away from reducing that price gap to support their new message of quality and innovativeness (Gielens et al. 2021). This hold almost universally across different types of economies, cultures and competitive settings. This strategy will be even more important for hedonistic PL products. Knowing that retailers have a clear interest in venturing more and more into more hedonistic categories with their PLs, avoiding the typical price (promotion) trap will be important for retailers to be successful in those categories in the long run.

In sum, whereas price-gap strategies can be set more globally, innovation requires more tailoring to each specific market and a one size-fits all strategy is not on the table.

What holds today may not necessarily hold over time. An overly myopic outlook towards what works now can be detrimental in years to come. Overly relying on past and current recipes for success may be dangerous, especially since the effectiveness of several drivers changes drastically over time. Even when innovation-focused strategies may not currently keep PLs at bay, their effectiveness is bound to increase in the future. Especially when taking into consideration that from a NBs' point of view PL price gap management and effectiveness may change not in the NBs' advantage, keeping an eye on the innovation game will be more required than ever. Also for retailers, to finetune their innovation strategy they have to keep a close watch on how the different markets in which they operate evolve. As markets further mature and middle-class shoppers become the norm rather than the exception, retailers have to be prepared to up their ante in the innovation game and offer the right mix of PLs to those consumers. Ultimately, to determine an optimal mix of strategies, a keen understanding of future market dynamics is necessary.

#### 7. Limitations

First, even though our geographic coverage, with over 50 countries from all inhabited continents, is much more extensive than in previous studies, several countries (especially from Western, Central and Eastern Africa) were not yet included. In addition, it would be interesting to complement the current global analysis with in-depth studies of individual markets, not only to identify further factors that may impede or accelerate further PL growth, but also to account for within-country differences in PL acceptance.

Moreover, PL quality perceptions are increasing over time, as documented by AC Nielsen (2011, 2014). Between 2011 and 2014 the cross-continental differences in PL quality perception<sup>19</sup> have decreased considerably. Unfortunately, two measurement points do not yet allow to distinguish absolute from partial convergence along that dimension. When more time-varying data become available, additional insights can be shed into how lingering quality-perception differences, if any, will help shape the resulting long-term PL shares, and/or assess how they moderate the effectiveness of marketing-support strategies.

Third, it would be useful to consider a wider set of KPIs, including profit, to paint a more complete picture of how different strategies will ultimately affect the retailers' and manufacturers' bottom line. Given the (relative and absolute) margin differences between different PL tiers (ter Braak et al. 2013), it would be useful to also conduct a convergence analysis at the PL quality-tier level and investigate the role that the price gap plays in, for example, the premium versus budget tier. Multi-tier offerings may (due to their better targeting) lead to an initial growth in many markets, but could eventually result in higher marketing and logistical costs and pose (analogous to the well-known wheel of retailing) an internal treat to PLs' long-term growth prospects.

Finally, as already emphasized in Bass (1969), any long-term forecasting remains to some extent a guessing game. It would be worthwhile to evaluate, as the future unfolds and more markets stabilize, how accurate our forecasts are, and especially how this accuracy varies across different markets to further improve our contingency framework. In so doing, it may be useful to also consider alternative functional forms for the convergence process. Underlying Eq. (3) is the idea that differences relative to the reference country become smaller at an exponential rate. More flexible patterns, as recently discussed in Michelacci and Zaffaroni (2000), who allowed for hyperbolic patterns through fractional beta convergence testing, or Lau (2010), who allows for threshold effects before convergence kicks in, may be useful in this respect.

#### **Declaration of Competing Interest**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

#### References

Ailawadi, K., Pauwels, K., & Steenkamp, J. B. E. M. (2008). Private-label use and store loyalty. *Journal of Marketing*, 72(6), 19–30. Alba, J. W. (2012). In defense of bumbling. *Journal of Consumer Research*, 38(6), 981–987.

<sup>&</sup>lt;sup>19</sup> Measured as the fraction of consumers who consider PLs a good alternative to NBs. The coefficient of variation across five continents decreased with almost 60% between 2011 and 2014 (from 0.277 to 0.117).

#### K. Gielens, M.G. Dekimpe, A. Mukherjee et al.

#### International Journal of Research in Marketing xxx (xxxx) xxx

Arrellano, M., & Bond, S. (1991). Some tests of specification for panel Data: Monte Carlo evidence and an application to employment equations. Review of Economic Studies, 58, 277–297.

Baltagi, B. H. (2013). Econometric Analysis of Panel Data (5th ed). Hoboken: John Wiley&Sons.

Bass, F. M. (1969). A New Product Growth Model for Consumer Durables. Management Science, 15(5), 215-227.

Bass (1995). Empirical Generalizations and Marketing Science: A Personal View. Marketing Science, 14 (3, supplement), G6-19.

Bass (2004), Comment on: New Product Growth for Model Consumer Durables the Bass Model, Management Science, 50 (12, Supplement), 1825-32. BCG. (2017). How Discounters Are Remaking the Grocery Industry. Boston Consulting Group.

Breugelsdijk, S., Maseland, R., & Van Hoorn, A. (2015). Are scores on hofstede's dimensions of national culture stable over time? A Cohort analysis. Global Strategy Journal, 5(3), 223-240.

Bronnenberg, B. J., & Ellickson, P. B. (2015). Adolescence and the Path to Maturity in Global Retail. Journal of Economic Perspectives, 29(4), 113-134.

Cavenaile, L., & Dubois, D. (2011). An empirical analysis of income convergence in the European union. Applied Economics Letters, 18(17), 1705–1708.

Cecchetti, S. E., Mark, N. C., & Sonora, R. J. (2002). Price index convergence among United States cities. International Economic Review, 43(4), 1081–1099.

Chu, J., Arce-Urriza, M., Cebollada-Calvo, J. J., & Chintagunta, P. K. (2010). An Empirical analysis of shopping behavior across online and offline channels for grocery products: The moderating effects of household and product characteristics. Journal of Interactive Marketing, 24(4), 251–268.

Colicey, A., Malshe, A., & Pauwels, K. (2018). Social media and customer-based brand equity: An empirical investigation in retail industry. Administrative Sciences 8 55

Datta, H., Ailawadi, K. L., & van Heerde, H. J. (2017). How well does consumer-based brand equity align with sales-based brand equity and marketing-mix response? Journal of Marketing, 81(3), 1-20.

Daymon (2020), "The Future of Private Brands," [https://www.daymon/publications].

Daymon, M. G., Parker, P. M. & Sarvary, M. (1998). Staged Estimation of International Diffusion Models: An Application to Global Cellular Telephone Adoption. Technological Forecasting and Social Change, 57 (1), 105-132.

Dekimpe, M. G., & Hanssens, D. M. (1995). The persistence of marketing effects on sales. Marketing Science, 14(1), 1-21.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the Estimators for Autoregressive Time Series with a Unit Root. Journal of the American Statistical Association, 74(366a), 427-431.

Euromonitor (2014). The New Face of Private Label: Global Market Trends to 2018. [http://go.euromonitor.com/new-face-of-private-label-global-markettrends-2018-strategy-briefing.html].

Gaulier, Guillaume, Hurlin, Christophe, & Jean-Pierre, Philippe (1999). Testing convergence: A panel data approach. Annales d'Économie et de Statistique.

Geyskens, I., Gielens, K., & Gijsbrechts, E. (2010). Proliferating private-label portfolios: How introducing economy and premium private labels influences brand choice. Journal of Marketing Research, 47(5), 791-807.

Gielens, K. (2012). New Products: The antidote to private label growth? *Journal of Marketing Research*, *49*(3), 408–423. Gielens, K., Ma, Y., Namin, A., Sethuraman, R., Smith, R. J., Bachtel, R. C., & Jervis, S. (2021). The future of private labels: Towards a smart private label strategy. Journal of Retailing, 97(1), 99-115.

Gielens, K., & Steenkamp, J. B. E. M. (2019). Branding in the Era of Digital (Dis)Intermediation. International Journal of Research in Marketing, 36(3), 367–384. Goldberg, P. K., & Verboven, F. (2005). Market integration and convergence to the law of one price: Evidence from the European car market. Journal of International Economics, 65(1), 49-73.

González-Benito, Ó., Martos-Partal, M., & San Martín, S. (2015). Brands as substitutes for the need for touch in online shopping. Journal of Retailing and Consumer Services, 27, 121-125.

Im, K. S., Pesaran, M. H., & Shin, Y. (2003). Testing for Unit Roots in Heterogeneous Panels. Journal of Econometrics, 115(1), 53-74.

Inglehart, R. & W.E. Baker (2000), Modernization, Cultural Change, and the Persistence of Traditional Values. American Sociological Review, 65 (1), 19-51.

Inglehart, R., Haerpfer, C., Moreno, A., Welzel, C., Kizilova, K., Diez-Medrano J., Lagos, M., Norris, P., Ponarin, E. & Puranen, B. (2020), World Values Survey: All Rounds - Country-Pooled Datafile. Madrid, Spain & Vienna. Austria: JD Systems Institute & WVSA Secretariat [http://www.worldvaluessurvey.org/ WVSDocumentationWVL.isp].

Inglehart, R. (1997), Modernization and Postmodernization: Cultural, Economic, and Political Change in 43 Societies. Princeton University Press.

IRI (2012). Private Label in Europe 2012 – Is There a Limit to Growth?. [https://www.scribd.com/document/110291374/Private-Label-in-Europe-2012-Isthere-a-limit-to-growth].

Islam, N. (1998). Growth Empirics: A Panel Data Approach – A Reply. Quarterly Journal of Economics, 113(1), 325–329.

Islam, N. (2003), What Have we Learn from the Convergence Debate. Journal of Economic Surveys, 17(3), 309-362.

Janssen, F., van den Hende, A., de Beer, J., & Van Wissen, L. (2016). Sigma and beta convergence in regional mortality: A case study of the Netherlands. Demographic Research, 35(4), 81-116.

Jiang, Z., Bass, F. M., & Bass, P. I. (2006). Virtual bass model and the left-hand data-truncation bias in diffusion of innovation studies. International Journal of Research in Marketing, 23(1), 93–106.

Keller, K. O., Dekimpe, M. G., & Geyskens, I. (2016). Let your banner wave? Antecedents and performance implications of retailers' private-label branding strategies. Journal of Marketing, 80(4), 1–19.

Kotabe, M. (2002). Using euromonitor database in international marketing research. Journal of the Academy of Marketing Science, 30(2), 172–175.

Kotabe, M., & Helsen, K. (2004). Global Marketing Management (3rd ed). New York: Johan Wiley & Sons.

Lamey, L., Deleersnyder, B., Steenkamp, J. B. E. M., & Dekimpe, M. G. (2018). New product success in the consumer packaged goods industry. International Journal of Research in Marketing, 35(3), 432-452.

Lau, C.-K.-M. (2010). Convergence across the United States: Evidence from Panel ESTAR Unit Root Test. International Advances in Economic Research, 16(1), 52-64.

Levin, A., Lin, C.-F., & Chu, C.-S.-J. (2002). Unit root tests in panel data: Asymptotic and finite-sample properties. Journal of Econometrics, 108(1), 1-24. Loebnitz, N., Zielke, S., & Grunert, K. G. (2020). Consumers' brand decision: A matter of social risk. International Journal of Retail & Distribution Management, 48(6) 575-589

Martikainen, E., Schmiedel, H., & Takalo, T. (2015). Convergence of European Retail Payments. Journal of Banking & Finance, 50, 81-91.

Michelacci, C., & Zaffaroni, P. (2000). (Fractional) Beta Convergence. Journal of Monetary Economics, 45, 129-153.

Monfort, P. (2008). Convergence of EU Regions, Measures and Evolution. European Union, Regional Policy Working Paper 01/2008.

Nickell, S. (1981). Biases in dynamic models with fixed effects. Econometrica, 19(6), 1417-1426.

Nielsen (2014). The State of Private Label around the Globe: Where it's Growing, Where it's Not, and What the Future Holds.

AC Nielsen (2011). The Rise of the Value-Conscious Shopper. A Nielsen Global Private Label Report".

Nielsen (2018). The Rise and Rise Again of Private Label.

Nielsen, I. Q. (2021). Unveiling the Public Demand for Private Label.

Nijs, V., Dekimpe, M. G., Steenkamp, J. B. E. M., & Hanssens, D. M. (2001). The category demand effects of price promotions. *Marketing Science*, 20(1), 1–22. Nijs, V. R., Srinivasan, S., & Pauwels, K. (2007). Retail-price drivers and retailer profits. *Marketing Science*, 26(4), 473–487.

O'Connell, P. G. J. (1998). The overvaluation of purchasing power parity. Journal of International Economics, 44(1), 1–19.

Ozturk, A., Cavusgil, S. T., & Ozturk, O. C. (2021). Consumption convergence across countries: measurement, antecedents, and consequences. Journal of International Business Studies, 52(1), 105–112.

Papies, D., Ebbes, P. & van Heerde, H. J. (2017). Addressing Endogeneity in Marketing Models. In Leeflang, P. S. H., Wierenga, J. W., Bijmolt, T. H. A. & Pauwels, d K. H. (Eds.), Advanced Methods for Modeling Markets, Springer Nature, 581-627.

Park, S., & Gupta, S. (2012). Handling endogenous regressors by joint estimation using copulas. Marketing Science, 31(4), 567-586.

#### K. Gielens, M.G. Dekimpe, A. Mukherjee et al.

Parker, P. M. & Sarvary, M. (2000), "Multimarket and Global Diffusion," in: V. Mahajan, E. Muller and Y. Wind, (eds.), New Product Diffusion Models, Kluwer Academic Publishers, 49-73.

Parker, P.M., Van de Gucht, L.M., Hanssens, D.M., Powers, K.I., 1998. Long-run abstinence after treatment for narcotics abuse: what are the odds? Management Science, 44 (11), 1478-92.

Pauwels, K. & Srinivasan, S. (2009). Pricing of National Brands versus Store Brands: Market Power Components, Findings and Research Opportunities. In Rao, V. R. (ed.), Handbook of Pricing Research in Marketing, Edward Elgar Publishing, 258-282.

Pauwels, K. & Srinivasan, S. (2004). Who Benefits from Store Brand Entry? *Marketing Science* 23 (3), 364-39.

Pesaran, M. H. (2004). General Diagnostic Tests for Cross Section Dependence in Panels. Cambridge Working Paper in Economics No. 435, University of Cambridge, and CESifo Working Paper Series No. 1229.

Pesaran, M. H. (2007), "A Simple Panel Unit Root Test in the Presence of Cross-Section Dependence," *Journal of Applied Econometrics*, 22 (2), 265-312. PLMA (2021), https://www.plmainternational.com/industry-news/private-label-today.

Rabobank (2013), "Private Label Goes to Asia," [https://www.rabobank.com/en/press/search/2013/20130812\_Rabobank\_Report-Private Label Goes to Asia Share in India and China expected to hit 25-30 by 203.html].

Sayman, S. and J.S. Raju (2007). Store Brands: From Back to the Future. In *Review of Marketing Research*, Volume 3, N.K. Malhotra (ed.), M.E. Sharpe Inc, 132-51.

Sebri, M., & Zaccour, G. (2017). Cross-country differences in private-label success: An exploratory approach. Journal of Business Research, 80, 116–126.

Sethuraman, R. (2018). Consumer Preference Distributions and Corresponding Store Brand Strategies: A Compilation. In K. Gielens & E. Gijsbrechts (Eds.), Handbook of Research on Retailing. Edward-Elgar Publishing.

Sethuraman, R., & Gielens, K. (2014). Determinants of Store Brand Share. Journal of Retailing, 90(2), 141–153.

Sheth, J. N. (2011). Impact of emerging markets on marketing: Rethinking existing perspectives and practices. Journal of Marketing, 75(4), 166–182.

Silver, S. (2010). Convergence in revealed preferences for automobiles as differentiated goods: U.S. and OECD Countries: 1970–1999. Atlantic Economic Journal, 38(1), 3–14.

Steenkamp, J. B. E. M., & I. Geyskens (2014). Manufacturer and retailer strategies to impact store brand share: Global integration, local adaptation, and worldwide learning. *Marketing Science*, 33 (1), 6-26.

Steenkamp, J. B. E. M., Heerde, H. J. & Geyskens, I. (2010), What Makes Consumers Willing to Pay a Price Premium for National Brands over Private Labels? Journal of Marketing Research, 47 (6), 1011-24.

Steenkamp, J. B. E. M., & L. Sloot (2018), Retail Disruptors. The Spectacular Rise and Impact of the Hard Discounters. New York, NY: Kogan Page.

Suvankulov, F., Lau, C. K., & Ogucu, F. (2012). Price regulation and relative price convergence: Evidence from the retail gasoline market in Canada. Energy Policy, 40(1), 325-334.

Talukdar, D., Sudhir, K., & Ainslie, A. (2002). Investigating new product diffusion across products and countries. Marketing Science, 21(1), 97-114.

Tellis, G. J., Stremersch, S., & Yin, E. (2003). The international takeoff of new products: The role of economics, culture and country innovativeness. *Marketing Science*, 22(2), 188–208.

ter Braak, A., Dekimpe, M. G., & Geyskens, I. (2013). Retailer private-label margins: The role of supplier and quality-tier differentiation. Journal of Marketing, 77(4), 86–103.

Thompson, N. (2017), "The Future of Private Label Brands," [https://www.traceone.com/it/blog/the-future-of-private-label-brands/].

Zeithaml, V. A., Bolton, R. N., Deighton, J., Keiningham, T. L., Lemon, K. N., & Petersen, J. A. (2006). Forward-looking focus: can firms have adaptive foresight? Journal of Service Research, 9(2), 168–183.