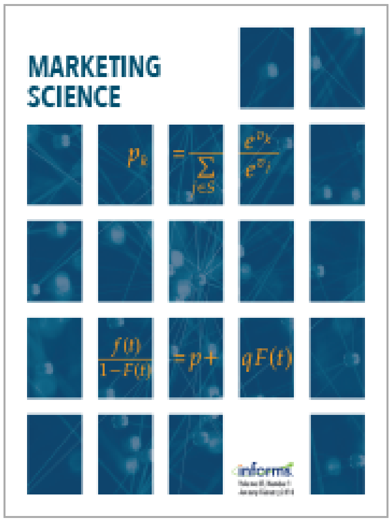

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Marketing Budget Allocation Across Countries: The Role of International Business Cycles

Yuri Peers,[a] Harald J. van Heerde,[b,c] Marnik G. Dekimpe[d,e]

[a] Erasmus University Rotterdam, 3062 PA Rotterdam, Netherlands; [b] Massey University, Auckland 0745, New Zealand; [c] CentER, Tilburg University, 5037 AB Tilburg, Netherlands; [d] Tilburg University, 5000 LE Tilburg, Netherlands; [e] KU Leuven, 3000 Leuven, Belgium

Contact: peers@ese.eur.nl (YP); heerde@massey.ac.nz (HJvH); m.g.dekimpe@uvt.nl (MGD)

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Abstract. A key conundrum facing organizations is how to adjust marketing budgets in response to the business cycle. While most firms use procyclical spending (spending less during economic contractions), academic studies often recommend countercyclical spending (spending more during contractions), which begs the following question: What is the right thing to do? The spending problem is compounded further when demand is not just driven by one country's business cycle, but by the (nonsynchronized) business cycles of multiple countries, as is the case for tourism marketing aiming to attract tourists originating from different countries. We derive insights into the best way to allocate marketing budgets across countries under varying economic conditions. We show that the allocation decisions are driven by the procyclical versus countercyclical nature of three factors: unit sales, marketing effectiveness, and per-unit profit contribution. To study how unit sales and marketing effectiveness respond to the business cycle, we develop a transfer function dynamic hierarchical linear model. We also model the responsiveness of the profit contribution to the business cycle. In an application to New Zealand tourism marketing, we find that a reallocation of the government's marketing budget could yield an increase in tourist revenues of NZD $121 million.

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1. Introduction

> In a boom, there is enough fat to absorb some bad judgment. In a recession, good management becomes a survival issue. (*Economist, The* 2002)

A key conundrum facing organizations is how to adjust marketing budgets in response to the business cycle. Is it better to lift expenditures during contractions (*counter*cyclical spending) or during expansions (*pro*cyclical spending)? The recent economic downturn further heightened these marketing-accountability concerns (Marketing Science Institute 2014, p. 6). During downturns, marketing budgets are typically under pressure, whereas during expansions, there is more scope for increases. This may explain why the predominant pattern observed in practice is to cut advertising support in economically tough times (Deleersnyder et al. 2009, Srinivasan et al. 2011) and to increase spending once economic conditions improve.

Such procyclical behavior stands in sharp contrast with the recommendations from most academic studies on the issue, which advocate countercyclical spending, i.e., to increase spending during contractions, and to cut back during expansions (Tellis and Tellis 2009).[1] Following a study on the cyclical sensitivity of advertising expenditures across 37 countries, Deleersnyder et al. (2009) conclude that "... [the company] should implement an advertising strategy that is inelastic—*or even anticyclical*—with respect to the business cycle" (p. 634, italics added). A similar conclusion is reached in Lamey et al. (2012), who study the impact of firms' cyclical marketing conduct on the private-label share evolution in over 100 consumer packaged goods (CPG) categories, and conclude "when the economy winds down, manufacturers should try to maintain their current spending *or even raise advertising* if that is financially feasible" (p. 15, italics added). Also Steenkamp and Fang (2011) recommend countercyclical spending, following their observation (based on a broad cross-section of over 1,000 firms across different industries) that advertising's effectiveness increases in economic downturns. Lamey et al. (2007) favor countercyclical national-brand spending as well, based on the cyclical dependence (found across different countries) of aggregate private-label shares. In a similar spirit, Talay et al. (2012) suggest that new products launched during mild recessions lead to higher sales.

In sum, there is a clear schism between marketing practice and marketing academia. Moreover, different studies offer a different motivation for their recommendation, and focus on the cyclical dependence of *either* the performance metric *or* advertising's effectiveness. What is lacking is a formal treatment of what determinants should drive procyclical versus countercyclical spending recommendations. We derive the new insight that whether procyclical or countercyclical marketing spending is preferable for an organization depends on the *trade-off* between *three* factors: (i) the sensitivity (elasticity) of unit sales (demand) to the business cycle, (ii) the sensitivity (elasticity) of marketing's effectiveness to the business cycle, and (iii) the sensitivity of the per-unit profit contribution to the business cycle. As Table 1 shows, no past research has considered the normative budget allocation implications of business cycle fluctuations.

A second contribution is that while the current literature has only looked at *one business cycle* at a time, there are many instances where organizations have to consider *business cycles for different countries* simultaneously, for example, in the context of export marketing or international tourism. We derive the allocation of a given marketing budget across countries and show how it depends on the business cycle in these countries.

A third contribution is the development of a new market response model. To gauge how unit sales and marketing effectiveness are driven by the business-cycle situation across multiple countries, we need a response model that addresses three key challenges. First, it needs time-varying parameters that are a function of the business cycle. Second, it needs to be able to cope with relatively few (annual) observations, because this is inherent to an empirical setting of (annual) budget allocation in response to the business cycle. Third, it needs to control for the endogeneity of marketing spend. To meet these challenges, we develop a transfer function dynamic hierarchical linear model (TF-DHLM). The model extends the dynamic hierarchical linear model (DHLM) by using covariates explaining cross-sectional and longitudinal parameter variation, reflected in the "transfer function" tag.[2]

In the application, we analyze international tourism to New Zealand. Tourism is a major economic sector

Table 1. Extant Business Cycle Research in Marketing

Study	Key substantial focus	Effect of business cycle on: Unit sales	Marketing effectiveness	Profit contribution	Formal normative implications
Deleersnyder et al. (2004)	The sales evolution of consumer durables over the business cycle	✓			
Lamey et al. (2007)	How business cycles contribute to private-label success	✓			
Deleersnyder et al. (2009)	Advertising's sensitivity to business cycles	✓			
Srinivasan et al. (2011)	The impact of the business cycle on firm performance and on the effectiveness of R&D and advertising	✓	✓	✓	
Steenkamp and Fang (2011)	The impact of the business cycle on the effectiveness of R&D and advertising	✓	✓		
Kamakura and Du (2012)	The impact of the business cycle on household budget allocation across expenditure categories	✓			
Lamey et al. (2012)	The impact of the business cycle on private-label share	✓			
Gordon et al. (2013)	The impact of the business cycle on price effectiveness	✓	✓		
Van Heerde et al. (2013)	The impact of the business cycle on price and advertising effectiveness	✓	✓		
Kumar et al. (2014)	The impact of the state of the economy on service purchase frequency, revenues, and customer experience effectiveness	✓	✓		
Lamey (2014)	The impact of the business cycle on discounters' market share	✓			
Dekimpe et al. (2016)	The impact of the business cycle on tourism numbers	✓			
This study	The impact of the business cycle on the allocation of the tourism marketing budget across countries	✓	✓	✓	✓

in the country. It is the second largest export industry (Statistics New Zealand 2015), making an adequate assessment on how to optimally insulate this sector from economic downturns of paramount importance. For New Zealand, very detailed arrival data are available. Because of the remote island nature of the country, (virtually) all travel is through flights or cruise ships, which enables detailed records of all incoming travel.

We find substantial variation in marketing effectiveness both across time and across countries. A key finding is that while unit sales move procyclically, marketing effectiveness moves even stronger in the countercyclical direction, whereas the revenue per visitor does not vary significantly with the business cycle. On balance, this implies a recommended *countercyclical* spending strategy. Furthermore, we find substantial differences between countries in their responsiveness to tourism marketing and in the elasticity of this responsiveness to the business cycle. This offers opportunities for a better allocation of the available budget across target countries. Our analysis suggests that a reallocation of the budget could yield a NZD $121 million annual increase in New Zealand's tourist revenues.

2. The Impact of the State of the Economy on Budget Allocation

We take the perspective of an organization (e.g., a national tourism agency) that sells goods or services (e.g., tourism to a destination country) around the world. We assume that the organization wishes to maximize annual profit. Profit from country i in period t equals unit sales q_{it} (e.g., the number of inbound tourists) times the profit contribution per demand unit p_{it} (e.g., average expenditure per tourist). In the context of international tourism, the expenditures per international visitor equal the profit contribution for the domestic economy because the marginal cost per visitor is (quasi) zero. In other words, profit maximization is the same as revenue maximization in this context. In other contexts, there will often be a nonzero cost, so the profit contribution becomes revenue per unit minus the cost per unit (e.g., Wright 2009).

The decision variable is the marketing expenditures for country i in period t (M_{it}), which is subject to a budget constraint. Quantity M_t is the total budget for marketing available for the focal period, which is, in line with Fischer et al. (2011), assumed to be given. Hence, we focus on the budget *allocation* decisions, rather than on determining its total size, as this is often done at another organizational level (Farris and West 2007). Also, we look at *absolute* expenditures because a manager has direct control over these, as opposed to *relative* expenditures expressed with respect to demand or competitive spending. Finally, we focus on how to allocate marketing budgets cross-sectionally in response to the state of the economy in the different target countries at a given point in time, as this is the type of problem that organizations such as national tourism agencies face. We do not consider how to make provisions in function of the expected future business-cycle evolution in the different countries, as this would entail a need to globally predict the business cycle in the future, a problem macroeconomists have also yet to resolve. Hence, unlike Fischer et al. (2011), we do not consider a multiyear planning horizon.

For the organization, the key challenge is to allocate its marketing budget across $i = 1, \ldots, n$ markets to maximize profit Π_t in period t

$$\underset{M_{it}}{\text{maximize}}\ \Pi_t = \sum_{i=1}^{n} p_{it} \times q_{it} - \sum_{i=1}^{n} M_{it}, \tag{1}$$

subject to the marketing budget constraint

$$\sum_{i=1}^{n} M_{it} \leq M_t. \tag{2}$$

Building on Fischer et al. (2011), the recommended expenditures in period t to country i can be shown to equal a fraction s_{it} of the total marketing budget M_t, with

$$s_{it} = \frac{W_{it}}{\sum_{j=1}^{n} W_{jt}}, \tag{3}$$

and W_{it} (the weight for country i) given by

$$W_{it} = q^*_{it} \times \varepsilon_{q^*_{it}} \times p_{it}, \tag{4}$$

where q^*_{it} is the level of optimized unit sales, $\varepsilon_{q^*_{it}}$ is the elasticity of unit sales with respect to marketing expenditures at the optimum

$$\varepsilon_{q^*_{it}} = \frac{\partial q_{it}}{\partial M_{it}} \frac{M_{it}}{q^*_{it}},$$

and p_{it} is the per-unit profit contribution. Equation (4) shows, ceteris paribus, that a country obtains a higher allocation if its unit sales q^*_{it} are higher, if its responsiveness $\varepsilon_{q^*_{it}}$ is stronger, and if its profit contribution per unit p_{it} is higher. The intuition is that the marketing expenditure needs to be proportional to the potential profit yield from a country, which is the product of the size of demand, how responsive demand is to marketing, and the per-unit profit contribution.

In a practical situation, Equation (4) cannot be applied directly, as it describes a relationship where q^*_{it} needs to be in its optimum. Therefore, in an applied setting, we need a heuristic (Fischer et al. 2011), which we also use later in Section 6.

Equation (4) helps us in understanding the impact of the business cycle on the allocation decision. We define BC_{it} to reflect the business cycle in country i in year t. The partial derivative of the allocation weight s_{it} to the business cycle ($\partial s_{it}/\partial BC_{it}$) tells us whether the weight increases ($\partial s_{it}/\partial BC_{it} > 0$) or decreases ($\partial s_{it}/\partial BC_{it} < 0$) when the business cycle improves. Ceteris paribus, an increase in weight means that the focal country i in year t should receive a higher fraction of the marketing budget in year t, while a decrease in weight implies a lower fraction.

We can express the elasticity of the allocation weight

$$\varepsilon_{\text{weight}} = \frac{\partial s_{it}}{\partial BC_{it}} \frac{BC_{it}}{s_{it}}$$

as (see Online Appendix A)

$$\varepsilon_{\text{weight}} = \varepsilon_{\text{demand}} + \varepsilon_{\text{mark.eff.}} + \varepsilon_{\text{profit}}, \tag{5}$$

with

$\varepsilon_{\text{demand}} = \dfrac{\partial q^*_{it}}{\partial BC_{it}} \dfrac{BC_{it}}{q^*_{it}}$ the elasticity of unit sales to the business cycle,

$\varepsilon_{\text{mark.eff.}} = \dfrac{\partial \varepsilon_{q^*_{it}}}{\partial BC_{it}} \dfrac{BC_{it}}{\varepsilon_{q^*_{it}}}$ the elasticity of marketing effectiveness to the business cycle, and

$\varepsilon_{\text{profit}} = \dfrac{\partial p_{it}}{\partial BC_{t}} \dfrac{BC_{it}}{p_{it}}$ the elasticity of the profit contribution to the business cycle.

The intuition for Equation (5) is that given that the allocation weight (Equation (4)) is the product of (i) size of demand, (ii) marketing effectiveness, and (iii) per-unit profit contribution, the elasticity of the allocation weight to the business cycle is the sum of the elasticities of (i)–(iii) to the business cycle. Equation (5) shows that the elasticity of the allocation weight $\varepsilon_{\text{weight}}$ depends on the trade-off among the three components on the right-hand side. Each of these components may vary with the business cycle. As for the first component: in an expansion period, unit sales q^*_{it} could be higher, which can be expected for durables (Deleersnyder et al. 2004) and also for luxury goods such as international tourism. For other products, unit sales may be lower during an economic expansion, as consumers switch away from groceries (Van Heerde et al. 2013) or private labels (Lamey et al. 2007, 2012). Thus, depending on the setting, $\varepsilon_{\text{demand}}$ may be positive or negative.

The second component, demand elasticity for marketing spend $\varepsilon_{q^*_{it}}$, may vary as economic conditions change. Two opposing forces are at work. The positive force during an expansion is that consumers have more money to spend (Mehra 2001), and/or are more willing to spend it (Katona 1975). This makes them more receptive to marketing investments (Kamakura and Du 2012), and hence $\varepsilon_{\text{mark.eff.}} > 0$. The negative force is that during a period of economic expansion, competitors increase their advertising expenditures (Deleersnyder et al. 2009). This leads to more competition for customers' attention (Danaher et al. 2008), which could make expenditures during expansions less effective: $\varepsilon_{\text{mark.eff.}} < 0$. Also, the price per advertising unit (broadcasting seconds, print pages, …) may go up during expansions, allowing for fewer exposures with the same budget (Steenkamp and Fang 2011), again leading to $\varepsilon_{\text{mark.eff.}} < 0$.

A third component affecting how the allocation weight changes over the business cycle is the profit contribution p_{it}. When there is an expansion and the consumers' willingness to pay goes up, firms may be able to earn higher margins (Deleersnyder et al. 2004) and $\varepsilon_{\text{profit}} > 0$. Conversely, some firms raise prices and margins during a downturn to make up for the loss in demand (Backus and Kehoe 1992, Marn et al. 2003) and hence $\varepsilon_{\text{profit}} < 0$. A downturn may also cause less affluent consumers to stay out of the market, increasing the average willingness to pay or expenditures for the remaining consumers.

In sum, there are theoretical and practical reasons why each of the three elasticities on the right-hand side of (5) could be negative or positive. Hence to determine how the net allocation weight changes in response to the business cycle, we need models that allow us to estimate the three elasticities: $\varepsilon_{\text{demand}}$, $\varepsilon_{\text{mark.eff.}}$, and $\varepsilon_{\text{profit}}$. We develop these models next.

3. Model Development

Both the elasticity of unit sales to the business cycle ($\varepsilon_{\text{demand}}$) and the elasticity of marketing effectiveness to the business cycle ($\varepsilon_{\text{mark.eff.}}$) require a model where demand is the dependent variable. We develop this model first, after which we present the model for the profit contribution, which allows us to estimate its elasticity to the business cycle, $\varepsilon_{\text{profit}}$.[3]

3.1. Demand Model

The model is for aggregate demand q_{it} in period t to country (market) i. We aim to capture both cross-sectional and longitudinal variation in demand and marketing effectiveness. The challenge is to do this in an efficient way, because we essentially need parameters for every time and cross section combination. The model should also allow for covariates explaining longitudinal and/or cross-sectional parameter variation, given our interest in quantifying the impact of the business cycle on marketing effectiveness.

Even though the business cycle is technically defined through changes in many economic indicators and sectors, it is well accepted that fluctuations in aggregate output are at the core of the business cycle (Deleersnyder et al. 2004, Stock and Watson 1999). A country's business cycle is therefore often inferred from the cyclical component in the country's GDP (typically in per-capita terms). Apart from the business cycle (denoted as BC_{it}), also the long-run trend in a country's GDP/capita (denoted as $EconTrend_{it}$) is likely to drive the overall demand evolution. We will explicitly account for both sources of longitudinal variation in our model specification. Exact operationalizations of both components are provided in Section 4.

In line with Fischer et al. (2011), we decompose demand into two components

$$q_{it} = g_i(t) \times f_i(M_{it}, BC_{it}, H_{it}), \tag{6}$$

with $g_i(t)$ a growth function describing the underlying demand over time, and $f_i(\cdot)$ a response function that measures the impact of the business cycle (BC_{it}), marketing (M_{it}), and a vector of control variables H_{it}. We can linearize Equation (6) by taking logs of both sides

$$\ln q_{it} = \ln g_i(t) + \ln f_i(M_{it}, BC_{it}, H_{it}). \tag{7}$$

For the *response function*, we adopt a log-log specification

$$\begin{aligned}\ln f_i(M_{it}, BC_{it}, H_{it}) \\ = \theta_{1it} \ln M_{it} + \gamma_{1i} \ln BC_{it} + \ln H_{it}\gamma_{2i} + u_{1it},\end{aligned} \tag{8}$$

where θ_{1it} is the marketing elasticity for country i and period t. Equation (7) combined with (8) yields

$$\ln q_{it} = \ln g_i(t) + \theta_{1it} \ln M_{it} + \gamma_{1i} \ln BC_{it} + \ln H_{it}\gamma_{2i} + u_{1it}. \tag{9}$$

Equation (9) is a model in levels, which could serve as the main demand model. In many time-series settings (including ours; see Section 4), however, variables are evolving, which means we need to take first differences

$$\begin{aligned}\Delta \ln q_{it} = \ln g_i(t) - \ln g_i(t-1) + \theta_{1it} \Delta \ln M_{it} \\ + \gamma_{1i} \Delta \ln BC_{it} + \Delta \ln H_{it}\gamma_{2i} + \nu_{1it}.\end{aligned} \tag{10}$$

For *the growth factor* $g_i(t)$ we use a flexible, yet parsimonious, specification such that the change in the growth from one year to another equals

$$\ln g_i(t) - \ln g_i(t-1) = \theta_{0it}. \tag{11}$$

After substituting (11) into (10), we obtain as the final demand model

$$\begin{aligned}\Delta \ln q_{it} = \theta_{0it} + \theta_{1it} \Delta \ln M_{it} + \gamma_{1i} \Delta \ln BC_{it} \\ + \Delta \ln H_{it}\gamma_{2i} + \nu_{1it}.\end{aligned} \tag{12}$$

We now discuss the parameter processes for the time-varying intercept θ_{0it} and the time-varying marketing elasticity θ_{1it}. We model θ_{0it} as a function of the economic growth, where economic growth is the year-on-year change in the long-run economic trend (i.e., $\Delta \ln EconTrend_{it} = \ln EconTrend_{it} - \ln EconTrend_{it-1}$)

$$\theta_{0it} = \theta_{0t} + \psi_{0i} + \psi_{1i} \Delta \ln EconTrend_{it} + \nu_{20it}. \tag{13}$$

In (13), ψ_{0i} is a country-specific intercept and ψ_{1i} captures the effect of the change in economic trend on demand growth. In (13), θ_{0t} is a general growth parameter, flexibly modeled as

$$\theta_{0t} = \theta_{0t-1} + \omega_{1t}. \tag{14}$$

In line with the notion that the marketing elasticity may vary in response to changes in the (log) business cycle, we specify

$$\theta_{1it} = \theta_{1t} + \psi_{2i} \Delta \ln BC_{it} + \nu_{21it}. \tag{15}$$

In line with Gatignon (1993), (15) has an error term ν_{21it} in the parameter process function, accounting for unobserved factors other than the business cycle that affect marketing effectiveness. The error term distributions are discussed in Online Appendix B. In (15), θ_{1t} captures a general pattern in marketing elasticity, modeled as

$$\theta_{1t} = \theta_{1t-1} + \omega_{2t}. \tag{16}$$

This reflects that, over time, there may have been a change in marketing effectiveness that is unrelated to the business cycle. For example, in recent decades, the advertising elasticity in many markets has decreased (see, for example, Sethuraman et al. 2011). This has been attributed to an increased media proliferation, maturing markets, and the rise of the Internet, among others. Since the composite effect of these developments may be nonlinear in nature, we capture this potential change in marketing effectiveness in a flexible way through a random walk in (16).

In Section 5, we consider, in line with Fischer et al. (2011), two extensions to this base specification: we allow marketing spend to also have an effect in the growth function, and to have dynamic (carryover) effects in the response model.

3.1.1. Elasticities Required for Allocation. The model allows us to calculate two of the three elasticities required for (5). The elasticity of unit sales to the business cycle is given by $\varepsilon_{\text{demand}} = \gamma_{1i}$. The elasticity of marketing effectiveness to the business cycle is derived from the linear-log specification in Equation (15), and is equal to the response parameter for the business cycle (ψ_{2i}) divided by the marketing elasticity (θ_{1it})

$$\varepsilon_{\text{mark.eff.}} = \frac{\partial \theta_{1it}}{\partial BC_{it}} \frac{BC_{it}}{\theta_{1it}} = \frac{\psi_{2i}}{\theta_{1it}}.$$

3.1.2. TF-DHLM. We cast model (12) as the observation equation in a TF-DHLM by defining $Y_{it} = \Delta \ln q_{it}$, $F_{1it} = [1\ \Delta \ln M_{it}]$, $K_{it} = [\Delta \ln BC_{it}\ \Delta \ln H_{it}]$, leading to

$$Y_{it} = F_{1it}\theta_{it} + K_{it}\gamma_i + \nu_{1it}, \tag{17}$$

where $\theta_{it} = (\theta_{0it}, \theta_{1it})'$ is the parameter vector specific for cross-section i and time period t; $\gamma_i = (\gamma_{1i}, \gamma_{2i})'$. The error term is ν_{1it}, which is allowed to have a heteroskedastic variance $\sigma^2_{\nu_1, i}$.

We rewrite (13) and (15) compactly as a structural equation that governs the longitudinal and cross-sectional parameter variation

$$\theta_{it} = F_{2t}\theta_t + X_{it}\psi_i + \nu_{2it}, \tag{18}$$

where F_{2t} is the mapping function, which shrinks the cross-sectional-specific time-varying parameters θ_{it} onto an underlying time-varying hyperparameter θ_t. This mapping function is part of the original DHLM (Gamerman and Migon 1993, Neelamegham and Chintagunta 2004). The "transfer function" that our model adds is $X_{it}\psi_i$, which captures the effect of covariates (X_{it}) on θ_{it} using heterogeneous parameters (ψ_i). In the application, the time-varying covariate of interest is the business cycle for country i in year t, and (15) allows us to study how it drives the responsiveness to tourism marketing spend (θ_{1it}).

Next, the system equation specifies how the hyperparameter varies over time

$$\theta_t = G\theta_{t-1} + \omega_t, \quad \text{where } \omega_t \sim N(0, \sigma^2_\omega). \tag{19}$$

Matrix G is set to an identity matrix (West and Harrison 1999), allowing for a random walk in the response parameters. This random-walk specification is well suited to approximate many dynamic patterns in response parameters. Next, we shrink the cross-sectional variation in γ_i

$$\gamma_i = \bar{\gamma} + u_{1i}, \quad \text{where } u_{1i} \sim N(0, \sigma^2_{u_1}), \tag{20}$$

while ψ_i is shrunk to its common hypermean

$$\psi_i = \bar{\psi} + u_{2i}, \quad \text{where } u_{2i} \sim N(0, \sigma^2_{u_2}). \tag{21}$$

We estimate the model with Bayesian methods, explained in Online Appendix B.

3.1.3. Endogeneity. The key independent variable in our model, marketing spend, is possibly endogenous. To correct for endogeneity, we estimate the observation equation, (17), together with equations for the endogenous variables with instrumental variables and exogenous variables on the right-hand side, and correlate the error terms (e.g., Greene 2000, p. 679; Ataman et al. 2010). We split the independent variables into those that are endogenous and those that are exogenous, $[F^{\text{Endo}}_{it}, F^{\text{Exo}}_{it}]$:

$$\begin{bmatrix} Y_{it} \\ F^{\text{Endo}}_{it} \end{bmatrix} = \begin{bmatrix} F^{\text{Endo}}_{it}, F^{\text{Exo}}_{it} & 0 \\ 0 & F^{\text{Exo}}_{it}, Z^{\text{IV}}_{it} \end{bmatrix} \begin{bmatrix} \theta_{it} \\ \gamma_{\text{Endo},1i} \end{bmatrix} + \begin{bmatrix} K_{it}\gamma_i \\ K_{it}\gamma_{\text{Endo},2i} \end{bmatrix} + \begin{bmatrix} \nu_{1it} \\ \nu_{\text{Endo},it} \end{bmatrix}, \tag{22}$$

with

$$\begin{bmatrix} \nu_{1it} \\ \nu_{\text{Endo},it} \end{bmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{bmatrix} \sigma^2_{\nu_1,i} & \sigma_{12} \\ \sigma'_{12} & \sigma^2_{\text{Endo},i} \end{bmatrix} \right).$$

In Equation (22), Z^{IV}_{it} are the instrumental variables, which are operationalized for the empirical context in Section 4.

3.2. Model for Profit Contribution

We also need to assess how the business cycle impacts the profit contribution. We use a classical log–log model to estimate this impact

$$\ln p_{it} = \gamma_{3i} + \gamma_{4i}\Delta \ln BC_{it} + \ln H_{1it}\gamma_{5i} + \varepsilon_{it}, \tag{23}$$

where H_{1it} is a vector of control variables for the profit contribution. This model is rather simple by necessity, because in the empirical application we only have 112 observations (eight countries, 14 annual observations per country). In a more complete data setting, the model can be expanded accordingly. In the empirical setting, $\ln p_{it}$ and $\ln H_{1it}$ are stationary, so we keep them in levels (more details in Section 4 below). We estimate model (23) with hierarchical Bayes. The model gives us the elasticity of the profit contribution to the business cycle as $\varepsilon_{\text{profit}} = \gamma_{4i}$.

4. Empirical Application: Tourism Marketing

International tourism has become a major part of the global economy. In 2012, tourism income was USD $1.3 trillion, representing 30% of the export of services, and 6% of the total worldwide export (UNWTO 2013a, b). Because of this potential, many governments invest in tourism marketing to promote their country as an attractive travel destination.[4] Among the biggest spenders are the United Kingdom (USD$160 million), the United States (USD$150 million), and Australia (USD$107 million; Edelson 2012). Even a relatively small country such as New Zealand spends over NZD$73 million (USD$63 million) per year on tourism marketing (Tourism New Zealand 2011). While the total budget is typically a government decision, the subsequent allocation over countries (regions) is performed by statutory entities, such as Brand USA, Tourism Australia, or Tourism New Zealand. We focus on the allocation decision that these entities face.

4.1. Marketing Literature on Tourism

In spite of the economic importance of tourism, a review of the six major marketing journals revealed that only a handful of studies have looked at tourism issues.[5] A few of these studies try to explain tourism demand. These include time-series (Geurts and Ibrahim 1975) and gravitational (Crampon 1966) models to forecast the number of tourists, and decision-support models for allocating tourism marketing expenditures (e.g., Gearing et al. 1973, Mazanec 1986). These studies, however, do not consider the role of the business cycle. A notable exception is the study by Kumar et al. (2014), which investigates how the state of the economy moderates the effects of customer experience factors on customers' service purchase behaviors using survey data from a single international airline carrier during the 2008–2011 financial crisis. Recently, Dekimpe et al. (2016) quantified the cyclical sensitivity of international tourism demand, which they found to be more volatile than the economy as a whole. However, they did not consider the cyclical sensitivity in marketing effectiveness—a key component in our framework, nor did they infer the optimality of countercyclical versus procyclical spending—the key focus of the current study.

4.2. Tourism Literature

Outside marketing, a large literature on the drivers of (international) visitor numbers has developed. Song et al. (2009, Table 2.1) give an extensive overview of dozens of econometric studies on tourism-demand modeling. The studies are characterized by a wide variety of choices for the dependent variable, for the drivers that are considered, for the econometric model, for the region that is studied, for the length of the time window, and for the data frequency. At the same time, there are some commonalities across studies (Song et al. 2009, Chapter 1). The most common dependent variable is tourist arrivals. The most commonly included drivers are *income* in the country of origin, *costs of travel* to the destination, and the *cost of living* for tourists in the destination (e.g., Crouch 1996). Population size is often captured by using per-capita variables (Song et al. 2009, p. 3). The most common functional form is a log–log model, and the most common data frequency is annual data. Importantly, "*Marketing has not often featured in tourism demand models*" (Song et al. 2009, p. 6; italics added).

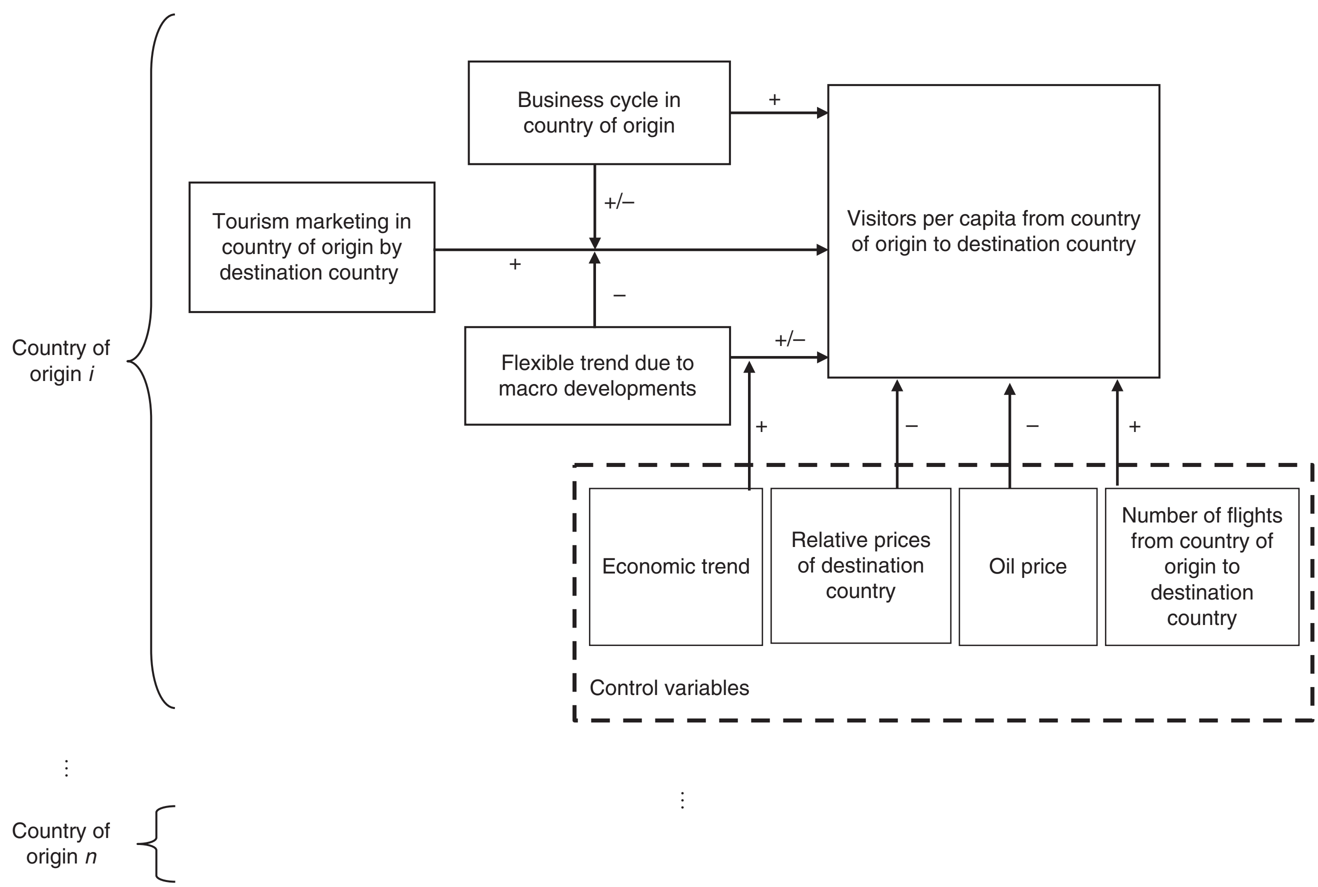
4.3. Conceptual Framework

Based on the literature, we propose the framework of Figure 1.

4.4. Dependent Variables

The dependent variable ($\Delta \ln q_{it}$) for the demand model (12) is the year-on-year change in the log annual number of holiday visitors per capita to a destination country, for each individual country of origin. In the application, we analyze holiday tourism to New Zealand. The detailed arrival records go back decades and record the purpose of travel (e.g., holiday versus business). This allows us to model the number of holiday visitors, who are most commonly targeted by the country's tourism-marketing efforts. We study the 18 countries with the most arrivals to New Zealand, which, combined, cover more than 85% of the total number of the country's foreign holiday visitors.[6] On

Figure 1. Conceptual Framework



average, the most visitors came from Australia, followed by the United States, Japan, and the United Kingdom (see Online Appendix Table C1). Figure 2 shows for five key markets how visitor numbers to New Zealand have developed over time. The (per-capita) numbers from Australia have grown steeply, especially in the past two decades. More recently, the inflow from China has risen spectacularly. Visitor numbers from Japan (the United Kingdom) peaked in the 1990s (2000s), but have retreated from those heights. Visitor numbers from the United States, in turn, show several peaks and troughs over time. Table 2 offers variable definitions and descriptive statistics.

The dependent variable ($\ln p_{it}$) for the profit-contribution model, Equation (23), is the log average expenditure per visitor. The New Zealand Ministry of Business, Innovation and Employment has collected annual survey data for eight major visiting countries since 1998, and we use the data from 1998–2011 (14 years).

4.5. Tourism Marketing

The focal independent variables are the marketing expenditures set by the destination country and the business cycle of the country of origin.[7] We expect a positive *main* effect of marketing expenditures, as they will enhance the preference for the country in question among prospective visitors. As tourism is a positional good, we expect a positive main effect for the business cycle as well (Kamakura and Du 2012).[8]

Figure 2 shows how the tourism marketing budget has been spent. The records from Tourism New Zealand (1981–2011), the organization responsible for marketing New Zealand to the world, distinguish between five regions: Australia, North America, Japan, Europe, and Asia other than Japan (Asia for short). The time series for tourism marketing vary across regions, ranging from a mostly steady increase (Australia) to very strong swings (Asia). In our model, we use the total budget per region as an independent variable (M_{it}) explaining the visitors per country in the various regions.[9] Discussions with industry experts confirmed that budgets are indeed set per region rather than per country. This is also backed up by the annual reports from Tourism New Zealand, discussing marketing expenditures and activities targeting regions (groups of countries) rather than individual countries.

4.6. Business Cycle

The business-cycle component is the focal moderating variable in our study. After a logarithmic transformation of the original GDP per-capita series, we extract the cyclical component through the well-known CF-filter (Christiano and Fitzgerald 2003). We next compute the change relative to the most recent trough or peak rather than to the previous year (e.g., Lamey et al. 2007, Van Heerde et al. 2013). This is in line with the notion that consumers gauge economic conditions relative to the most recent high or low (Siems 2012). We define

$$\Delta \ln BC_{it} \equiv \begin{cases} \ln GDP_{CF,it} - \text{prior trough in } \ln GDP_{CF,it} \\ \quad \text{if } \Delta \ln GDP_{CF,it} > 0 \\ -(\text{prior peak in } \ln GDP_{CF,it} - \ln GDP_{CF,it}), \\ \quad \text{if } \Delta \ln GDP_{CF,it} \le 0 \end{cases} \quad (24)$$

where $\ln GDP_{CF,it}$ is the CF-filtered log-transformed GDP per-capita series for country i in year t.

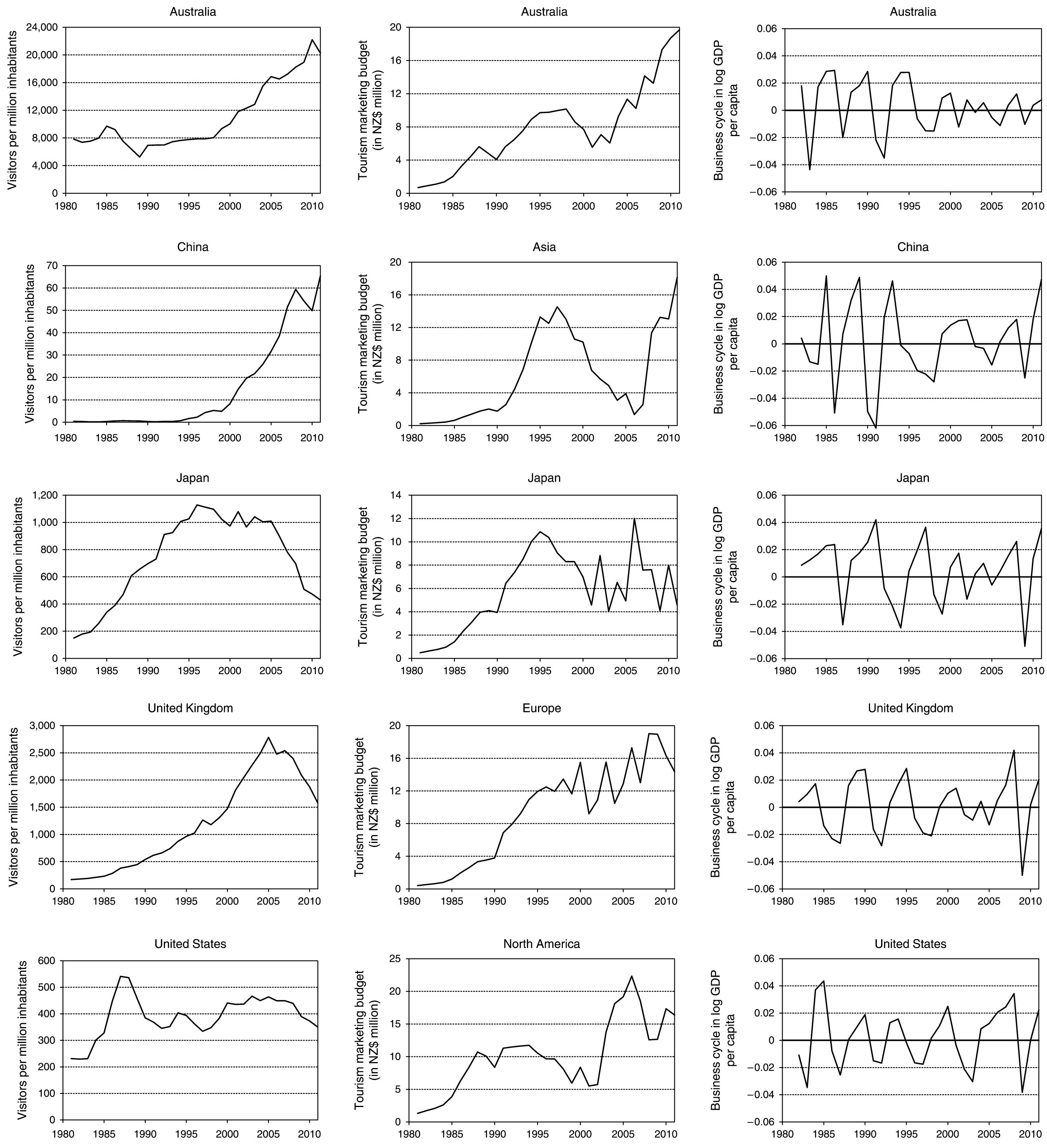
We use "$\Delta \ln BC_{it}$" as the label to indicate that this is a change variable that is measured on a log scale. The parameter estimate for its effect on demand (also measured on a log scale) can be interpreted as an elasticity (Deleersnyder et al. 2009; Lamey et al. 2007, 2012). Figure 2 shows the business-cycle metric ($\Delta \ln BC_{it}$) for the same five key markets. There are some stark differences between countries in terms of the evolution of their business cycle. Whereas the global financial crisis (2009–2010) caused the deepest trough for the United States, the United Kingdom, and Japan, it was not as severe in China or Australia. Instead, the downturns in these two countries were much more pronounced in the 1980s and 1990s. The timing of peaks and troughs is not entirely synced either. For instance, Japan went through a deep downturn around 1993–1995, whereas Australia experienced a strong upturn in the same period. The correlations between the business cycles range from 0.90 (Malaysia and Thailand) to −0.23 (United States and Indonesia), with an average correlation of 0.36, well below unity.

4.7. Control Variables

We also need to control for other important drivers of tourism demand based on the review by Song et al. (2009, Chapter 1). Equation (13) includes a fixed effect for each country of origin (i.e., ψ_{0i}) to account for time-invariant factors, such as the distance to the destination country. Equation (13) also controls for economic growth via $\Delta \ln EconTrend_{it}$, where $\ln EconTrend_{it} = \ln GDP_{it} - \ln GDP_{CF,it}$, and where $\ln GDP_{it}$ is the log-transformed GDP per capita and $\ln GDP_{CF,it}$ is the cyclical component also used in (24).

Equation (12) includes a vector $\ln H_{it}$ of three control variables. One is the relative price of the destination country, as is common in the tourism literature (Song et al. 2009, p. 29). It is the exchange rate between the country of origin and the destination country, corrected by the consumer price index of both countries (Li et al. 2006). We expect a negative effect of the log relative price ($\ln Price_{it}$) on the number of visitors. To control for the cost of travel to the destination country, we use the log oil price ($\ln OilPrice_{it}$). This is a proxy for airline-ticket prices, with an expected negative effect on visitor numbers.[10] To capture the availability of travel options to

Figure 2. Holiday Visitors to New Zealand, Tourism Marketing Budgets, and Business Cycle for Five Key Markets



the destination country, we use $\ln Flights_{it}$, the log number of flights per capita from the country of origin to the destination country (Hanssens 1980). More access via more flights should enhance the number of visitors. In robustness checks (see Section 5), we extend the set of control variables with the price of competing destinations and lagged tourism marketing expenditures. None of these additional terms is significant.

For the profit-contribution model (Equation (23)), we include in the vector of control variables $\ln H_{1it}$ the economic trend ($\ln EconTrend_{it}$), log relative price, and log oil price because these variables are likely to directly impact the (remaining) budgets that visitors can spend.

Tables C2 and C3 in Online Appendix C give the correlations between the model variables for Equations (12) and (23), respectively. The tables show that

Table 2. Variable Definitions and Descriptive Statistics

Symbol	Operationalization	Source	Mean[a] (s.d.)	Minimum	Maximum
$\ln q_{it}$	Log number of visitors to New Zealand, per one million inhabitants for country i in year t	*Visitors*: Statistics New Zealand *Population*: Oxford Economics	5.84 (2.06)	−1.75	10.01
$\ln M_{it}$	Log tourism marketing budget (in NZD$ millions) set by New Zealand in year t, allocated to the region to which country i belongs	Tourism New Zealand (Annual reports)[b]	1.57 (1.19)	−1.53	3.11
$\Delta \ln BC_{it}$	Business cycle component, computed according to Equation (24)	Oxford Economics	0.003 (0.033)	−0.132	0.101
$\ln p_{it}$	Log profit contribution: log average expenditure (in NZD$) per visitor from country i in year t	International Visitors Survey, available through Statistics New Zealand	8.23 (0.258)	7.65	8.68
Control variables					
$\ln Price_{it}$	Log of relative price of New Zealand, where relative price is defined as the exchange rate multiplied by the ratio of the consumer price index (CPI) of New Zealand and country i (e.g., Li et al. 2006) $[(CPI_t^{NZ}/CPI_{it}) \cdot ExchangeRate_{it}]$	*Exchange Rate*: International Financial Statistics (IMF) *CPI*: National Statistics bureaus (e.g., Australian Bureau of Statistics)	1.74 (2.35)	−0.99	7.88
$\ln OilPrice_{it}$	Log of price of crude oil (USD$ per barrel) in year t	OECD Economic Outlook	3.33 (0.56)	2.51	4.53
$\ln Flights_{it}$	Log number of flights to New Zealand, per one million inhabitants for country i in year t[c]	*Flights*: OAG Aviation *Population*: Oxford Economics	2.67 (2.20)	0	6.86
$\ln EconTrend_{it}$	Log economic trend: The noncyclical component of log gross domestic product (GDP) per capita in constant prices of country i in year t	Oxford Economics	9.74 (0.93)	6.34	10.90

[a]The statistics are reported for the ln-transformed series prior to differencing.

[b]For all years, the annual reports give the total budget, and for most years it gives the regional budgets. The information per region was not available before 1988 and was missing in 1990 and 1992–1994. For the period 1981–1987, we used the observed regional allocation in 1988 to obtain regional budgets, allowing us to retain these initial seven years of data (we checked the appropriateness of this procedure with industry experts). We also ran a robustness check (reported in Online Appendix D) omitting the pre-1988 data, leading to similar findings. We use linear interpolation to obtain regional budgets for 1990 and 1992–1994.

[c]Because there are no nonstop flights from Europe to New Zealand, we calculate the relative availability of flights over time by the total number of flights available from the major hubs in the Asian countries and the West Coast of North America (i.e., Los Angeles, San Francisco, and Vancouver).

multicollinearity is not a concern since all correlations between independent variables are 0.35 or less in magnitude.

4.8. Unit Roots

We conduct the Im et al. (2003) panel unit-root test to test for stationarity of the variables in the demand model (12). We use the Akaike Information Criterion (AIC) to determine the optimal lag length, with a maximum of seven. We cannot reject the null hypothesis of a unit-root ($p > 0.10$) for visitor numbers, advertising, number of flights per capita, relative price, and economic trend. After taking first differences, we reject ($p < 0.05$) the unit-root null, indicating stationarity of the variables in differences. For oil price, we use a regular augmented Dickey–Fuller unit-root test because the series is the same for each country, and conclude that we cannot reject the unit-root null hypothesis ($p > 0.10$) either. After taking first differences, we again reject the unit-root null ($p < 0.05$). Hence, all variables enter model (12) in first differences, as expressed by the Δ symbol. For the profit contribution model (23), only 14 observations per series are available. Because of this, we restrict the maximum lag length to one. The unit-root tests conclude that neither $\ln p_{it}$ nor the variables in $\ln H_{1it}$ have a unit root ($p < 0.05$) for these 14 years. Hence these variables enter model (23) in levels.

4.9. Instrumental Variables

We treat the marketing expenditure variable as a potentially endogenous variable. As instrumental variables (IVs), we need variables that correlate with marketing budgets, but that are unlikely to be related to the error term in visitor numbers. First, two reorganizations took place (in 1991 and 1999) in the governance structure of Tourism New Zealand (Tourism New Zealand 1992, 2000). These reorganizations are likely to affect budget decisions, but are not related to changes in demand. As an IV, we use an indicator variable for these reorganizations. In line with the tradition of using IVs based on other markets (e.g., Nevo 2001, Ma et al. 2011), we use the marketing expenditures for the *other* four regions as IVs, since these are unlikely to affect demand from the focal region. For example, for Australia, these are the expenditures for North America, Europe, Asia, and Japan. These variables serve as independent variables (in first difference) in the system. To avoid overlap between IVs and independent variables elsewhere in the system, we use the expenditures for the other regions observed at $t-2$ as IVs. Together the five IVs are sufficiently strong ($p < 0.01$; pooled incremental F-test for instrument strength) and valid ($p > 0.10$; pooled Sargan test for overidentification).

5. Model Estimation Results

Table 3 shows the estimation results for the demand model (12). The model has a good model fit, as measured by a correlation of 0.97 between the actual and predicted dependent variable. For the parameter estimates, we first focus on the hyperparameters, which hold for the average country. As for the control variables, the hyper price elasticity is negative (−0.16) and significant, as expected.[11] The more expensive the destination country for visitors, the fewer visitors will come. The hyper oil-price elasticity has the expected negative effect (−0.02), but is not significant. The hyperparameter estimate for the number of flights is, in line with Hanssens (1980), positive (0.14) and significant, reflecting that better connections to the destination country enhance visitor numbers. Thus, the face validity of the control variables is good.

5.1. Impact of Tourism Marketing and Business Cycle on Demand

Marketing has, as expected, a significant positive effect on the number of visitors. Its hyperelasticity estimate of 0.14 is close to the 0.12 short-term meta-analytic advertising elasticity reported in Sethuraman et al. (2011). The hyperparameter for the business cycle (0.54) is positive and significant. Thus, unit sales move

Table 3. Estimation Results Demand Model and Robustness Checks

			Benchmark models: Additional variables			Benchmark models: Alternative specifications	
	Expectation	TF-DHLM	BM1 tourism marketing in growth function	BM2 lagged tourism marketing	BM3 competitor price	BM4 DHLM with just intercept time varying	BM5 partial adjustment model
Key response parameters							
Tourism marketing elasticity[a]	+	0.14***	0.11***	0.13***	0.10**	0.09**	0.10**
Business cycle elasticity	+	0.54**	0.46**	0.54**	0.52**	0.25	0.35*
Moderating effect of business cycle on tourism marketing elasticity	+/−	−2.07***	−1.73**	−1.94***	−1.95**	−1.91***	−3.06***
Response parameters in growth function							
Elasticity to economic growth	+	2.94***	3.19***	2.80***	3.09***	3.02***	2.90***
Elasticity to tourism marketing on the growth function	+		0.01				
Response parameters for control variables							
Relative price elasticity	−	−0.16**	−0.16**	−0.15**	−0.07	−0.17**	−0.16***
Oil price elasticity	−	−0.02	−0.02	−0.01	−0.03	−0.02	−0.06**
Number-of-flights elasticity	+	0.14***	0.13***	0.14***	0.13***	0.13***	0.08**
Lagged tourism marketing elasticity	+			0.04			
Competitor price elasticity	+/−				−0.11		
Lagged visitors elasticity	+/−						0.07
Deviance information criterion		−12.86	−12.86	−12.82	−12.87	−12.80	−10.80
Correlation between actual and predicted dependent variable		0.97	0.97	0.92	0.97	0.96	0.58

Note. This interval is tested one-sided when we expect a specific direction of the effect as expressed in the Expectation column and two-sided otherwise.
[a]Mean across time.
*Significance at the 10% level; **significance at the 5% level; ***significance at the 1% level based on the highest posterior density interval.

procyclically, and a 1% improvement in the business cycle in the country of origin leads to a 0.54% increase in the number of tourists originating from that country.

Importantly, the hyperparameter for the effect of the business cycle on tourism marketing's effectiveness is significant and negative (−2.07). This implies that marketing's impact moves countercyclically. It becomes more effective during downturns, consistent with a reduced competitive clutter in such times (Danaher et al. 2008) and more reach for the same budget (Steenkamp and Fang 2011).

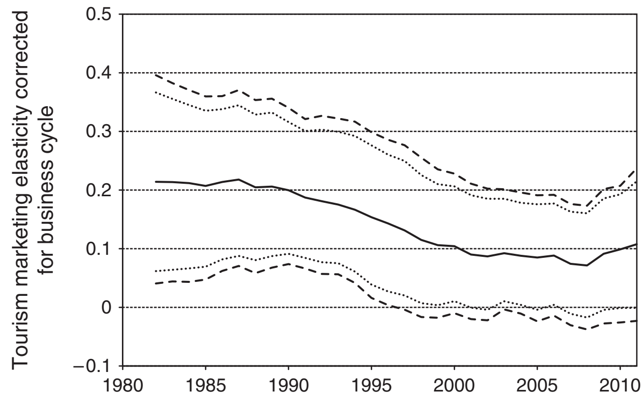
5.2. Evolution in Marketing Effectiveness Over Time

Figure 3 shows, for the past three decades, the evolution in tourism marketing effectiveness that is unrelated to the business cycle (i.e., θ_{1t} in Equation (15)). Figure 3 shows an overall decline in the tourism marketing elasticity over time. The elasticity starts around 0.2 in the 1980s, but slides back to less than 0.1 in the most recent decade, with a bit of recovery near the end. This pattern is consistent with the general downward trend in advertising effectiveness documented in Sethuraman et al. (2011).

5.3. Impact of Business Cycle on Profit Contribution

Table 4 shows the results for the profit-contribution model (23). The fit is good, with a correlation of 0.89 between the actual and predicted dependent variable. While the hypermean for the business cycle elasticity is negative (−0.27), it fails to reach significance. It is also not significant for any of the eight individual countries. Thus, in this context, there appears to be no significant effect of the business cycle on the profit contribution.[12]

Figure 3. Overall Trend in Tourism Marketing Elasticity (TF-DHLM)



Notes. The tourism marketing elasticity is part of the elasticity that is unrelated to the business cycle. The dotted (dashed) lines represent the 90% (95%) highest posterior density interval.

5.4. Trade-off Between Elasticities Within Countries

Table 5 reports, for the same eight leading countries of origin, the estimates of (i) the tourism marketing elasticity, (ii) the elasticity of unit sales to the business cycle, (iii) the elasticity of the tourism marketing elasticity to the business cycle, and (iv) the elasticity of the profit contribution to the business cycle.

Table 5 shows that the tourism-marketing elasticity is more than 30% stronger for the most receptive country (0.147 for Germany) than for the least receptive country (0.111 for Australia). The European countries, which are the furthest away from New Zealand, tend to be the most receptive to tourism marketing, followed by medium-distance countries in North America and

Table 4. Estimation Results for Model for Profit Contribution (Average Expenditure)

	Intercept	Business cycle elasticity	Elasticity economic trend	Oil price elasticity	Relative price elasticity
Expectation		+/−	+/−	+/−	−
Australia	6.10*	−0.26	0.17	0.02	−0.61**
Canada	6.16	−0.28	0.20	0.03	−0.69***
China	8.59***	−0.27	0.05	0.01	−0.68***
Germany	5.73	−0.29	0.23	0.12**	−0.71***
Japan	9.77*	−0.30	0.18	0.09*	−0.70***
South Korea	10.27***	−0.26	0.17	0.04	−0.66***
United Kingdom	4.50	−0.27	0.29	0.12**	−0.66***
United States	6.15	−0.24	0.18	0.05	−0.78***
Hypermean		−0.27	0.19	0.06	−0.68***
Deviance information criterion			−8.72		
Correlation between actual and predicted dependent variable			0.89		

Note. This interval is tested one-sided when we expect a specific direction of the effect as expressed in the Expectation row and two-sided otherwise.

*Significance at the 10% level; **significance at the 5% level; ***significance at the 1% level based on the highest posterior density interval.

Asia, while the closest neighbor Australia is the least receptive. A tentative explanation for this inverse relationship between distance and effectiveness is that the further away the market, the more novel or exotic the destination country appears, and the more noteworthy its tourism marketing. Also, a larger fraction of the Australian population may already have visited New Zealand, reducing the remaining potential (Hanssens et al. 2014).

Importantly, the elasticity of tourism-marketing effectiveness to the business cycle is quite large in magnitude, varying between −16.3 for South Korea and −14.2 for Germany. To address the question of whether budgets need to be spent procyclically or countercyclically, we must consider the cyclicality of unit sales, the cyclicality of marketing effectiveness, and the cyclicality of the profit contribution, as argued in Section 2. Empirically, we observe a very interesting mixed case of a procyclical unit sales ($\varepsilon_{\text{demand}} > 0$), a countercyclical marketing effectiveness ($\varepsilon_{\text{mark.eff.}} < 0$), and a noncyclical per-unit profit contribution ($\varepsilon_{\text{profit}} \cong 0$). Evaluating the sum of the three as per Equation (5), we find that the net elasticity is significantly negative for all countries except Australia (last column of Table 5). A significant negative sum calls for countercyclical spending as the allocation weight decreases in response to the business cycle. As a countercyclical spending in every country may not be practical, we explore in Section 6 how a given budget can best be allocated across countries. Before that, we will discuss benchmark models.

5.5. Benchmark Models and Robustness Checks

We fit a number of alternative specifications to test the robustness of the findings, listed as benchmark (BM) 1 to 5 in Table 3. While the current model includes the impact of marketing spend through the second component of Equation (7) (i.e., the fluctuations around the growth trend), it may also drive the growth in demand. If that is the case, the optimal allocation needs to take the growth elasticity into account as well (Fischer et al. 2011). BM1 extends the model by also including marketing expenditures as a driver of growth in Equation (13). The effect (0.01) is not significant. Another possibility is that marketing spend has a long-term effect, in which case the optimal allocation has to use the long-term elasticity (Fischer et al. 2011). To test for this possibility, BM2 adds last-year tourism marketing expenditures to the demand model (12)—the effect (0.04) is insignificant. BM3 adds the average price of competing destinations to model (12), leading to an insignificant effect (−0.11) as well. Because none of the benchmarks 1–3 adds a significant effect to the core model, nor do they provide a better fit, we opt to keep the more parsimonious focal model (TF-DHLM).

BM4 is a simplification of the full model, where only the intercept is time varying, whereas marketing effectiveness is not. This simplification leads to a slightly

Table 5. Model Estimation Results for TF-DHLM

Country[a]	Tourism marketing effectiveness (elasticity)[b] (mean of θ_{1it} across time)	I. Elasticity of unit sales to business cycle[b] $\left(\varepsilon_{\text{demand}} = \frac{\partial q_{it}}{\partial BC_{it}} \frac{BC_{it}}{q_{it}}\right)$	II. Elasticity of marketing effectiveness to business cycle[c] $\left(\varepsilon_{\text{mark.eff.}} = \frac{\partial \theta_{1it}}{\partial BC_{it}} \frac{BC_{it}}{\theta_{1it}}\right)$	III. Elasticity of profit contribution to business cycle[c] $\left(\varepsilon_{\text{profit}} = \frac{\partial p_{it}}{\partial BC_{it}} \frac{BC_{it}}{p_{it}}\right)$	Trade-off[c] (I + II + III)
Germany	0.147***	0.434	−14.152**	−0.285	−14.053**
United Kingdom	0.139***	0.547**	−14.940**	−0.268	−14.629**
Canada	0.139***	0.557**	−15.011**	−0.278	−14.716**
United States	0.137***	0.625**	−15.069**	−0.243	−14.625**
China	0.135**	0.547*	−14.737*	−0.273	−14.458*
Japan	0.131***	0.566**	−15.782**	−0.295	−15.491**
South Korea	0.126***	0.592**	−16.276**	−0.258	−15.882**
Australia	0.111	0.539*	−16.125	−0.263	−15.865

Note. This interval is tested one-sided when we expect a specific direction of the effect, and two-sided otherwise.

[a]The countries are ordered by a descending magnitude of the tourism marketing effectiveness elasticity. Because of space considerations, we present the elasticity estimates for the same selection of eight leading countries as in Table 4.

[b]Effect expected to be positive, hence we tested using a one-sided interval.

[c]No expected direction of the effect, hence we tested using a two-sided interval.

*Significance at the 10% level; **significance at the 5% level; ***significance at the 1% level based on the highest posterior density interval.

worse fit. To test for an alternative form of dynamics, including a possible carryover effect, in BM5 we look at a classical partial adjustment model (Hanssens et al. 2001, p. 147). This model has considerably lower fit than any of the other models, and results in an insignificant effect of the lagged dependent variable.

6. Budget Allocation in Function of the Business Cycle

We now use the estimates to study the allocation of the tourism marketing expenditures across countries to optimize the overall revenues. We determine the optimal proportion of the total budget to be allocated to each of the five world regions, in line with our institutional setting. We use the optimization heuristic of Fischer et al. (2011), as explained in Online Appendix E.

In line with Van Heerde et al. (2013), we compare the prescribed allocation in the recent global financial crisis (i.e., 2009–2010) to the one in the preceding period of expansion (i.e., 2006–2008). On average, all countries experienced an expansion in 2006–2008 (i.e., $\frac{1}{3}\sum_{t=2006}^{2008} \Delta \ln BC_{it} > 0,\ \forall\, i$) and a contraction in 2009–2010 (i.e., $\frac{1}{2}\sum_{t=2009}^{2010} \Delta \ln BC_{it} < 0,\ \forall\, i$). The number of years is not the same for the two periods, in line with contractions being typically shorter and more pronounced than expansions (Deleersnyder et al. 2004, Lamey et al. 2007).

Table 6 shows, for both periods, five alternative budget allocations. The first is the actual, empirically observed, allocation. The second is an allocation proportional to marketing effectiveness (elasticities), in the spirit of the well-known Dorfman–Steiner (1954) allocation rule. The third allocation is proportional to the expected unit sales,[13] which could appeal to managers because it is easy to apply, although it does not take differences in marketing effectiveness into account. The fourth one is proportional to the profit contribution. The final allocation is the optimal one, proportional to the product of the marketing elasticity, the expected unit sales, and profit contribution.

Table 6 shows that the five allocations yield quite different recommendations. Australia, for example, received 20.6% of the budget during the expansion period, while the optimal allocation is 45.8%. What happens is that during the expansion, Australia combines high unit sales with a relatively strong marketing elasticity, leading to a high optimal allocation weight. By contrast, Australia's allocation is only 11.0% when based on the elasticity-proportion rule, 32.7% based on the market-size-proportion rule, and 4.2% based on the profit contribution per visitor.

Table 6 also documents a substantial difference in the optimal allocation going from the expansion period (2006–2008) to the contraction period (2009–2010). For example, the optimal budget allocated to Australia drops from 45.8% to 32.2%, whereas the share for

Table 6. Actual vs. Alternative Allocations of the Tourism Marketing Budget

Region	Marketing elasticity[a]		Unit sales[b]	Average expenditures[c]	Actual allocation (%)	Allocation proportional to: Marketing elasticity (%)	Allocation proportional to: Unit sales (%)	Allocation proportional to: Average expenditures (%)	Optimal allocation (%)
				Expansion (2006–2008)					
Australia	0.085		0.340	0.273	20.6	11.0	32.7	4.2	45.8
North America	0.016	(U.S.)	0.149	0.384	29.2	6.0	14.3	11.9	6.4
	0.031	(Canada)		0.396					
Japan	0.054		0.106	0.387	14.9	7.0	10.2	5.9	13.9
Europe	0.031	(U.K.)	0.236	0.484	27.0	20.3	22.6	44.2	18.6
	0.017	(Germany)		0.484					
Asia	0.046	(China)	0.211	0.302	8.3	55.7	20.2	33.8	15.3
	0.028	(South Korea)		0.253					
				Contraction (2009–2010)					
Australia	0.153		0.404	0.290	25.8	5.8	39.8	4.2	32.2
North America	0.132	(U.S.)	0.145	0.409	21.5	10.7	14.3	11.9	14.7
	0.151	(Canada)		0.414					
Japan	0.151		0.072	0.451	8.7	5.7	7.1	6.5	9.6
Europe	0.148	(U.K.)	0.224	0.459	25.3	40.8	22.1	43.2	32.9
	0.205	(Germany)		0.536					
Asia	0.096	(China)	0.169	0.354	18.8	37.0	16.7	34.1	10.6
	0.116	(South Korea)		0.235					

[a]Because of space considerations, we present the elasticity estimates for some illustrative countries in the region. In the optimization, we used the elasticity estimates for each individual country in the region.
[b]The unit sales is the lagged number of visitors (i.e., q_{it-1}) multiplied by the growth multiplier in the current year (i.e., $\exp(\theta_{0it})$).
[c]The average expenditures are the expectation based on the estimated model.

Table 7. Allocating the Tourism Marketing Budget: Revenue Implications

			Allocation proportional to			
		Actual allocation	Marketing elasticity	Unit sales	Average expenditures	Optimal allocation
		Expansion (2006–2008)				
Arrivals (million)		1.062	1.084	1.099	1.064	1.109
Revenue (million NZD$)[a]		3,712	3,765	3,809	3,722	3,832
Optimal vs. actual allocation	Revenue increase in million NZD$ (%) [likelihood it is larger]					+121 (+3.2%) [82%]
Optimal vs. allocation proportional to marketing elasticity	Revenue increase in million NZD$ (%) [likelihood it is larger]					+64 (+1.7%) [66%]
Optimal vs. allocation proportional to unit sales	Revenue increase in million NZD$ (%) [likelihood it is larger]					+17 (+0.5%) [64%]
Optimal vs. allocation proportional to average expenditures	Revenue increase in million NZD$ (%) [likelihood it is larger]					+111 (+3.0%) [67%]
		Contraction (2009–2010)				
Arrivals (million)		1.032	0.971	1.060	0.961	1.055
Revenue (million NZD$)		3,715	3,580	3,801	3,561	3,821
Optimal vs. actual allocation	Revenue increase in million NZD$ (%) [likelihood it is larger]					+106 (+2.9%) [84%]
Optimal vs. allocation proportional to marketing elasticity	Revenue increase in million NZD$ (%) [likelihood it is larger]					+210 (+5.9%) [85%]
Optimal vs. allocation proportional to unit sales	Revenue increase in million NZD$ (%) [likelihood it is larger]					+21 (+0.5%) [62%]
Optimal vs. allocation proportional to average expenditures	Revenue increase in million NZD$ (%) [likelihood it is larger]					+231 (+6.5%) [84%]

Note. Results represent the median of a sample of draws, using every 10th draw of all of the draws after burn-in, this gives a sample of 5,000 draws.

[a]The revenue figure is obtained by using predicted expenditures per visitor for each country of origin, based on the estimated model.

North America goes from 6.4% to 14.7%. It is interesting to see to what extent the changes in unit sales and marketing elasticity influence these allocations (remember that the profit contribution is statistically invariant to the business cycle). Table 6 shows that fluctuations in unit sales are relatively small compared to the fluctuations in marketing elasticity. Hence, to explain what happens to the optimal allocation we need to consider predominantly the elasticity fluctuations. We find that during the contraction, the marketing elasticities increase for both Australia (from 0.085 to 0.153) and North America (from 0.016 to 0.132 for the United States, and from 0.031 to 0.151 in Canada), but the rate of increase is much stronger in North America because the global financial crisis was felt much stronger there than in Australia. Consequently, during the contraction period it becomes relatively more attractive to invest tourism marketing dollars in North America than in Australia, explaining the shift in optimal allocation. Interestingly, the observed allocation percentages are aligned closer with the optimal ones in the contraction than in the expansion period. Thus, Tourism New Zealand seemed to have a better sense of the best way to spend the budget in the recent downturn than in the boom period leading up to it.

How much of an impact do the alternative allocations have on arrivals and tourism revenue? For each allocation, we calculate the expected demand. To ascertain the stability of the results, we use 5,000 posterior parameter draws (Campo et al. 2000). Table 7 shows the median of the number of arrivals and revenue. For revenue, we also give the comparison of the optimal allocation with the actual outcome and the four alternative allocations. At first glance, Table 7 suggests that the increase that can be realized in terms of expected revenue is rather limited: 2.9% relative to the actual allocation in the contraction period, and 3.2% in the expansion period. This is in line with the flat-maximum principle (Tull et al. 1986), which says that the profit function is quite flat around the optimum. However, in absolute terms, this corresponds to an annual revenue increase of NZD$121 ($106) million in expansion (contraction) years. These are substantial amounts for an annual tourism budget of around NZD$73 million. Moreover, in spite of the underlying parameter uncertainty (Campo et al. 2000), there is a sizable likelihood (e.g., 84% in the contraction period) that the optimal revenue is higher than the actual amount.

7. Discussion and Conclusion

Whether procyclical or countercyclical marketing spending is recommended has intrigued marketing scholars and practitioners for decades, resulting in a sharp discord between managerial practices on one hand (procyclical spending) and academic recommendations on the other hand (countercyclical spending). This paper offers new insights to resolve this conundrum. Based on the result from Fischer et al. (2011) that optimal marketing spending is proportional to the product of (i) size of demand, (ii) marketing effectiveness, and (iii) per-unit profit contribution, we derive the new insight that three factors play a role in determining whether the budget needs to be adjusted procyclically or countercyclically. Those are the cyclicality of demand to the business cycle, the cyclicality of marketing effectiveness, and the cyclicality of the profit contribution. If all three evolve procyclically, spend should be procyclical as well. If all move countercyclically, spend should be countercyclical. If their evolution differs (one or two are pro, the other(s) is (are) counter), the elasticity magnitudes need to be compared, and the directionality (procyclical or countercyclical) of the net elasticity determines which policy is recommended. Importantly, such an opposing evolution is not uncommon. Van Heerde et al. (2013), for example, document that for groceries, unit sales move countercyclically, whereas advertising effectiveness evolves procyclically. In this paper, we find the reverse scenario for international tourism: unit sales develop procyclically, while tourism marketing effectiveness progresses countercyclically, while the per-unit profit contribution is noncyclical.

The derivation of the optimal budget allocation becomes even more complex if an organization has to deal with multiple business cycles, as it should account for both longitudinal and cross-sectional variation in the focal elasticities and unit sales. To achieve this, we develop a transfer function dynamic hierarchical linear model. The model allows for a flexible trend in marketing effectiveness over time, and for the potential endogeneity of tourism marketing budgets. Importantly, the transfer function allows us to test the effect of one or more moderators (here, the business cycle) on a response parameter of interest (here, tourism marketing effectiveness). The ability to *explain* parameter variation over time (rather than just observe it) is an important advantage of the proposed TF-DHLM over a standard DHLM.

In the application, we analyze the effectiveness of tourism marketing for New Zealand over time and across countries. We find that the tourism marketing elasticity decreased substantially, approximately halving across the considered time span. This is in line with the literature that suggests that advertising elasticity has decreased over time (Sethuraman et al. 2011). In terms of our focal research question, we find that the countercyclicality in marketing effectiveness dominates the procyclicality of unit sales, which combined with a noncyclical profit contribution leads to a recommended countercyclical spending pattern. When looking simultaneously at the business-cycle dependencies across all countries, we find that a careful reallocation of the marketing budget results in a sizable absolute increase in revenues. Given that this is achieved with a constant overall budget, we do not call for spending more (which would play to the often-heard criticism that marketing managers always want to spend more), but for spending the available budget smarter.

Taking a broader perspective beyond this specific application, we offer a number of learnings to both managers and researchers. As we explained in Section 1, the former tend to cut marketing expenditures during contractions. This is a quite natural and understandable response when demand is shrinking during downturns. Demand is a readily observable metric, and going with the flow (procyclical spending) will likely require less persuasion in the organization than going against the grain (countercyclical spending). Academic research so far often suggests that in fact countercyclical spend is best, but most of this research is based on less readily observable metrics such as marketing effectiveness. What this paper does is show how neither recommendation may be uniformly preferable, as we argue that the net recommendation does not depend just on unit sales nor just on elasticities, but that both should be taken into account, along with changes in profit contribution.

Limitations and further research. One shortcoming of this study is that the empirical setting limits us in terms of the number of observations (18 countries, 31 years per country). Although these numbers already cover multiple decades and regions of the world, this may have limited the statistical significance of some of the response parameters. This data limitation also precludes the use of more parametrized dynamic models, such as vector error correction models. Another limitation is that we apply our model to only one target country and industry (tourism). The method can be applied to other settings where multiple business cycles are relevant to consider; for example, for companies exporting to different countries or considering expansions into different parts of the world. Further research is required to obtain empirical generalizations in the area.

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Endnotes

[1] An exception is Van Heerde et al. (2013). Based on a study of 150 CPG brands, they find advertising's long-run sales elasticity to be significantly larger in economic expansions, leading them to recommend procyclical spending.

[2] This use of the term "transfer function" is consistent with the DLM tradition (West and Harrison 1999, p. 284). In the time-series literature, "transfer functions" refer to distributed lags (Hanssens et al. 2001, p. 286).

[3] Because in the empirical setting there are some data limitations for the profit-contribution model, it is less sophisticated than the demand model.

[4] As in Kulendran and Dwyer (2009), the marketing expenditures considered are the public funds governments allocate to the promotion of their country as a travel destination.

[5] We checked the *International Journal of Research in Marketing*, the *Journal of Consumer Research*, the *Journal of Marketing*, the *Journal of Marketing Research*, *Management Science*, and *Marketing Science*. Checking all issues since the start of each journal till now, we found only 29 publications (including several one- or two-page research notes) with "tourism," "tourist," or "travel" in the title or as a keyword, where we excluded papers where "travel" was used in a non-touristic sense (e.g., travel costs in retail shopping).

[6] The 18 countries are from different parts of the world: Australia, North America (Canada, United States), Europe (France, Germany, the Netherlands, Sweden, Switzerland, and the United Kingdom), and Asia (China, Hong Kong, Indonesia, Japan, Malaysia, Singapore, South Korea, Taiwan, and Thailand).

[7] The model captures the within-year effect of advertising, which is in line with the empirical generalization that most advertising effects last less than a year (Leone 1995). In Section 5, we also consider a model with an additional lagged marketing variable and find that the parameter is insignificant. Additionally the model has a worse penalized fit (higher deviance information criterion) than the focal model with only the within-year effects.

[8] For other contexts (e.g., private-label share), a directionally opposite main effect could be postulated based on prior research (Lamey et al. 2007, 2012).

[9] Other institutional marketing settings are also characterized by such a difference in aggregation level between the dependent (performance) and the independent (advertising) variable. For example, brand performance at a given retailer is often linked to the brand's national advertising support (Gielens 2012 or Ter Braak et al. 2013).

[10] We also tried a variant where we multiplied the oil price by the distance to the destination country. Given that distances are constant and given that we use a fixed-effect specification in a log–log model, the coefficient for ln(oil price $\times$ distance) is exactly the same as for ln oil price.

[11] Significance is determined based on the 95% highest posterior density. In particular, if zero lies in the highest posterior density interval, then the estimate is insignificant.

[12] In an unreported analysis, we found an insignificant effect of tourism marketing on the profit contribution.

[13] Note that we cannot take the current unit sales, as this is the variable we need to optimize. We define the expected sales as the lagged unit sales multiplied with the expected growth multiplier, i.e., $\exp(\hat{\theta}_{0it})$.

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