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Modelling seasonality in innovation diffusion

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ABSTRACT

The ability to forecast new product growth is especially important for innovative firms that compete in the marketplace. Today many new products exhibit very strong seasonal behaviour, which may deserve specific modelling, both for producing better forecasts in the short term and for better explaining special market dynamics and related managerial decisions. By considering seasonality as a deterministic component to be estimated jointly with the trend through Nonlinear Least Squares methods, we have developed two extensions of the Guseo–Guidolin model that are able to simultaneously describe trend and seasonality. Such models are based on two different but equally reasonable approaches: in one case we consider a simple additive decomposition of a time series and design a model in which seasonality is directly added to the trend and jointly estimated with it; in the other we design a more complex structure, mimicking that of a Generalized Bass model and embed two separate seasonal perturbations within the dynamic market potential and the corresponding adoption process. The different characteristics of two products, a pharmaceutical drug and an IT device, make it possible to appreciate empirically various modelling options and performances. Both models are quite simple to implement and to interpret from a managerial point of view.

1. Introduction

The ability to model and predict the diffusion of innovations is particularly important for firms that develop and launch new products and services in increasingly complex and competitive markets. Diffusion research is aimed at describing the spread of an innovation by modelling its entire life-cycle. There is a quite long tradition in this field: wide research has been produced to capture several phenomena visible in sales data. Particular effort has been devoted to extending the structure of the basic and most known Bass model, BM [1], by taking into account price dynamics, competition, targeted or pulsing advertising strategies, network externalities, consumer heterogeneity and technological generations (for a review, see [2,14,11]), arguing that these may help explain turning points in life-cycle such as take-off, saddle and technological substitution. One of the most famous generalisations of the Bass model is the Generalized Bass model, GBM, by Bass et al. [3]. By the multiplicative inclusion of a general intervention function $x(t)$, the GBM is able to capture the effect of many external actions that modify the speed of the diffusion process, by advancing or delaying adoptions. Depending on the form of $x(t)$, the GBM may identify intense and fast shocks or more stable ones that may be imputed to marketing strategies, political regulations or environmental upheavals. The GBM represents an essential answer to include the effect of external actions into diffusion, thanks to a closed-form solution due to an interpretable Riccati equation. However, as in the BM, in the GBM the market potential is constant, which indicates that $x(t)$ acts on the temporal shape of diffusion and not on its size. A recent model generalising the BM with a variable market potential has been proposed by Guseo and Guidolin in [7]. The closed-form solution of this model shows that the market potential has a general and multiplicative structure.

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A particular specification of it is given in [7] where the market potential is made dependent on a communication process that co-evolves with adoption. Several applied cases have shown the efficiency of this model for descriptive and predictive purposes, moreover giving an alternative explanation to the saddle between two overlapping subcycles often observed in product growth (see [8]). Indeed, a typical focus of diffusion models is to provide an efficient description and interpretation of the mean trajectory of a life-cycle so that a seasonal pattern in sales data has not been often studied in an explicit way, although several products are clearly characterised by it. A pioneering work in the area of seasonal diffusion of innovations modelling is the paper by Radas and Shugan [13]. In this work the authors focus on "any predictable seasonal pattern caused by exogenous factors (i.e., beyond one firm's control) such as holidays, government actions, industry traditions, weather, social phenomena, summer and school years." In this view, seasonality is considered as a given pattern, which arises independently from agents' decisions. However, an interesting definition of seasonality is provided by Hylleberg in [9], who states that it is *the systematic, although not necessarily regular, intra-year movement caused by the changes of weather, the calendar, and timing of decisions, directly or indirectly through the production and consumption decisions made by the agents of the economy*. While seasonality is considered less relevant for long-term evaluations, it is much more important in medium-short periods both for demand prediction and for supply organisation. Seasonality may be exploited by firms for building their marketing strategies. Seasonal behaviour is typically visible when data are collected with monthly or quarterly frequencies and some works on diffusion concentrated on the issue of temporal aggregation of data: in [12] quarterly or monthly seasonally adjusted data are compared with annual data, finding that the former perform better in terms of parameter estimates and in [10] it has been noticed that the smooth development of sales typical of the Bass model matches better with data at yearly frequency than at higher frequency. Indeed, the aggregation of monthly or quarterly data to obtain a smoother shape of sales determines a loss of information. Moreover, since product life-cycles are increasingly shortening due to high competition, it becomes more and more necessary to have short-term projections, by accurately analysing not only the trend of sales but also their oscillations within the year, which in some cases may be very strong. In fact, the sales pattern of many technological devices exhibits strong seasonal oscillations, which may be partly explained by the behaviour of consumers and partly by the business strategies of the producer (see [5]). Following Wei [17], for instance, typical methods developed in time series analysis for seasonality modelling are:

a) the *regression method*, which assumes that the seasonal component is deterministic and may be described as a linear combination of seasonal dummy variables (see, for instance [10]) or as a linear combination of harmonic functions of various frequencies (see, among others [6]). Notice that this second method gives rise to more parsimonious models, due to the Fourier approximations;
b) the *moving average method*, which estimates the nonseasonal component of a series, $N(t)$, by using a symmetric moving average operator. The seasonal component, $S(t)$, is obtained by subtracting the estimated nonseasonal component $N(t)$ from the original series $Y(t)$. The series with seasonal component removed, $Y(t) - S(t)$ is referred to as the *seasonally adjusted series*;
c) the *autoregressive method*, which extends stochastic ARIMA models with the seasonal ARIMA models, SARIMA or SARMAX, developed by [4], assuming a stochastic nature of seasonality.

In particular, the SARMAX approach interprets seasonality as a "polynomial" structure within the autoregressive moving average effects of the residual process. If $z'(t) = f(t,\beta) + \varepsilon(t)$ denotes a general diffusion model, where $f(t,\beta)$ is the systematic part and $\varepsilon(t)$ a stationary process including seasonal components, then we may estimate β at a first stage with the NLS technique, which is nonparametric in nature, and, at a second stage, the specific SARMAX parameters, such as,

$$\Psi(B)\Phi(B^s)\left(z'(t)-f\left(t,\hat{\beta}\right)\right) = \vartheta(B)\Theta(B^s)a_t \tag{1}$$

with a_t a WN process, B, B^s the standard and seasonal backward operators and $\Psi(B)$, $\Phi(B^s)$, $\vartheta(B)$ and $\Theta(B^s)$ the usual backward polynomials of order p, P, q and Q, respectively. For an example, see [8]. In this paper we consider seasonality as a deterministic component to be estimated jointly with the trend through the Nonlinear Least Squares, NLS, technique (see [15]). Specifically, we develop two special extensions of the Guseo–Guidolin model in [7], able to describe trend and seasonal components simultaneously. Such models are designed by starting from very different approaches:

a) in one case we consider a classical additive decomposition of a time series, conveniently modified to account for the effect of life-cycle dynamics on the seasonal pattern, and develop a model where seasonality is added to the trend and estimated simultaneously with it;
b) in the other we mimic the structure of a Generalized Bass model and embed seasonal perturbations in a Guseo–Guidolin model, which may operate either on the communication process, on the adoption one, or on both. This proposal appears particularly stimulating both in theoretical and empirical terms, because it allows identify two possible sources of seasonality, that is consumer attitudes on the one hand and firm communication/distribution efforts on the other. A basic suggestion for introducing seasonality into the GBM, through the intervention function, was proposed by [13].

The paper is structured as follows. In Section 2 we present the basic features of the Generalized Bass model and of the Guseo–Guidolin model. In Section 3 we illustrate the two seasonal extensions of the Guseo–Guidolin model, highlighting the different approaches adopted in model building. In particular subsection 3.1 is dedicated to presenting the Guseo–Guidolin model with an additive seasonal component, while subsection 3.2 proposes the generalisation of the Guseo–Guidolin model with the introduction of two seasonal intervention functions. In

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