

Nonlinear models for new product growth

New product life cycle: phases

- ① Introduction
- ② Growth
- ③ Maturity
- ④ Decline

What are the variables influencing a product's life cycle?

Marketing strategies play an essential role ...

but the success of a new product ultimately depends on consumers accepting them.

Diffusion of innovations

Diffusion is the process by which an innovation is communicated through certain channels over time among the members of a social system (Rogers, 2003).

Four key elements for describing an innovation diffusion process:

- innovation
- communication channels
- time
- social system

Innovation

An innovation is:

- New product, new service, new technology, new production process, new way of doing things (Schumpeter, 1947).
- Typical distinction: radical vs incremental innovations.
- Radical innovations could be hindered from barriers and social inertia.

New product growth models

General aim: depict the successive increases in the number of adopters and predict the continued development of a diffusion process already in progress (Mahajan and Muller, 1979).

- Fourt and Woodlock model (1960)
- Mansfield model (1961)
- Bass model (1969)
- Generalized Bass model (1994)

Bass Model

The Bass Model is defined by a **first order differential equation**

$$z'(t) = \left(p + q \frac{z(t)}{m} \right) (m - z(t))$$

Bass Model

innovation

$$z'(t) = \left(p + q \frac{z(t)}{m} \right) (m - z(t))$$

Bass Model

$$z'(t) = \left(p + q \frac{z(t)}{m} \right) (m - z(t))$$

imitation

Bass Model

$$z'(t) = \left(p + q \frac{z(t)}{m} \right) (m - z(t))$$

word-of-mouth

Bass Model

If we pose $\frac{z(t)}{m} = y(t)$ the model becomes

$$y'(t) = (p + qy(t))(1 - y(t))$$

Bass Model: solution

The Bass Model has a closed-form solution

$$y(t) = F(t; p, q) = \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p}e^{-(p+q)t}} \quad t > 0.$$

or, by posing $z = ym$

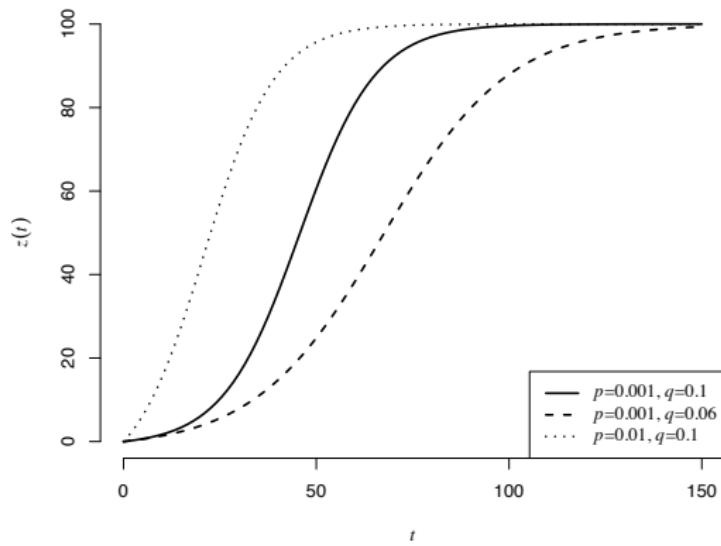
$$z(t) = m F(t; p, q) = m \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p}e^{-(p+q)t}} \quad t > 0.$$

Cumulative sales $z(t)$ 'depend' on parameters p and q .

The market potential m is a scale parameter and is assumed **constant**.

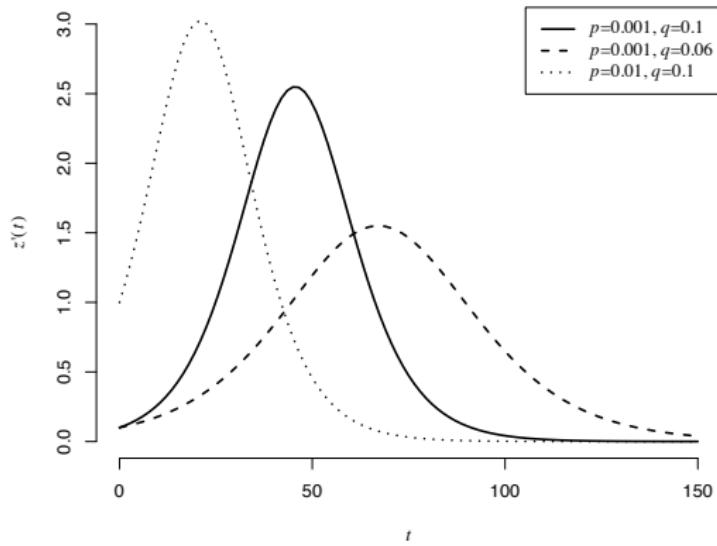
Bass Model

Cumulative process



Bass Model

Instantaneous process



Bass Model: estimation

The Bass Model is a **nonlinear model**

$$Z(t) = f(\beta, t) + \varepsilon(t)$$

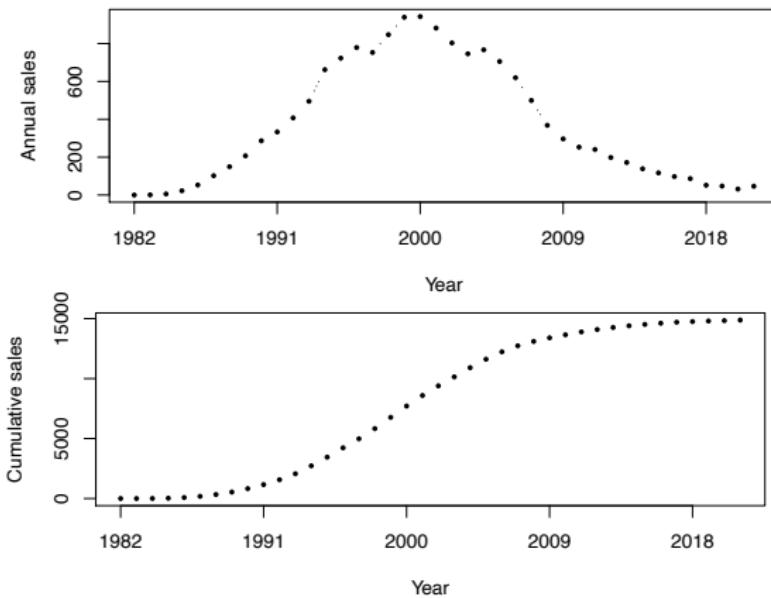
where $Z(t)$ is the dependent variable, $f(\beta, t)$ is the deterministic term, function of $\beta \in R^k$ and of time t .

The second term, $\varepsilon(t)$, is the error term, for which usual assumptions hold, namely $M(\varepsilon(t)) = 0, Var(\varepsilon(t)) = \sigma^2, Cov(\varepsilon(t), \varepsilon(t')) = 0, t \neq t'$.

Bass Model: estimation

- Typical starting values for p and q are 0.01 and 0.1.
- Estimating m is the most difficult task.
- Parameter estimates are very sensitive to the number of available data.
- Reliable estimates are obtained after the maximum peak, but . . . “*By the time sufficient observations have been developed for reliable estimation, it is too late to use the estimates for forecasting purposes*” (Mahajan, Muller, Bass, 1990).

Compact Discs in USA



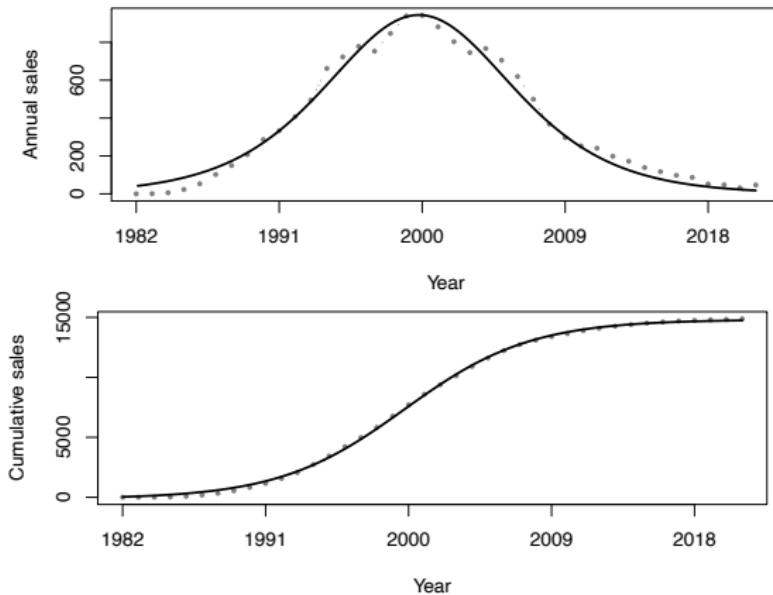
Compact Discs in USA

Bass Model for CD: estimates and 95% CIs

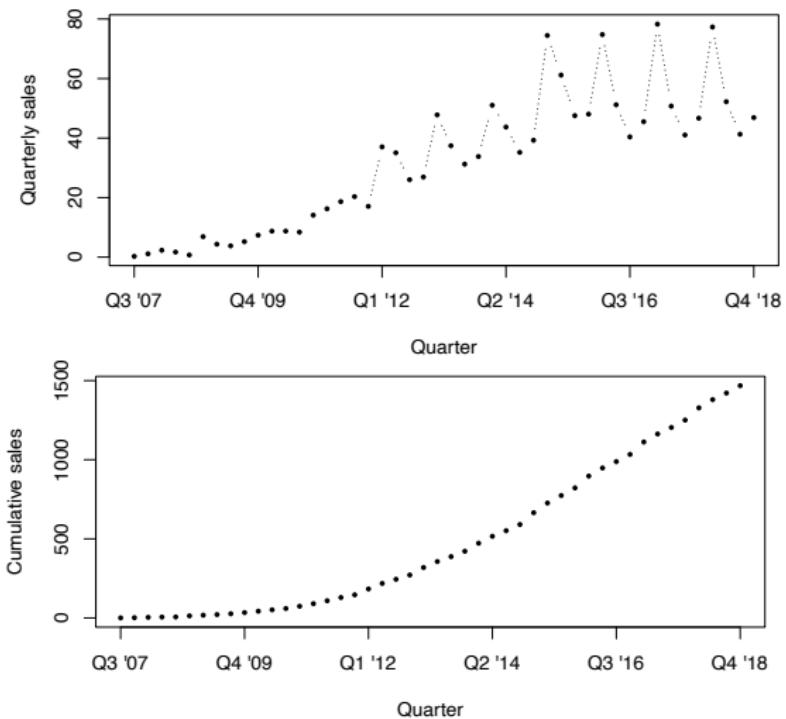
	Estimate	Std.Error	Lower	Upper	p-value
m	14814	49	14716	14911	<0.0001
p	0.0022	0.0001	0.0020	0.0024	<0.0001
q	0.25	0.0035	0.24	0.26	<0.0001

$$R^2 = 0.9998$$

Compact Discs in USA



Apple iPhone



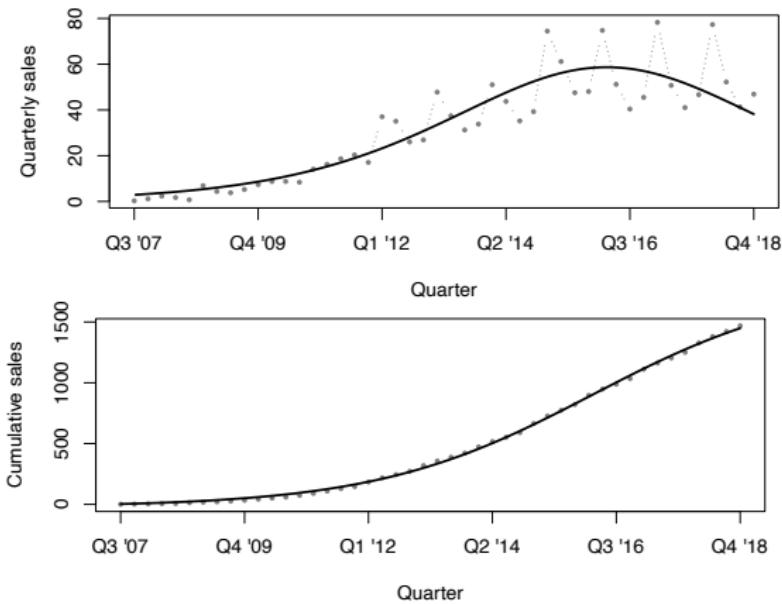
Apple iPhone

Bass Model for iPhone: estimates and 95% CIs

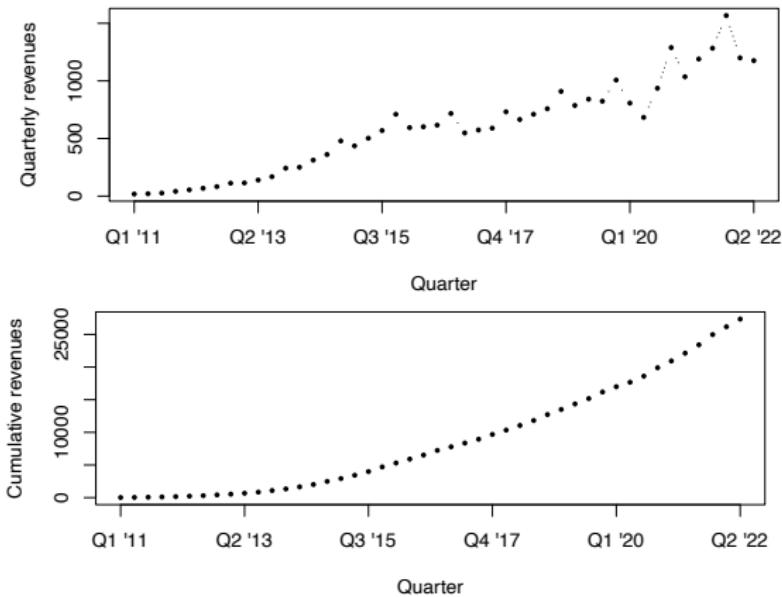
	Estimate	Std.Error	Lower	Upper	p-value
m	1823.7	34.12	1756.8	1890.6	<0.0001
p	0.0014	0.0001	0.0013	0.0015	<0.0001
q	0.1259	0.0027	0.1206	0.1311	<0.0001

$$R^2 = 0.9995$$

Apple iPhone



Twitter revenues



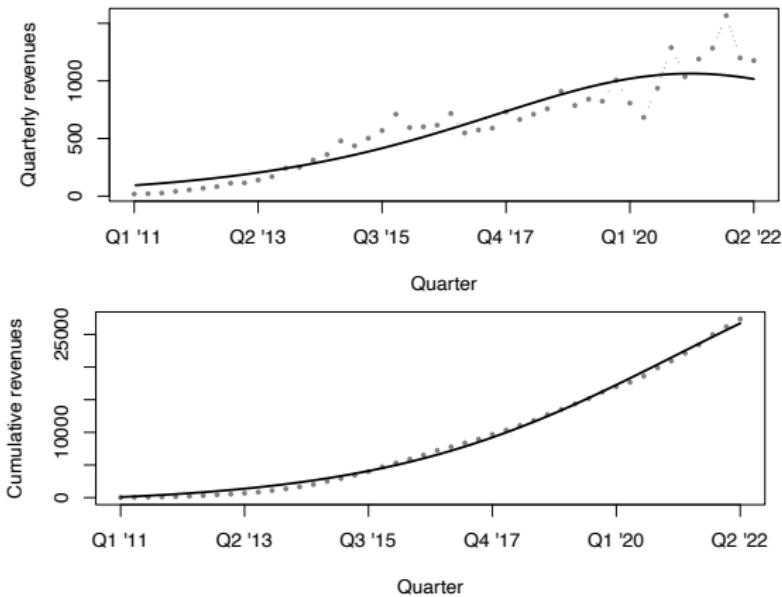
Twitter revenues

Bass Model for Twitter: estimates and 95% CIs

	Estimate	Std.Error	Lower	Upper	p-value
m	44633.7	3557.9	37660.3	51607.0	<0.0001
p	0.0019	0.0001	0.0018	0.0021	<0.0001
q	0.09	0.004	0.08	0.10	<0.0001

$$R^2 = 0.9995$$

Twitter revenues



Bass Model: interesting properties

- Parsimonious model with just three parameters m , p , q .
- Only needs aggregate sales data.
- Easy to interpret.

Bass Model: limitations

- The market potential m is constant along the whole life cycle.
- The Bass Model does not account for marketing mix strategies.
- It is a model for products with a limited life cycle: needs a hypothesis.

Generalized Bass Model

The Bass Model does not account for the effect of **exogenous variables**, such as marketing mix, public incentives, environmental shocks. Besides, in some cases the diffusion process does not have a bell shape curve, but a more complex structure.

Generalized Bass Model

The Generalized Bass Model (Bass et al., 1994) adds an intervention function $x(t)$

$$z'(t) = \left(p + q \frac{z(t)}{m} \right) (m - z(t))x(t).$$

where $x(t)$ is an integrable, non negative function.

- The Bass Model is a special case where $x(t) = 1$.
- if $0 < x(t) < 1$ the process **slows down**,
- if $x(t) > 1$ the process **accelerates**.

Generalized Bass Model: closed-form solution

The closed-form solution of the model is

$$z(t) = m \frac{1 - e^{-(p+q) \int_0^t x(\tau) d\tau}}{1 + \frac{q}{p} e^{-(p+q) \int_0^t x(\tau) d\tau}}, \quad t > 0.$$

Interesting: function $x(t)$ does not modify the market potential m !

Function $x(t)$ modifies the speed of the process.

Modelling $x(t)$: exponential shock

Function $x(t)$ may take several forms in order to describe various types of shock.

A strong and fast shock may take an **exponential form**

$$x(t) = 1 + c_1 e^{b_1(t-a_1)} I_{t \geq a_1},$$

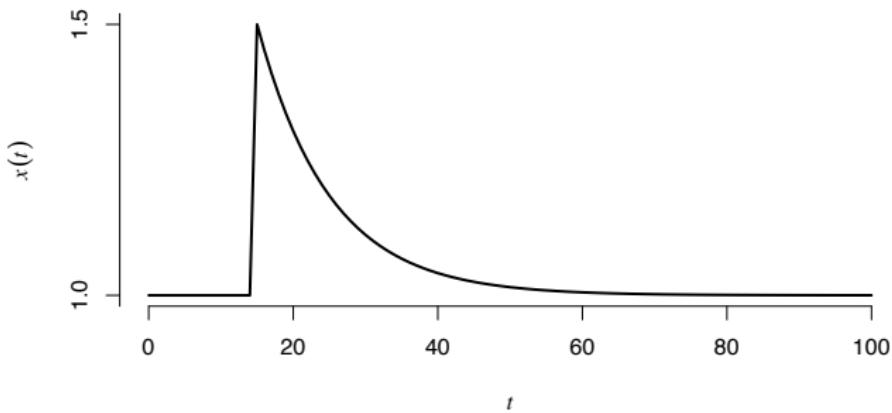
where parameter c_1 is **intensity** and **sign** of the shock, b_1 is the '**memory**' of the effect and is typically negative, and a_1 is the **starting time** of the shock.

Modelling $x(t)$: exponential shock

The use of exponential shock is suitable for identifying the positive effect of **marketing strategies** or **incentive measures**, in order to speed up the diffusion process.

Also, a negative shock may represent a fast slowdown in sales due to the entrance of a competitor.

Modelling $x(t)$: exponential shock



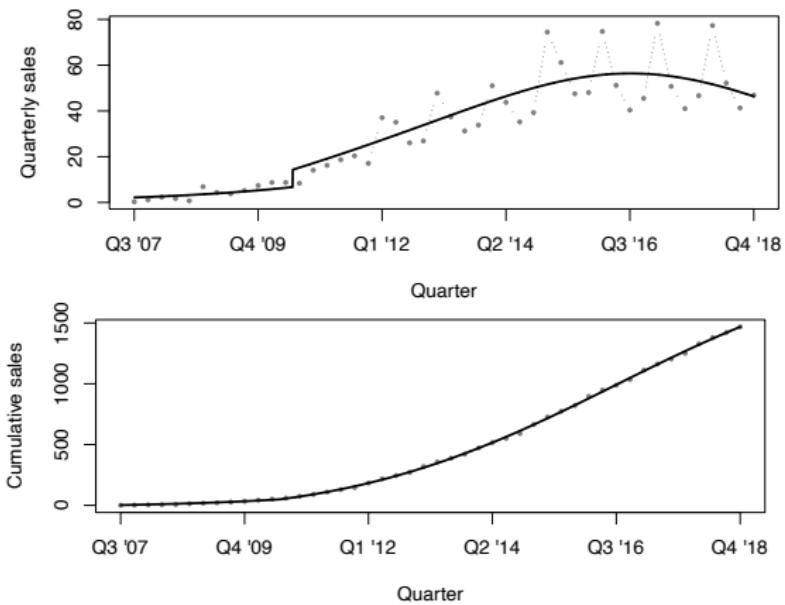
Apple iPhone

GBM for iPhone: estimates and 95% CIs

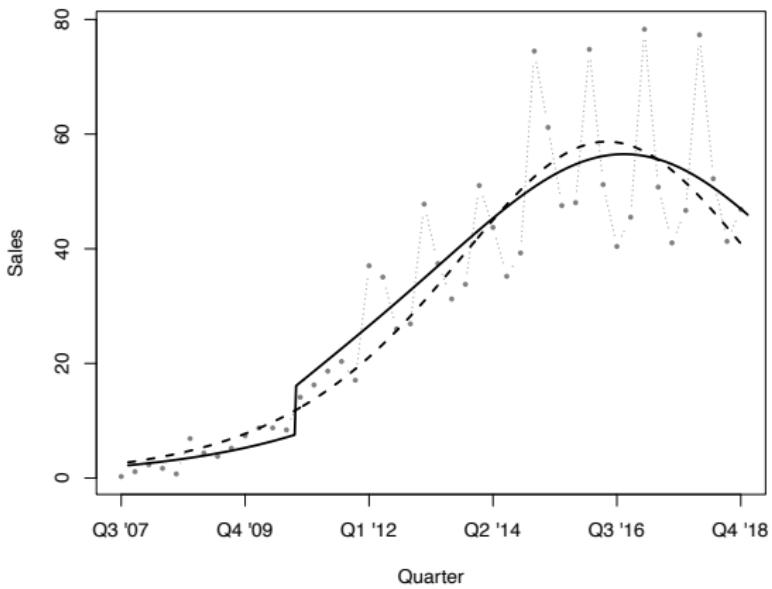
	Estimate	Std.Error	Lower	Upper	p-value
m	2108.9	124.9	1864.1	2353.8	< 0.001
p	0.0009	0.0001	0.0008	0.0011	< 0.001
q	0.10	0.001	0.08	0.12	< 0.001
a_1	12.5	0.99	10.56	14.44	< 0.001
b_1	-0.14	0.06	-0.25	-0.03	0.02
c_1	1.13	0.17	0.78	1.47	< 0.001

$$R^2 = 0.9998$$

Apple iPhone



Apple iPhone



Modelling $x(t)$: rectangular shock

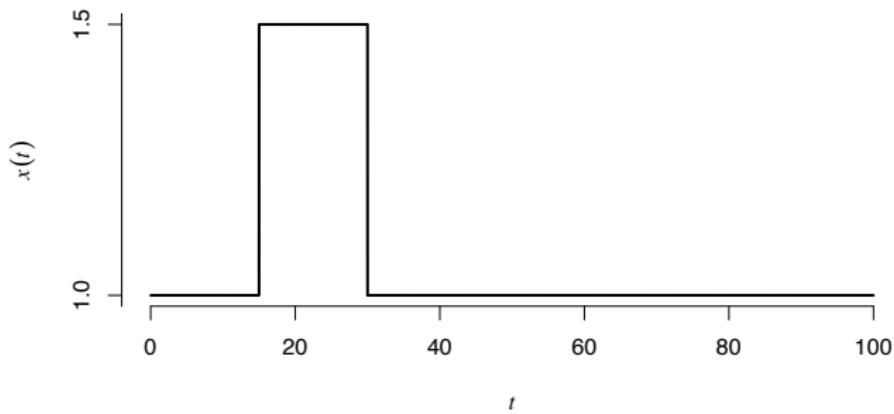
A more stable shock, acting on a longer period of time, may be modeled through a **rectangular shock**

$$x(t) = 1 + c_1 I_{t \geq a_1} I_{t \leq b_1},$$

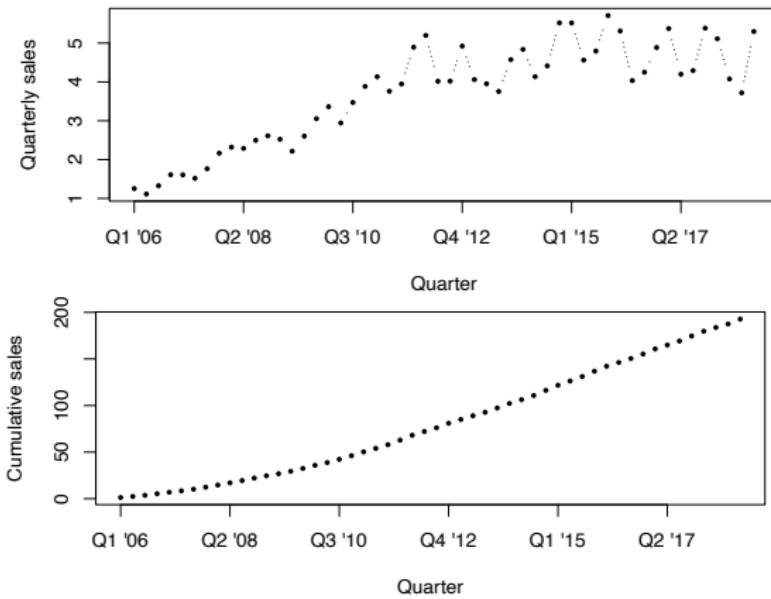
where parameter c_1 describes **intensity** of the shock, either positive or negative, parameters a_1 and b_1 define **beginning** and **end** of the shock (con $a_1 < b_1$).

The **rectangular shock** is useful to identify the effect of policies and measures within a limited time interval.

Modelling $x(t)$: rectangular shock



Apple iMac



Apple iMac

GBM for iMac: estimates and 95% CIs

	Estimate	Std.Error	Lower	Upper	p-value
m	281.66	3.58	274.65	288.68	< 0.0001
p	0.0047	0.0042	0.0047	0.0048	< 0.0001
q	0.061	0.001	0.059	0.063	< 0.0001

$$R^2 = 0.9999088$$

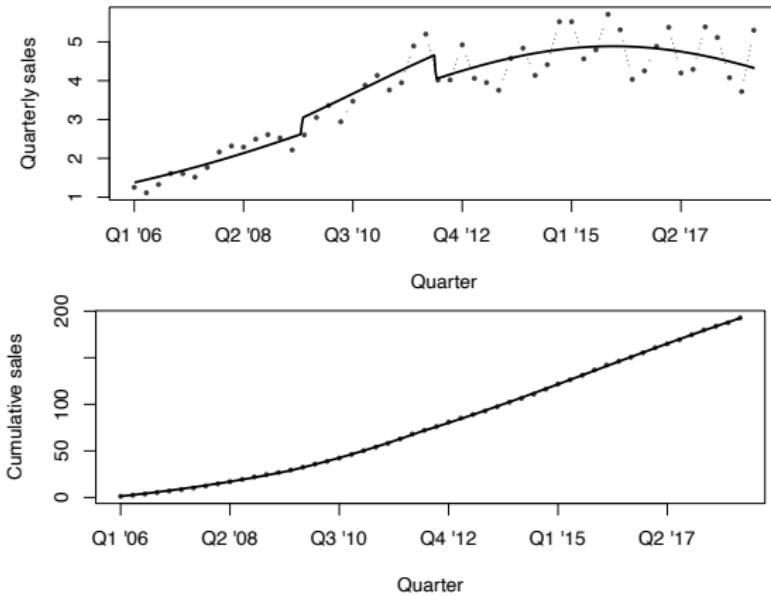
Apple iMac

GBM for iMac: estimates and 95% CIs

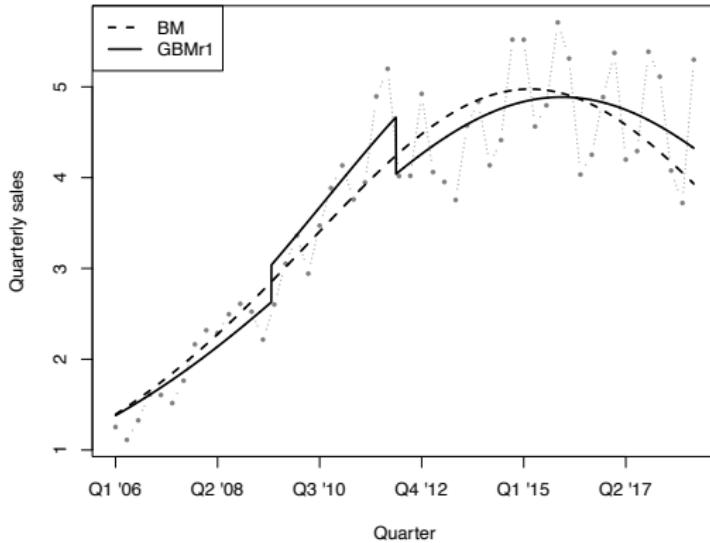
	Estimate	Std.Error	Lower	Upper	P-value
m	304.1	3.67	296.9	311.3	< 0.0001
p	0.0043	0.00001	0.0042	0.0044	< 0.0001
q	0.055	0.00	0.053	0.056	< 0.0001
a_1	14.67	0.96	12.79	16.54	< 0.0001
b_1	25.95	0.71	24.55	27.35	< 0.0001
c_1	0.16	0.02	0.13	0.20	< 0.0001

$$R^2 = 0.9999$$

Apple iMac



Apple iMac



Model comparison ...

Modelling $x(t)$: mixed shock

It may be useful to have more than one shock of different nature. A simple case is made of a couple of shocks, rectangular and exponential,

$$x(t) = 1 + c_1 I_{t \geq a_1} I_{t \leq b_1} + c_2 e^{b_2(t-a_2)} I_{t \geq a_2}$$

Other combinations are possible.

Model performance and selection

The usual performance indicator is the R^2

$$R^2 = \frac{SST - SSE}{SST} = \frac{\sum(y_i - \bar{y})^2 - \sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$$

where y_i , $i = 1, 2, \dots, n$ are calculated with the selected model.
Further evaluations are performed through analysis of residuals (e.g. residual plots, Durbin-Watson statistic).

Model selection: \tilde{R}^2

In order to select between two 'nested' models, a suitable tool is the \tilde{R}^2

$$\tilde{R}^2 = \frac{\text{SSE}_{m_1} - \text{SSE}_{m_2}}{\text{SSE}_{m_1}} = (R_{m_2}^2 - R_{m_1}^2) / (1 - R_{m_1}^2),$$

where $R_{m_i}^2$, $i = 1, 2$ is the R^2 of model m_i .

If $\tilde{R}^2 > 0.3$ then the more complex model is significant.