Predicting the Demand for New Products and Services

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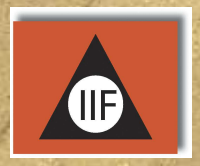
International Institute of Forecasters

First International Conference on Foresight and Forecasting - 2010

11-12 June 2010

Hustai National Park, Mongolia



Abstract

In a competitive environment, companies are driven to introduce new products and services at an ever-increasing pace. Technological innovation, new customers' expectations, market liberalization and aggressive competition have increased the motivation for companies to enhance their capabilities to develop new products and services. Industry estimates have shown that new product share of total sales has exceeded 34% in the US and 25% in Western Europe. Innovation is vital in many sectors and especially in such areas as the ICT (Information Communication Technologies) and Media, the Automotive and the bio-technology industries.

The development and introduction of any new product or service is an inherently risky venture. There are many methods for forecasting the demand for new products and services. Among the most used methods are those based on (a) management's subjective estimates, (b) an analogy to a similar product that was previously introduced to the market, (c) consumer studies, and (d) statistical modeling such as diffusion models.

This presentation is aimed first to show how to develop forecasting models for new products and services and how to run, evaluate, and choose the "best" model for demand forecasting. In the second part, we will see how to adjust the forecasts based on models with benchmarking inputs.

Lastly, I will present a case study to show how diffusion models are applied to new products and services in the ICT (Information Communication Technologies) industry.

Agenda

- Introduction
- What is a new product
- Classification of forecasting methods
- The product and service life cycle phases
- Different forecasting methods for different phases in the life cycle
- The main S-shaped curves
- The data
- The analogy approach
- Benchmarking the internal forecasts
- The collaborative forecasting approach
- Case Study: "*Forecasting the Messaging Services in Western Europe*"
- Conclusion

Introduction (1/2)

- The development and introduction of a new product and service could be a risky venture.
- Reduce the risks associated with new products (investments, market share) has become an established practice within the marketing and sales research industry.
- Forecasting sales of new products is fraught with risks, and forecasts can often be off the mark.
- High risk of great error for new products that represent something fundamentally new and different.
- The choice of the “best” forecasting method requires :

  - a good understanding of the market behavior and its drivers
  - a good description of the “history” of similar products and their life cycle
  - a good overview of the main forecasting approaches and methods that could be applied to new product

Introduction (2/2)

- Technological innovation, new customers' expectations, market liberalization and aggressive competition have increased the motivation for companies to enhance their capabilities to develop new products and services.

- Industry estimates have shown that new product share of total sales has exceeded 34% in the US and 25% in Western Europe

- Appropriate forecast of product market adoption enables optimal planning of :
  - resources
  - investments
  - revenue
  - marketing
  - sales

What is a new product

- **Product improvement**: resulting from technological developments

  - iPhone, iPad

iPhone iPad

GPS

- **Line extension**: same product lines while number of products versions increases

  - Airbus and the concept of « family »:

  - Netbook

netbook

- **Market extension**: new package design, new advertising campaign, diversification to other markets

Classification of Forecasting Methods (1/2)

Extrapolative, Causal and Judgemental Methods:

- **Extrapolative Methods**

Recognizing a pattern in the past data history - assuming the same pattern applies to the future

- **Causal forecasting**

Past relationships in the data are identified and assumed to hold in the future

- **Judgemental Forecasting**

Based on individual views of the future and these may be combined, sometimes in formal ways to produce the final forecast

Classification of forecasting methods (2/2)

Subjective and judgmental forecasting

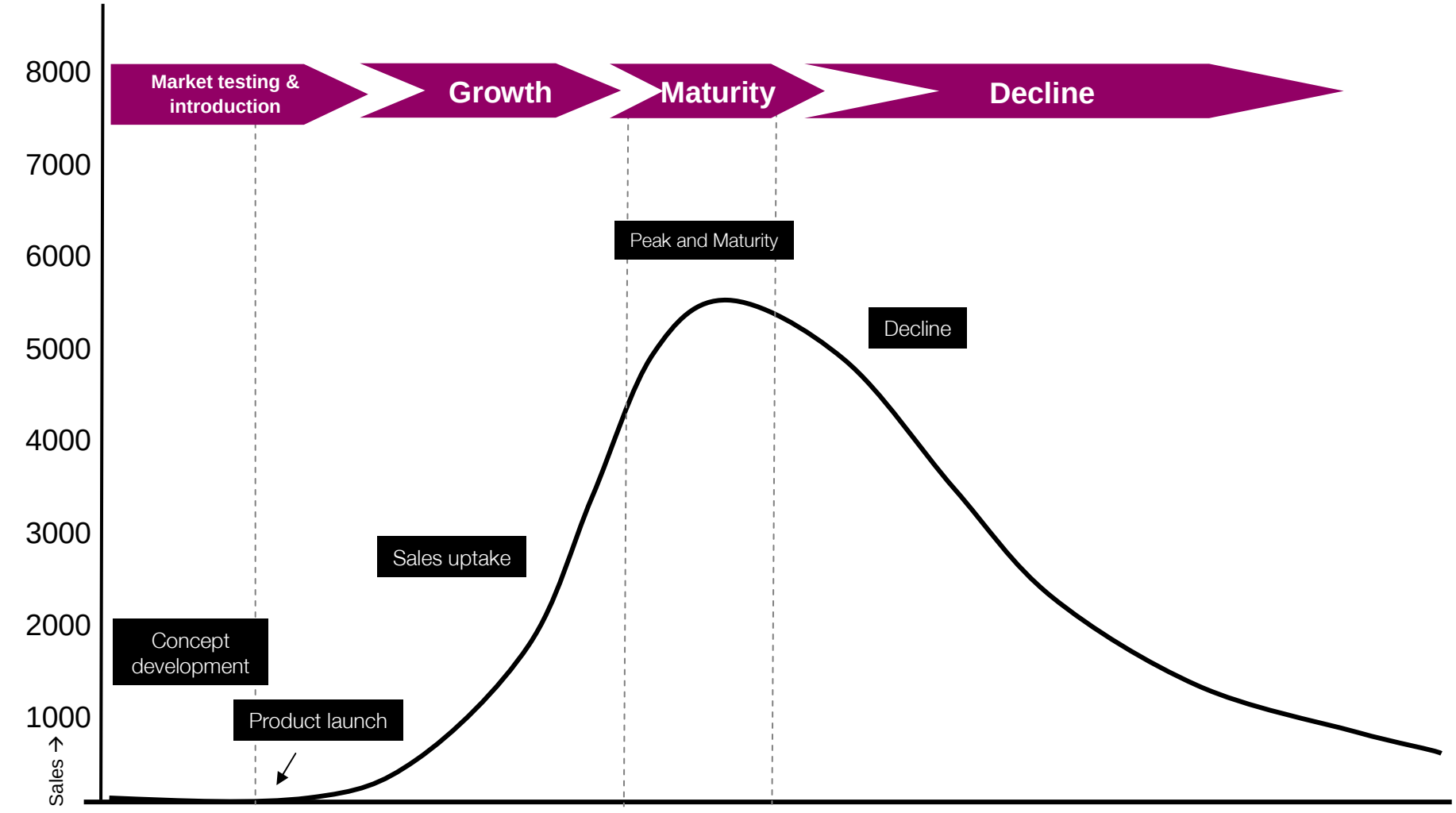
- is useful when a product and service does not have an order history, for example, new products or product upgrades.
- these forecasts are subject to biases like **optimism** and **overconfidence**.
- the main disadvantage of this type of forecasting is the possibility of misleading information, which could prove costly to the business.

Objective forecasting

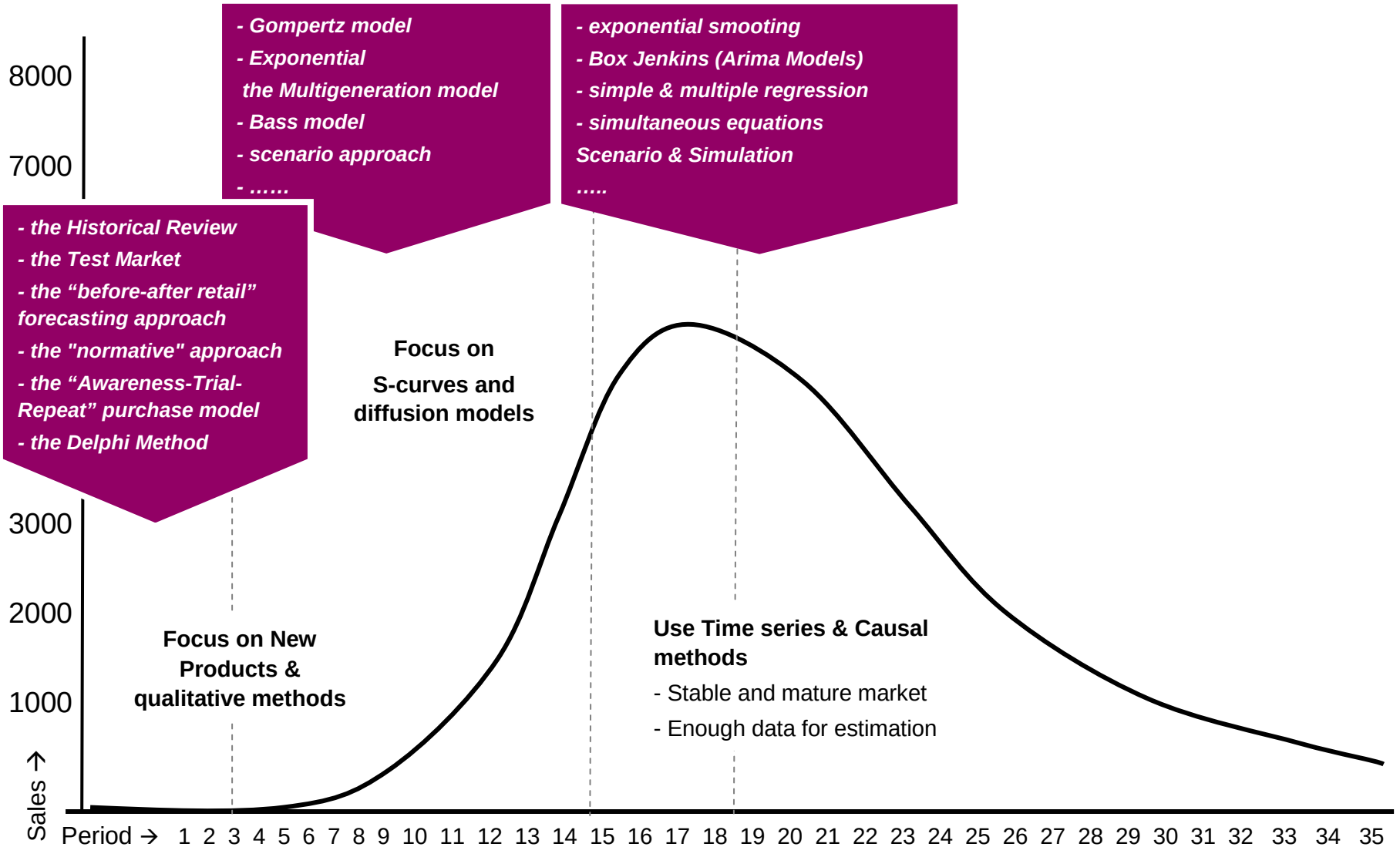
- is most often used on existing product lines.
- this involves research and analysis to determine what is needed based on empirical data.
- in order to gather the most accurate data on future product usage, we need to:
  - *examine historical data*
  - *identify and interpret trends*
  - *analyze existing usage*
  - *"guess" factors in known changes in future demand*

Objective forecasting is less risky than subjective methods, as it relies on past performance and quantitative facts to create more accurate forecasts.

The product and service life cycle phases



Different forecasting methods for different phases in the life cycle



The main S-shaped curves (1/2)

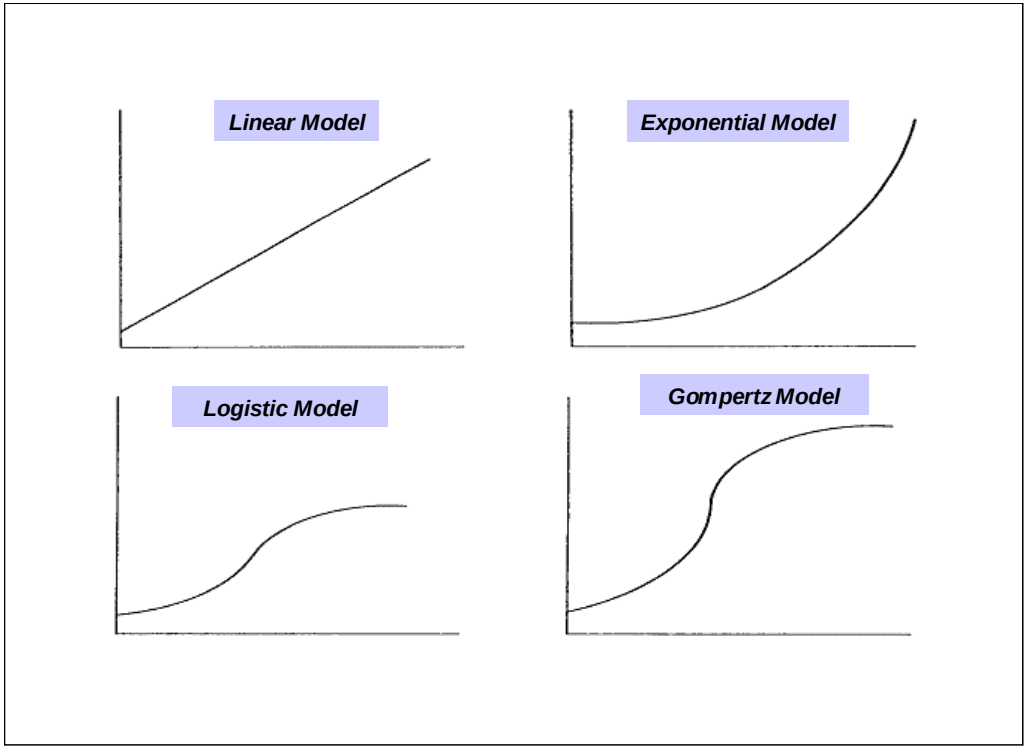
Linear: $Y_t = a + bt$

Parabolic: $Y_t = a + bt + ct^2$

Exponential: $Y_t = ae^{bt}$

Simple Logistic: $Y_t = \frac{M}{1 + ae^{bt}}$

Gompertz: $Y_t = M(a)^{bt}$



Where

Yt is the new product/service at time *t*
a, b, c, are parameters to be estimated
M is a parameter describing the saturation level of the the new product/Service

The *Logistic* and *Gompertz* curves differ from the *Linear, Parabolic* and *Exponential* curves by having saturation level . This saturation level can be estimated in the model or fixed.

The main S-shaped curves (2/2)

The Bass model

- Frank Bass has developed in 1969 a model describing the process of how new products get adopted as an interaction between users and potential users.

- Its objective is to capture the S shaped adoption of any new product or new service;

- $\frac{dN(t)}{dt}$ [p+(q/m)N(t)][m-N(t)]

- $\frac{dN(t)}{dt}$ represents number of any new product or new service in period t

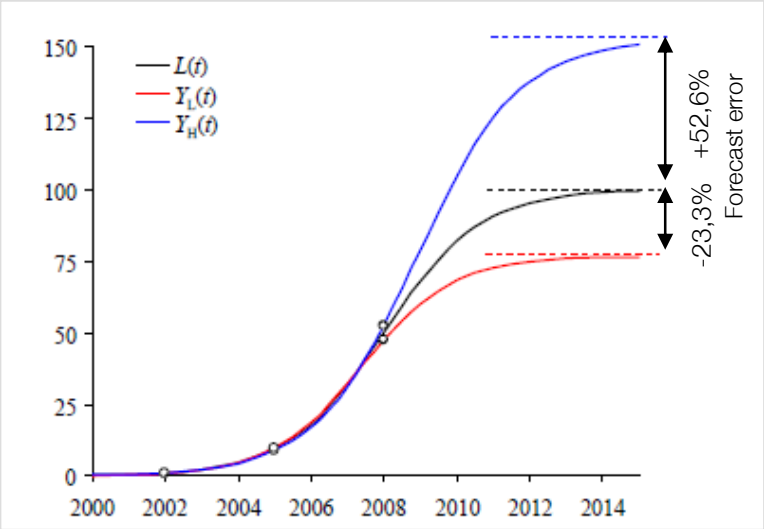
- N(t) is cumulative adopters
- p is the coefficient of innovation
- m is the market potential
- q is the coefficient of imitation

The data

Errors in measured data could lead to important uncertainty of new service forecast.

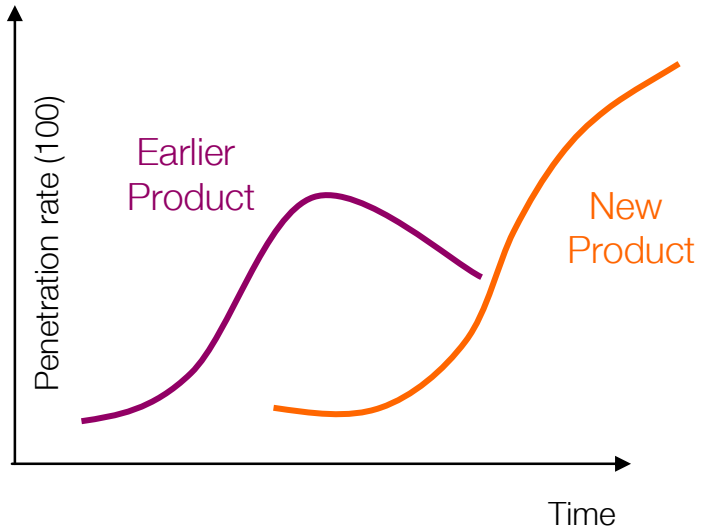
Example of case when known data points have measurement error of ±5 % :

- For this new telecom service, only 3 observations about the number of users are known (2002, 2005 and 2008) but with measurement error of ±5 %.
- Resulting service market capacity without error should be *M* = 100.
- Encompassing possible error of measurement, market capacity lies is the interval from *M*L = 76.6 (-23.3 %) to *M*H = 152.6 (+52.6 %).



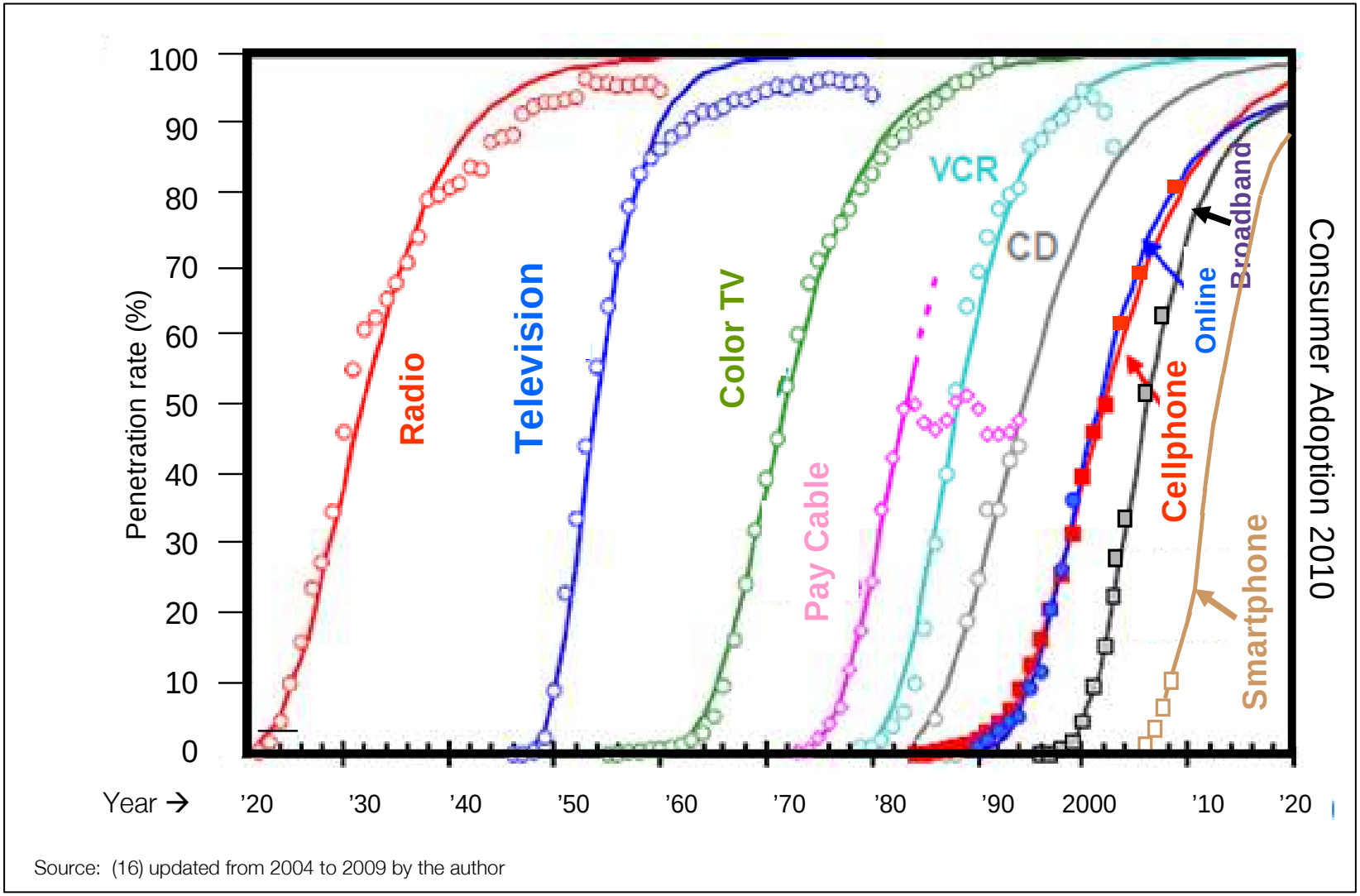
The analogy approach

- Find analog products that are similar to the one to be launched
- Similar analog product: same characteristics as the new product (customer profile, order of entry in the market, …)
- Modelling the life-cycle growth curve of the new product
- Test the most suitable « S » shaped growth curve



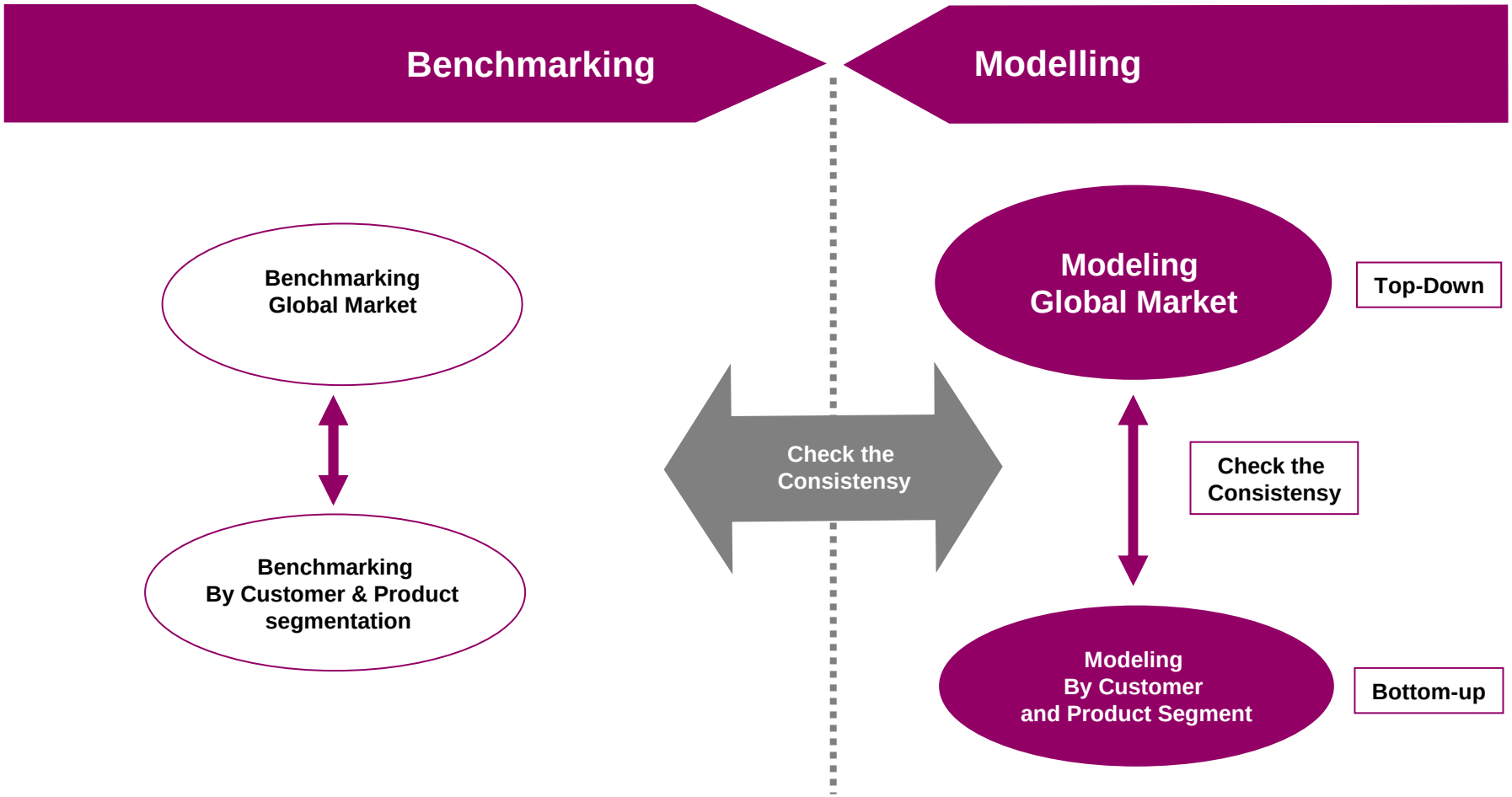
- Start with the main classes of models: the Bass Model, the Gompertz curve and the Logistic curve
- Refine the modelling process with more sophisticated specification within each class of models

Some examples of consumer adoptions using Gompertz model



Source: (16) updated from 2004 to 2009 by the author

Benchmarking the internal forecasts



It is important to:
> challenge our forecast with other « external » ones
> check the consistency between them

example: in house forecast in 2009 = +15%
- source 2 = +8,1%
- source 3 = +6.9%
- source 4 = +7.2%

The collaborative forecasting approach

• Better and more integrated information is not sufficient for a good forecast. Design the process so that social and political dimensions of the organization are effectively managed.

• Create an independent group to manage the forecast process, not the forecast itself. This helps to stabilize the political dimension.

• The person or the team must:

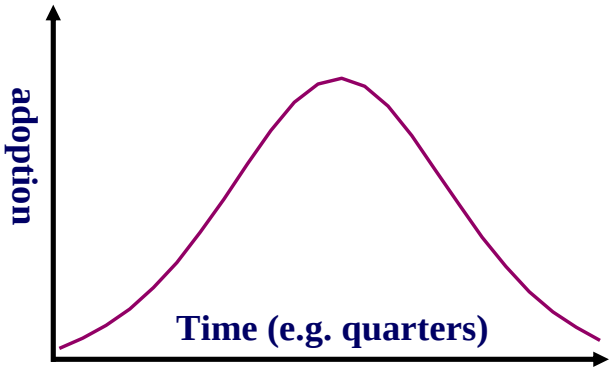
- be transparent
- be process oriented
- understand the organization
- highly skilled (forecasting techniques, business intelligence, market, competition, regulation, …)
- be credible

Case Study: Forecasting the *Messaging Services* in Western Europe

- The aim is to forecast the "Messaging Services" which include SMS, MMS and IM (Instant Messaging)
- Forecasts are derived by (a) Connections and by (b) Revenue

The data set

- Observations: The data set includes quarterly observations from Q1-2005 to Q2-2006, i.e. short Data set.
- We have considered only active users who were connected to the considered services at least 10 times monthly.
- Seven countries were considered



- The analysis of data set excludes model estimation using only a single country data.
- The more suitable framework for modeling short data series seems to be pooling multi-country data

The Multi-Country Pooling Modelling (1/2)

- **Specification & Modelling (Generalized Least Squares Estimation)**

$$y_{ct} = f(m_c, \phi) + \varepsilon_{ct}$$

$$y_{ct} = \ln(Y_{ct} / Y_{ct-1}) = \phi\left((\ln m_c - \ln Y_{ct-1})\right) + \varepsilon_{ct}$$

$$\ln(Y_{ct} / Y_{ct-1}) = \phi \ln m_c - \phi \ln Y_{ct-1} + \varepsilon_{ct}$$

where

y_{ct} is the cumulative number of adopters of SMS at time t

ϕ is the growth rate

m_c is the market saturation level

ε_{ct} is an error term

We have considered and estimated two pooling models using Linearised Gompertz, i.e.

→ **Fixed Effect** and

→ **Cross Sectionally Varying** (CSV) model.

The Multi-Country Pooling Modelling (2/2)

- **Specification & Modelling (Generalized Least Squares Estimation)**

→ The Fixed Effect Model:

In this case, the market saturation (i.e. mc) for each country is estimated but slope or growth coefficient (i.e. ϕ) is common across all the countries

→ The Cross-Sectionally Varying (CSV) Model

In this case :

- the market saturation, mc for each country depends of a number of covariates , slope or growth coefficients (i.e. ϕ) is common across all the countries

- the covariate considered here is the number of digital cellular connections. The Cross-Sectionally Varying (CSV) saturation estimates becomes mc = b0 + b1*Digital Cellular Conn. + ec. Here b_0 is market saturation intercept and b_1 determines the relationship between market potential and digital connection, ec is the error term.

The Forecasting Performance of Multi-Country Pooling

Fixed effect	2 quarters ahead **MAPE**	4 quarters ahead **MAPE**	6 quarters ahead **MAPE**
Germany	6,03	12,64	17,27
Italy	3,53	6,95	9,64
Netherlands	2,93	6,89	10,81
Spain	4,43	6,17	16,24
Switzerland	12,10	27,31	28,20
UK	7,13	13,23	20,66
France	11,34	23,71	29,16

CSV	2 quarters ahead **MAPE**	4 quarters ahead **MAPE**	6 quarters ahead **MAPE**
Germany	3,78	5,36	12,47
Italy	9,67	13,79	21,13
Netherlands	4,56	8,57	23,65
Spain	14,54	19,41	27,12
Switzerland	2,66	5,98	12,07
UK	2,56	3,77	9,31
France	11,98	22,37	29,41

- The MAPE is used to compare the performance as it has been widely used in comparable studies in the past and it is easily interpretable.

- The forecasting performance of both the models differ depending the country :

→ *Same performance : France*

→ *Fixed Effect better performance : Italy, Netherlands, Spain,*

→ *CSV better performance : UK & Switzerland*

- **The CSV model was estimated with only a single covariate i.e. number of digital connections**

The Forecasting Performance of Multi-Country Pooling

Ratio of Saturation Estimates

Countries	Fixed Effect	CSV
Germany	1,4784	2,7664
Italy	1,3328	1,9264
Netherlands	1,512	1,2656
Spain	1,3328	1,6128
Switzerland	1,1984	1,8928
UK	1,2544	1,8032
France	1,1424	1,4784

- As we are estimating model with only 6 quarters data (i.e. very small sample size), we have also investigated plausibility of market saturation estimates.
- If the market saturation estimates are lower than last sample observation, the suitability of the model will be in doubt.
- In all the cases, the ratio of saturation estimates and last sample observation is greater than 1.

The Forecasting Performance of Multi-Country Pooling

The estimates of market saturation coefficients of CSV model

Sample		Estimates	t-ratio
Q1-05 to Q2-06	intercept	3.3153	38.78
	B_Digital Cell	0.0182	6.91
	Growth Coeff.	0.3867	12.51
Q1-05 to Q1-06	intercept	3.5097	29.44
	B_Digital Cell	0.0181	19.65
	Growth Coeff.	0.4417	10.67
Q1-05 to Q4-05	intercept	3.9158	28.74
	B_Digital Cell	0.0195	15.44
	Growth Coeff.	0.5071	9.82
Q1-05 to Q3-05	intercept	4.7917	28.12
	B_Digital Cell	0.0232	15.53
	Growth Coeff.	0.6068	8.07
Q1-05 to Q2-05	intercept	4.9651	26,13
	B_Digital Cell	0.0287	12,05
	Growth Coeff.	0.7321	11,95

- The estimates have changed slightly over time and reaching a stable level.

Conclusion

■ Qualitative and subjective methods are based on hidden assumptions and include human judgment, and if these underlying assumptions or judgments are off the mark, the corresponding forecast can be inaccurate

■ Quantitative and “objective” forecasting is typically accurate enough to be a valuable ally in new product decision making, and is very economical compared to the cost of a major test market.

■ However, the main problem that face forecasters is the limited dataset. Practically, running S-curves will provide “poor” forecasts and this is impossible because of statistical problems.

■ Delphi Method is more used for “technological” products (not really for new services) and for long term. But forecasters use “mini-delphi” approach which is a simplification of Delphi method that could be applied for short term and for various products and services

■ Many types of curve will fit the limited data equally well. They produce very different forecasts; but how do you choose between the alternative curves ?

The best way to build a reliable and accurate forecasts for new products and services is to combine many methods accordingly to constraints: limited data, cost in terms of time and finance, background in forecasting methodologies, … and share them within a collaborative forecasting process

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Thank you

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