



# Customer and Marketing Analytics

Introduction to assignment 1

Kathleen Cleeren

# Different types of data

- Aggregation level:
  - At which level is the observation collected?
    - Aggregated
    - Disaggregated: individual data
- Time series versus cross-sectional
  - Periodicity of observations

# Elasticities

Percentage change in output when the input increases with a particular percentage:

$$\textit{Elasticity} = \frac{\textit{Fraction change in } q}{\textit{Fraction change in } p} = \frac{(q_1 - q_0)/q_0}{(p_1 - p_0)/p_0}$$

# Interpretation of price elasticities

$$\text{Return} = \text{sales} * \text{price}$$



-1

Unit elasticity:

- percentage increase in sales = percentage decrease in price
- Price decreases have no effect on revenues

# Interpretation of price elasticities

$$\text{Return} = \text{sales} * \text{price}$$

Elastic demand:

- Percentage increase in sales > percentage decrease in price
- Price decreases increase revenues



-1



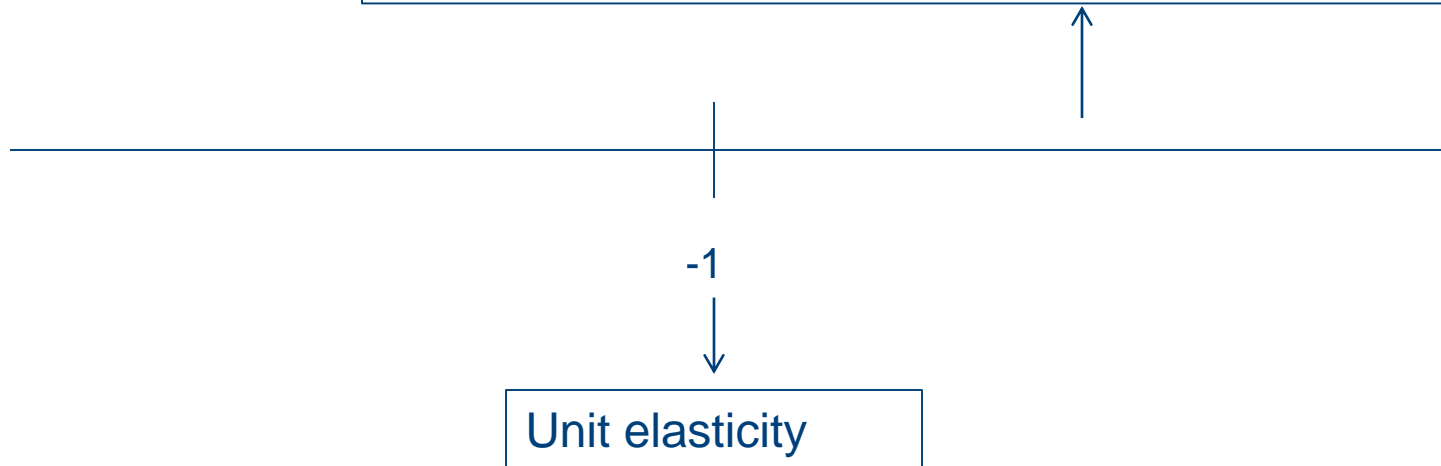
Unit elasticity

# Interpretation of price elasticities

$$\text{Return} = \text{sales} * \text{price}$$

Inelastic demand:

- Percentage increase in sales < percentage decrease in price
- Price decreases decrease revenues



# Why use elasticities?

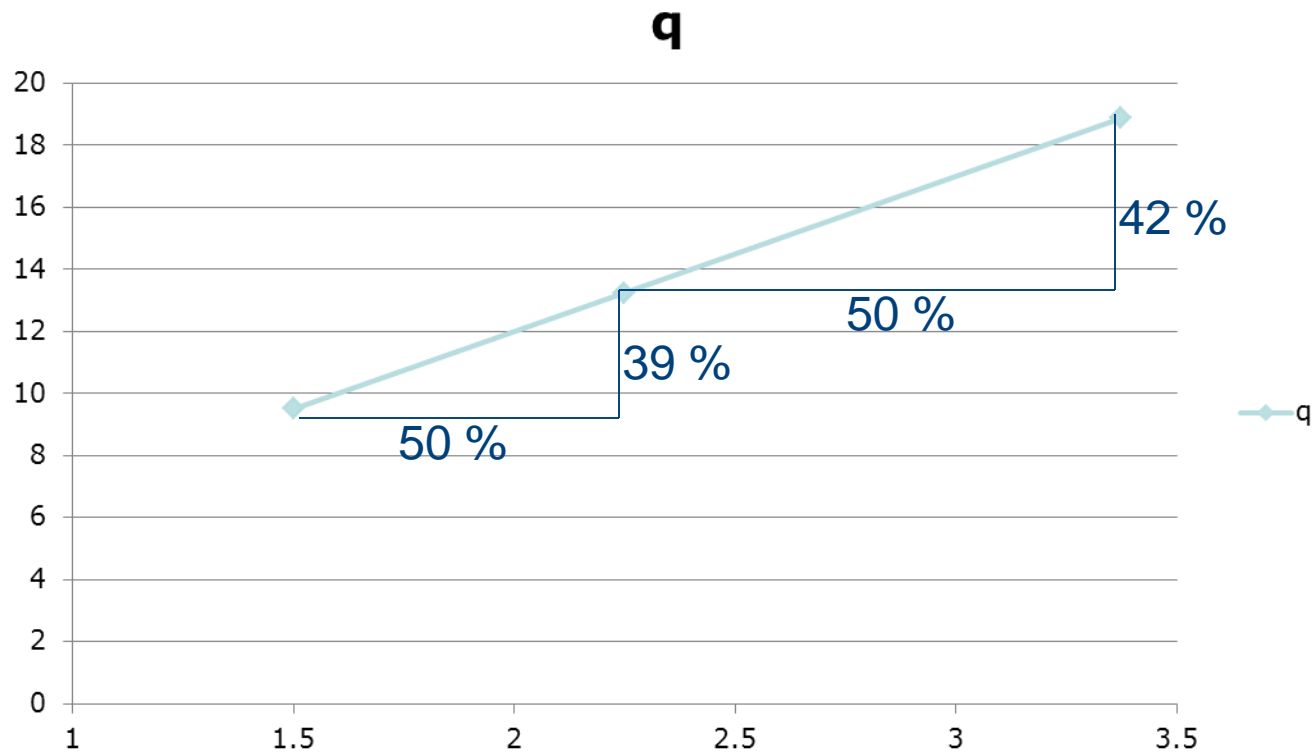
- Unit free:
  - Independent of the industry
  - Independent of the size of the variables
- Interesting direct economic interpretation
- Can also be used for other input variables!

# How to estimate an elasticity?

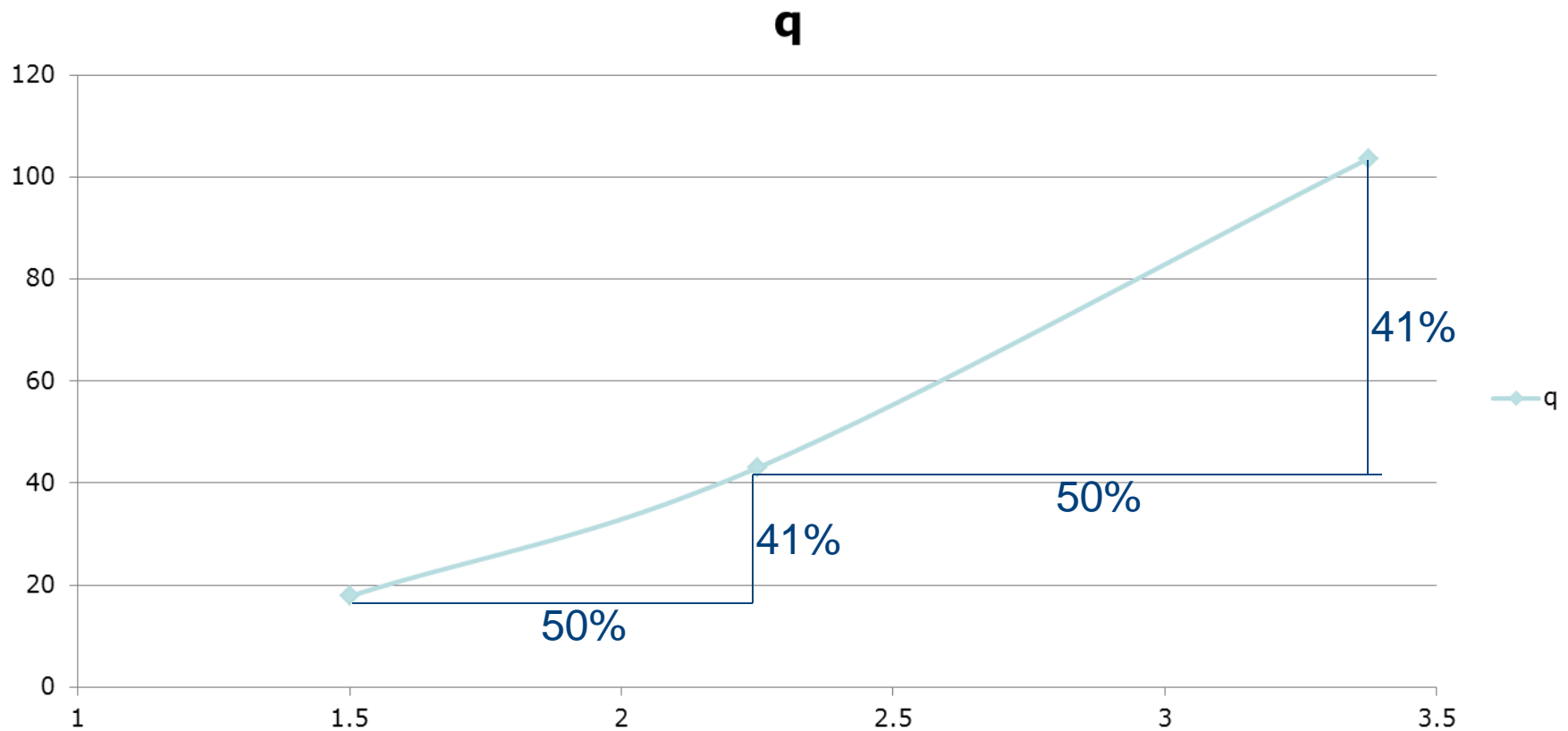
- Market response model that links an input variable to an output variable
- Linear model:
  - Constant change in output
  - Elasticity is dependent on the size of the input variable given that we look at a percentage change
- Log-log model:
  - Curvilinear relationship
  - Constant elasticity



# Linear model: $\text{sales} = 2 + 5 \cdot \text{input}$



Log-log model:  $\log(\text{sales}) = 2 + 5 \cdot \log(\text{input})$



# How to estimate an advertising elasticity?

- Regress  $\log(\text{sales})$  on  $\log(\text{advertising})$ :

$$\log(\text{sales}) = \beta_0 + \beta_1 \log(\text{advertising}) + \varepsilon_t$$

- Parameter of  $\log(\text{advertising})$  is the elasticity

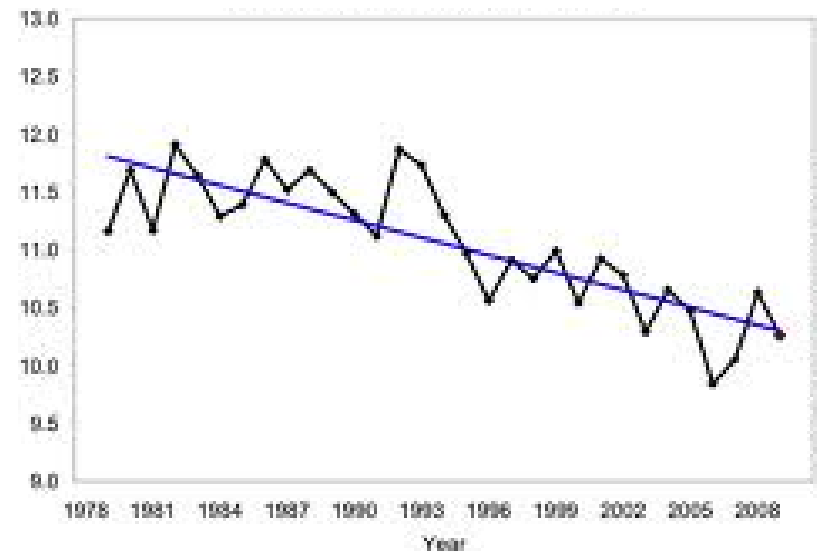
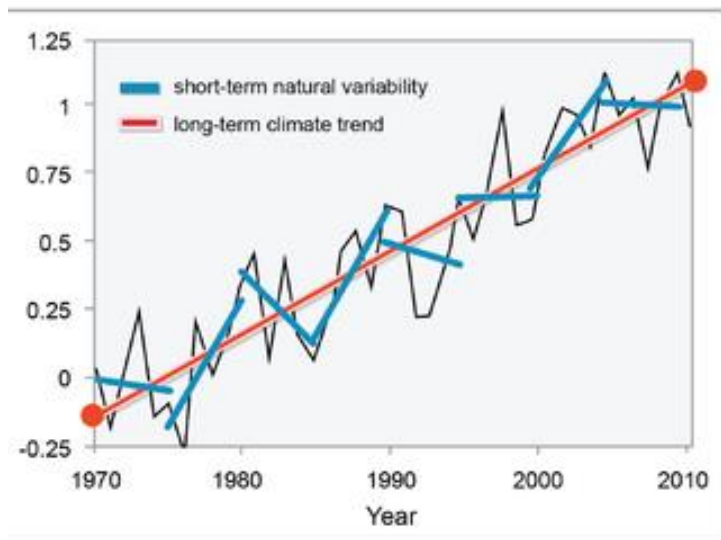
# Add environmental factors

- Not the focus of the model but:
  - Improve the fit of the model (don't forget "simpler is better")
  - Improve the estimation of the elasticities
  - Provide extra insights into the effect of the control variables
  - Extra validity checks

# Specific time series controls

- Long-term trend
- Season

# Long-term trend



# Control for the long-term trend

- Add a trend variable to the model:
  - Create a variable that indicates the period of the observation:
    - Trend = 1 for the first observed period
    - Trend = 2 for the second observed period
    - ...
    - Trend = N for the last observed period
- This is a linear trend

# Season effect





# Controlling for the effect of the season

- Create dummy variables to control for:
  - Season
  - OR month
  - OR trimester
  - OR ...
- Only for datasets for which the periodicity is smaller than one year!

# Adding dynamic effects

- Static model: “contemporaneous” relations
- Adding dynamic effects:
  - X influences sales in the future
  - X influences sales in the past

# Adding dynamic effects

- Adding leads and lags
- Working with a predefined distribution of dynamic effects

# Lags

- Controlling for input from the past:

$$Output_t = \beta_0 + \beta_1 Input_t + \beta_2 Input_{t-1} + \varepsilon_t$$

Contemporaneous effect

Lagged effect

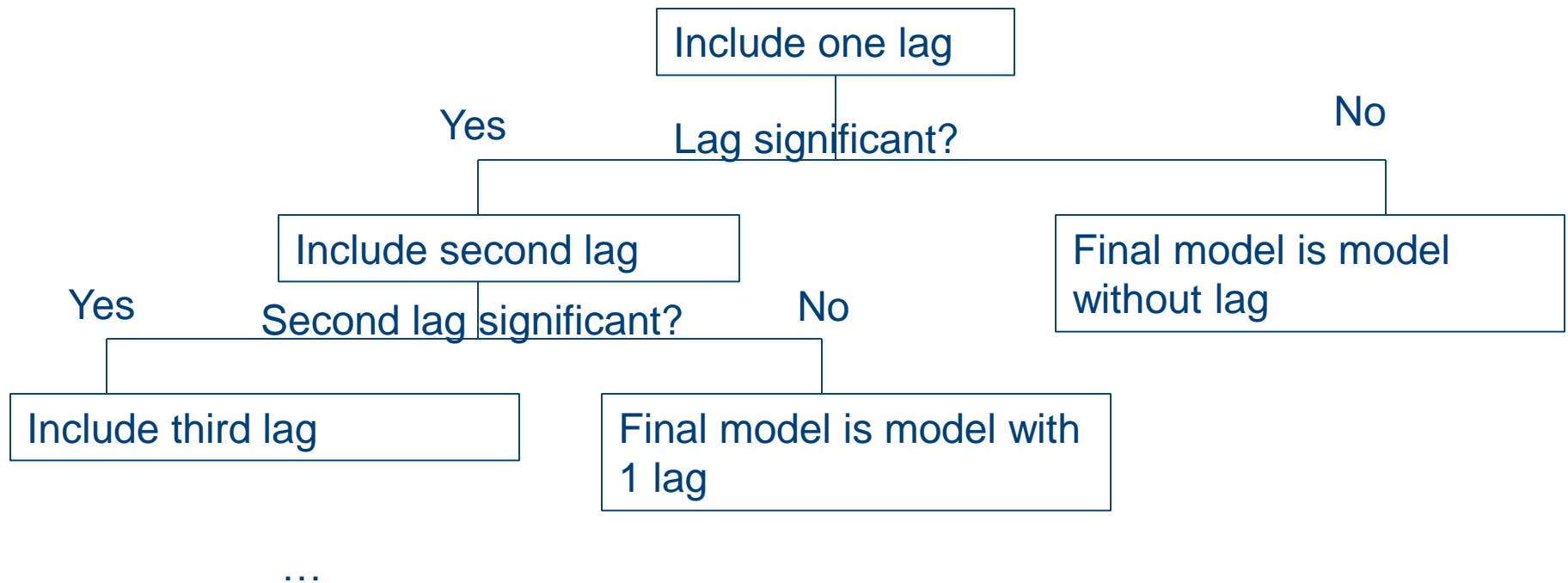
# Creating lagged variables

Period	Input <sub>t</sub>	Input <sub>t-1</sub>	Input <sub>t-2</sub>
1	100		
2	200	100	
3	300	200	100
4	400	300	200
5	500	400	300
6	600	500	400
7	700	600	500
8	800	700	600
9	900	800	700

# Be careful!

- Make sure the dataset is correctly sorted
- Look at the missing values!

# Deciding on the number of lags



# Leads

- Controlling for the influence of input in the future:

$$Output_t = \beta_0 + \beta_1 Input_t + \beta_2 Input_{t+1} + \varepsilon_t$$

The diagram illustrates the components of the regression equation. An arrow points from the term  $\beta_1 Input_t$  to the text "Contemporaneous effect". Another arrow points from the term  $\beta_2 Input_{t+1}$  to the text "Lead effect".

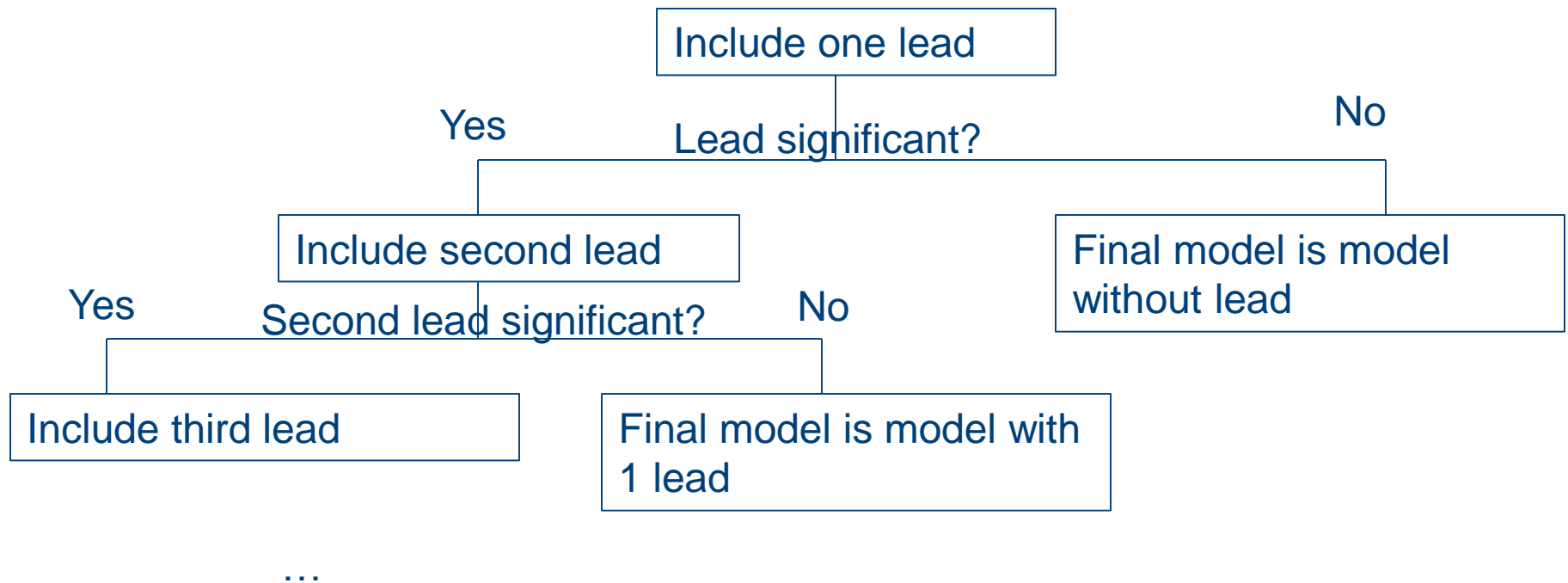
- Forward looking



# Creating lead variables

Period	Input <sub>t</sub>	Input <sub>t+1</sub>	Input <sub>t+2</sub>
1	100	200	300
2	200	300	400
3	300	400	500
4	400	500	600
5	500	600	700
6	600	700	800
7	700	800	900
8	800	900	
9	900		

# Deciding on the number of leads



# Leads and lags

- Combination of leads and lags in one model is possible
- Very flexible way to control for dynamic effects
- Does not always lead to a simple model
- Interpretation can be hard

# Stock variables

$$Stock_t = \alpha Input_t + (1 - \alpha) Stock_{t-1}$$

- Stock of input variable
- Effect of input dependent on:
  - Level of input in the same period
  - Stock of the previous period
- Weight of both components is determined by alpha

# Predetermined distribution of values from the past

$$Stock_t = \alpha Input_t + (1 - \alpha) Stock_{t-1}$$

$$Stock_t = \alpha Input_t + (1 - \alpha) (\alpha Input_{t-1} + (1 - \alpha) Stock_{t-2})$$

$$Stock_t = \alpha Input_t + \alpha (1 - \alpha) Input_{t-1} + (1 - \alpha)^2 Stock_{t-2}$$

...

$$Stock_t = \alpha Input_t + \alpha (1 - \alpha) Input_{t-1} + \dots + \alpha (1 - \alpha)^{n-1} Input_{t-n+1}$$

# Interpretation of alpha

$$Stock_t = \alpha Input_t + (1 - \alpha) Stock_{t-1}$$

- Alpha is the contemporaneous effect of the input
- $1 - \alpha$  is the carryover of the stock

# Calculating the stock variable

Period	Input <sub>t</sub>	Stock <sub>t</sub> $\alpha = 0.1$	Stock <sub>t</sub> $\alpha = 0.9$
0		0	0
1	300	30	270
2	0	27	27
3	0	24.3	2.7
4	100	31.87	90.27
5	0	28.683	9.027
6	400	65.8147	360.9027
7	0	59.23323	36.09027
8	0	53.30991	3.609027
9	0	47.97892	0.360903

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$$=0.1*300+0.9*0$$




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$= 0.9 \cdot 100 + 0.1 \cdot 2.7$

# Calculating the stock variable

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# Deciding on the correct value of alpha

- Estimate different models with stock variables on the basis of different values of alpha
- Select the model with the highest fit

# Using stock variables to control for dynamic effects

- Number of parameters to estimate is limited (one coefficient and one alpha)
- Model is simple
- Interesting interpretation of alpha
- Assumes a fixed distribution of a decreasing impact

# Assignment 1

- Measure and discuss the effectiveness of advertising expenditures of two brands after a product-harm crisis
- Build a market response model step by step
- Think about which variables to include and the implication of adding variables to the model
- Focus is on interpretation!

# Different steps

1. Take a look at the data
2. Estimate the advertising elasticities
3. Add control variables
4. Add competition
5. Add dynamic effects
6. Critical reflection

# Document to hand in

- Word document of maximum 15 pages (all included!)
- Line spacing 1.5; font size 12
- 1 document per team
- Hand in in paper by e-mail to [kathleen.cleeren@kuleuven.be](mailto:kathleen.cleeren@kuleuven.be) on Thursday March 12

# Teams

Surname	Name	Team
Amidei	Juvenal Willi	A
Aslanidis	Odyseas	B
Belzaino	Salvatore	C
Bugge	Stephanie Caytton	D
Cecchini	Oscar	E
Diaz Fraga	Paul Alexander	A
Ekel	Jeremy Mejia	B
Ghiani	Marco	C
		D
Kantipudi	Venkata Sriharsha Chowdary	E
Melucci	Pierfrancesco	
		A
Awad	Mohamed Alaaeldin Mohamed	
Pantaleoni	Marco	B
Petruzzelli	Nicola	C
Rendine	Flavio	D
Ronsisvalle	Carlo Manfredi	E
Saarinen	Veli Henrik	A
Tedino	Simone	B
Vattikonda	Prasanth	C
Zalizniak	Valeriia	D
Zolezzi Labarca	Alejandro Andrés	E