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# Overview of models

# Overview of models

The following tables provide an overview of the specified models, with model extensions/changes highlighted in **bold**. Please note that the input data are assumed to be complete for each model ( i.e., no missing data ).

Model	Dependent variable	Constant & trend component
1	continuous, Normal, iid err	pooled, linear
2	continuous, Normal, iid err	<b>individual effects</b> , linear
3	continuous, Normal, iid err	individual effects, <b>quadratic</b>
4	<b>count, Poisson</b> , iid err	individual effects, quadratic

Table 1: Overview of specified models

# Overview of models — continued

Placeholder

Model	Dependent variable	Constant & trend component
5	placeholder	placeholder

Table 2: Overview of specified models — continued

# General notation

# General notation

Individual  $n$ , for  $n = 1, \dots, N$ , where  $N$  is the number of individuals

Time period  $t$ , for  $t = 1, \dots, T$ , where  $T$  is the number of time periods

$\mathbf{Y}^{obs}$  is a  $N \times T$  matrix representing the observed dependent variable

$\mathbf{Y}^{pred}$  is a  $N \times T$  matrix representing the predicted dependent variable

$\mathbf{X}$  is a matrix of size  $N \times T$  representing the explanatory variable ( e.g., time periods, starting at zero )

## General notation — continued

Latent class ( aka, sub-population )  $c$ , for  $c = 1, \dots, C$ , where  $C$  is the number of classes

$\Pi$  is a  $N \times C$  matrix representing the mixture proportion ( e.g., the probability that individual  $n = 1$  belongs to class  $c = 1$  ); thus,

$$0 \leq \pi_{n,c} \leq 1 \quad \text{and} \quad \sum_{c=1}^C \pi_{n,c} = 1 \quad (1)$$

# Model 1



# Model 1 — dependent variable

Continuous

Normal ( aka, Gaussian )

iid err: independent ( i.e., uncorrelated over individuals and time periods )  
and identically distributed errors

No missing data

## Model 1 — constant and trend component

Constant **without** interindividual differences within-class ( i.e., the constant is allowed to vary between classes but not within classes )

Linear ( i.e., non-stationary, deterministic ) trend component **without** interindividual differences within-class ( i.e., the trend component is allowed to vary between classes but not within classes )

Based on Koop (2003), the assumptions of **no** interindividual differences within-class regarding the constant and trend component correspond to a pooled model ( i.e., a pooled model for each class )

According to Ram and Grimm (2009), latent class growth analysis ( or LCGA for short ) refers to a subset of GMMs assuming **no** interindividual differences within-class regarding the constant and trend component

## Model 1 — likelihood

$$y_{n,t}^{obs} \sim \sum_{c=1}^C \pi_{n,c} \text{Normal}(\mu_{c,n,t}, \sigma_c) \quad (2)$$

where  $\mathbf{M}$  is a  $C$ -tuple containing  $N \times T$  matrices, and  $\boldsymbol{\sigma}$  is a row vector of size  $C$ .

$$\mu_{c,n,t} = \beta_{0,c} + \beta_{1,c} x_{n,t} \quad (3)$$

where  $\beta_0$  is a row vector of size  $C$  representing the constant, and  $\beta_1$  is a row vector of size  $C$  with

$$\beta_{1,c} < \beta_{1,c+1} \quad (4)$$

for identification. In combination with  $\mathbf{X}$ ,  $\beta_1$  represents the linear trend component.

## Model 1 — prior

$$\boldsymbol{\pi}_n \sim \textit{Dirichlet}(\boldsymbol{\alpha}) \quad (5)$$

where  $\boldsymbol{\alpha}$  is a row vector of size  $C$  with  $\alpha_c = 1$  ( i.e.,  $\boldsymbol{\pi}_n$  is assigned a flat, proper prior ).

$$\beta_{0,c} \sim \textit{Normal}(0, 5) \quad (6)$$

$$\beta_{1,c} \sim \textit{Normal}(0, 1) \quad (7)$$

$$\sigma_c \sim \textit{Normal}(0, 1) \mathbf{1}(\sigma_c > 0) \quad (8)$$

where the Normal distribution is truncated to the left at zero, modeled via the indicator function  $\mathbf{1}(\sigma_c > 0)$ .

## Model 2

## Model 2 — dependent variable

Continuous

Normal ( aka, Gaussian )

iid err: independent ( i.e., uncorrelated over individuals and time periods )  
and identically distributed errors

No missing data

## Model 2 — constant and trend component

Constant **with** interindividual differences within-class ( i.e., the constant is allowed to vary between classes and within classes )

Linear ( i.e., non-stationary, deterministic ) trend component **without** interindividual differences within-class ( i.e., the trend component is allowed to vary between classes but not within classes )

Based on Koop (2003), the assumptions of **interindividual differences** within-class regarding the constant and **no interindividual differences** within-class regarding the trend component correspond to an individual effects model ( i.e., an individual effects model for each class )

## Model 2 — likelihood

$$y_{n,t}^{obs} \sim \sum_{c=1}^C \pi_{n,c} \text{Normal}(\mu_{c,n,t}, \sigma_c) \quad (2)$$

where  $\mathbf{M}$  is a  $C$ -tuple containing  $N \times T$  matrices, and  $\boldsymbol{\sigma}$  is a row vector of size  $C$ .

$$\mu_{c,n,t} = \beta_{0,n,c} + \beta_{1,c} x_{n,t} \quad (9)$$

where  $\mathbf{B}_0$  is a  $N \times C$  matrix representing the constant, and  $\beta_1$  is a row vector of size  $C$  with

$$\beta_{1,c} < \beta_{1,c+1} \quad (4)$$

for identification. In combination with  $\mathbf{X}$ ,  $\beta_1$  represents the linear trend component.



## Model 2 — prior

$$\boldsymbol{\pi}_n \sim \textit{Dirichlet}(\boldsymbol{\alpha}) \quad (5)$$

where  $\boldsymbol{\alpha}$  is a row vector of size  $C$  with  $\alpha_c = 1$  ( i.e.,  $\boldsymbol{\pi}_n$  is assigned a flat, proper prior ).

$$\beta_{0,n,c} \sim \textit{Normal}(0, 10) \quad (10)$$

$$\beta_{1,c} \sim \textit{Normal}(0, 1) \quad (7)$$

$$\sigma_c \sim \textit{Normal}(0, 1) \mathbf{1}(\sigma_c > 0) \quad (8)$$

where the Normal distribution is truncated to the left at zero, modeled via the indicator function  $\mathbf{1}(\sigma_c > 0)$ .

# Model 3

Koop, G. (2003). *Bayesian Econometrics*. Wiley.

Ram, N. & Grimm, K. J. (2009). Growth Mixture Modeling: A Method for Identifying Differences in Longitudinal Change Among Unobserved Groups. *International Journal of Behavioral Development*, 33(6), 565-576.