AN INTERNATIONAL WORKSHOP OF

EARLY CHANGE PROJECT

International Perspectives on Early Childhood Education

Workshop PROCEEDINGS

January 2014

EARLY CHANGE WORKSHOP

'International Perspectives in Early Childhood Education'

PROCEEDINGS

Lifelong Learning Program, Comenius Multilateral

(Project no: 517999-LLP-2011-GR-COMENIUS-CMP)

THE PROJECT COORDINATOR

E. ZACHOPOULOU, PROFESSOR
Alexander Technological Educational
Institution of Thessaloniki
Dept. of Early Childhood Education

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PART I
Conference Program

Education and Culture DG
Lifelong Learning Programme

'EARLY CHANGE Workshop':

International Perspectives on Early Childhood Education

25th of January 2014
Venue: Convention Center of Bank of Piraeus
(Katouni 12 – 14, Thessaloniki)

9.00-9.30	Registration
9.30-9.45	Welcoming remarks
	1st SESSION
9.45-10.15	**Early Childhood Education evaluation and monitoring systems: a case study in Brazil** Eliana Bhering, Federal University of Rio de Janeiro, Brazil
10.15-10.45	**Understanding observation as assessment tool in early childhood education** Domna Kakana & Kafenia Botsoglou, University of Thessaly, Greece
10.45-11.15	**Observation in Early Childhood Education: Video Feedback Intervention** Michael Gluer, University of Bielefeld, Germany
11.15-11.30	Discussion
11.30-12.00	*Coffee Break*
	2nd SESSION
12.00-12.30	**An appraisal and some recent methodological developments in multilevel and longitudinal random effects models** Nikos Tzavidis, University of Southampton, UK
12.30-12.50	**Quality of early childhood environment in six European countries through 'Early Change' project** Jarmo Liukkonen, University of Jyvaskyla, Finland
12.50-13.10	**Quality of early childhood environments and child outcomes in Portugal** [1]Teresa Leal, [1]Ana Madalena Gamelas, [2]Sílvia Barros, [2]Manuela Pessanha [1]University of Porto, Portugal [2]Polytechnic Institute of Porto, Portugal
13.10-13.30	**Early Change: Good practices from six early childhood education systems** Athanasios Gregoriadis, Aristotle University of Thessaloniki, Greece
13.30-13.50	**Best Practice in Denmark** Lise Sanders Olesen & Claus Henriksen,, University College Sealand, Denmark

13.50-14.00	Discussion
14.00-15.00	*Lunch Break*
	3rd SESSION
15.00-15.15	**Presentation of 'THALES' project** Evridiki Zachopoulou, ATEI of Thessaloniki, Greece
15.15-15.30	**Photo-presentation of 'EARLY CHANGE' project** Vasilis Grammatikopoulos, University of Crete, Greece
15.30-15.45	Closing remarks

PART II
Abstracts of Keynote Speeches

Early Childhood Education evaluation and monitoring systems: a case study in Brazil

Eliana Bhering
Federal University of Rio de Janeiro, Brazil

Abstract

There has been an increasing demand for ECE in the past decade in Brazil, with a fast growing number of enrolments of babies, toddlers and young children in ECE centers. ECE is considered part of the educational system and the Brazilian legislation has established that it is a right of all children to have access to an ECE with a good level of quality. As ECE policies get into place, demand is also growing as far as quality is concerned. Central government as well as municipalities (who are responsible for ECE) start to explore ways of assessing and monitoring current ECE policies and practices so as improvement can take place constantly. A study has been developed in the city of Rio de Janeiro that included assessing 149 ECE public centers using ITERS-R and ECERS-R and analyses were carried out in order to identify aspects of the practices (and policies) that should be taken into consideration in the process of building a fair monitoring system. For that, the classical theory of measurement was used. Results revealed 9 and 10 different dimensions from the ITERS-R and the ECERS-R data respectively. Both included aspects like access to materials and toys, aspects of daily routine and of the classroom environment, space and furniture, use of language, etc. Analysis has also strongly indicated the need to monitor all levels of policies instead of focusing only on practices. ECE quality involves implementing policies and developing practices that are aligned.

Key-words: ECE quality; assessment and monitoring; policies and practices

Observation in Early Childhood Education: Using multi-media

Dr. Michael Glüer
University of Bielefeld, Department of Psychology

Abstract
To evaluate process quality in classrooms (i.e. sensitivity, interaction quality) or to assess children's developmental process different methods like psychometric test, questionnaires and observation scales exist. In daily routine most of them are challenging to apply due to limited time and resources available in early childhood institutions (i.e. child/staff ratio, financial support or training). Contrariwise observation can be applied easily in daily work without additional effort. Observation can be used to gain a deeper understanding of the child and the own professionalism. It can improve process quality if it used to evaluate pedagogical actions. With the development of new media and technical equipment like camcorders, computers and mobile phones, observation can be supported and facilitated to gain an easier insight in pedagogical processes and children's development. In this presentation the importance of observation for high quality education will be discussed. Strategies for using camcorders, software and other technical equipment in early childhood centres will be introduced.

Understanding observation as assessment tool in early childhood education

Domna Kakana, Kafenia Botsoglou
University of Thessaly, Greece

Abstract
Observing children is something everyone enjoys doing. Children are charming, creative, active, and emotional. It provides vital information about each child's needs, interests, abilities and learning styles. In this presentation we will focus in alternative assessment methods and in techniques for collecting and recording observations. Many examples will be given, in order to understand the power of this tool which can help us to know deeper each child individually and to organize effectively the pedagogical process.

An appraisal and some recent methodological developments in multilevel and longitudinal random effects models

Nikos Tzavidis
Southampton Statistical Sciences Research Institute
University of Southampton

Multilevel and longitudinal models that include random effects are popular tools that are often employed in applied statistical analysis. In this talk I will present an appraisal and some recent methodological developments in multilevel and longitudinal data analysis. The talk will start by motivating the use of such models to account for the effects of clustered sampling designs and natural hierarchical structures. Having motivated the need for using such models, I will then present some simple, yet popular examples of multilevel models for example, the random intercepts and random coefficients models. I will then focus on specific examples of recent methodological developments and more specifically, on extensions of multilevel models to quantile random effects regression for continuous and discrete outcomes. The talk will present examples of using multilevel models for the analysis of educational data in particular, the use of contextual value added models and the analysis of cohort data on behavioural outcomes of young children in England.

PART III
Conference Presentations - Speeches

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Statistical Models in Educational Research

Nikos Tzavidis
University of Southampton

Thessaloniki, January 25, 2014

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Review of Linear Regression Models

Extensions: Random Effects (Multilevel) Models

Beyond Averages: Introduction to Quantile Regression

Quantile Regression: Extensions

Measuring School Performance via Value Added Models

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Linear Regression: A Review

- **Linear regression**: Popular approach for studying association between an outcome variable y and covariates $\mathbf{x}$

$$y = \beta_0 + \beta_1 * x_1 + ... + \beta_p * x_p + \epsilon$$

- Model for the **mean** of y given $\mathbf{x} \rightarrow E(y|\mathbf{x}) = \mathbf{x}^T\beta$
- Conventional Assumptions:
  - $\epsilon \sim N(0, \sigma^2)$
  - ϵ are independent
  - independence between ϵ and $\mathbf{x}$
  - linearity
  - The effects of $\mathbf{x}$ are constant across the distribution of y

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Independence Assumption

- Survey data rarely comes from a Simple Random Samples
- Data collection process generates observations that are not independent
- Clustered/Multi-stage designs
- Cost advantages **BUT**
- OUTCOME: Clustered data!

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Why does Clustering Matter?

- If observations within the clusters are correlated assuming independence will result in wrongly estimated standard errors
- We will find evidence of significant effects when we should not

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More on Clustering

- Even if we have collected our data in an un-clustered way there is still natural clustering in the population
- Model-based approach build a model that represents the population from which the data was selected
- Impact of clustering is no longer just a nuisance but is of substantive interest in its own right.
- **Example**: Pupils within classes within schools
  - The performance of a pupil does not only depend on their characteristics but also on the class they are in and the school from which that class is drawn, (Goldstein, 1995/2003)

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Model-based Methods to Account for Clustering Multilevel Models

- **Random Intercepts model**: Simplest multilevel model
- **Notation**: i-Level 1 (e.g. pupil); k-Level 2 (e.g. school)

$$y_{ik} = (\beta_0 + u_k) + \mathbf{x}_{ik}^T \boldsymbol{\beta} + \epsilon_{ik}$$

- $\epsilon_{ik} \sim N(0, \sigma_\epsilon^2)$
- $u_k \sim N(0, \sigma_u^2)$
- **Variance Components**:σ_ϵ^2,σ_ϵ^2
- σ_ϵ^2: Within schools between pupil variance
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- u_k: School random effect

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Example

- y_{ik} = Exam score at age 16
- x_{ik} = Exam score at age 11
- i = pupil and k = school
- For a given school, the effect of a 1-unit increase in x_{ik} for a pupil is β_1 units increase in $E(y_{ik})$
- For a given pupil, u_k is the school effect and is constant for all pupils within school k
  - $u_k > 0$ - **Above average school**
  - $u_k = 0$ - **Average school**
  - $u_k < 0$ - **Below average school**

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Intra-Cluster Correlation Coefficient

$$\rho = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_\epsilon^2}$$

- **Definition 1**: The fraction of the total unexplained variability due to the grouping structure
- **Definition 2**: Correlation of level one units within a level two unit after controlling for the effect of $\mathbf{x}$.
- Example: ρ quantifies the similarity of performance scores of two pupils that attend the same school after controlling for the effect or their prior performance scores

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Extensions I - Random Coefficients (Slopes) Model

- **Random Intercepts**: Impact of pupil's prior performance is constant across classrooms
- Assumption can be relaxed by allowing for random slopes

$$y_{ik} = (\beta_0 + u_{0k}) + (\beta_1 + u_{1k}) * PriorScore + \epsilon_{ik}$$

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Extensions I - Random Coefficients (Slopes) Model

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- For longitudinal data usually random slopes (on time) more appropriate correlation structure

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Introduction to Quantile Regression

- Until now we have presented models for the mean of y given $\mathbf{x}$
- Sometimes the mean model may not be informative enough
- Extend regression to model the quantiles of y given $\mathbf{x}$
- **Quantile Regression**
- **Special case**: Median regression
- When is quantile regression useful?
  - With asymmetric data (Mean different from Median)
  - With heteroscedastic data

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A General Framework for Regression

- Regression: model for the **mean** of y given $\mathbf{x}$
  $\rightarrow E(y|\mathbf{x}) = \mathbf{x}^T\beta$
- Quantile regression: model for the **quantiles** of y given $\mathbf{x}$
  $\rightarrow Q_y(q|\mathbf{x}) = \mathbf{x}^T\beta(q)$
  (Koenker and Bassett, 1978)
- M-Quantile regression: $\rightarrow Q_y(q|\mathbf{x};\psi) = \mathbf{x}^T\beta(q)$
  (Breckling and Chambers, Biometrika, 1988; Chambers and Tzavidis, Biometrika, 2006)

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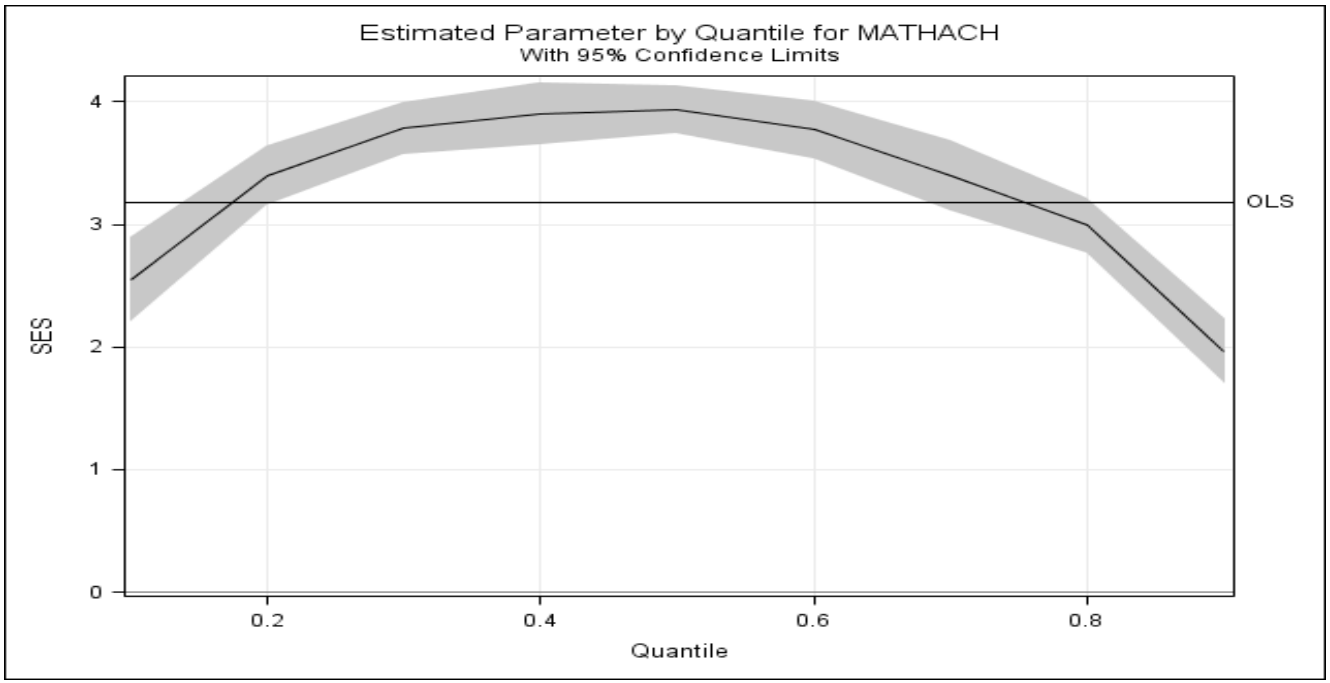
Example: Logan & Petscher

- How socio-economic status impacts on Mathematics score



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Example: Logan & Petscher (Cont'd)

- Does the relation with SES vary across the distribution of math achievement?
- The relation is strongest at the 50th the percentile (median)
- The relation is weaker for high performing pupils

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Quantile Regression: Extensions

- What if data is collected with clustered sampling designs?
- How to account for multilevel structures?
- How to account for longitudinal structures?

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Quantile Regression: Extensions (Cont'd)

Quantile/M-quantile Regression with Random Effects

A continuous random variable y follows an asymmetric Laplace distribution, $y \sim ALD(\mu, \sigma, q)$ with pdf

$$p(y|\mu, \sigma, \tau) = \frac{q(1-q)}{\sigma} \exp \frac{-|y-\mu|}{\sigma}$$

- Geraci and Bottai (2007, 2013)
- $p(y, u|\beta, \sigma, \Gamma) = p(y|\beta, \sigma, u)p(u|\Gamma)$
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- $p(u|\Gamma)$, Normal or random effects
- An M-quantile random effects model (Tzavidis et al., 2014)

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Analysis of Linked PLASC/NPD Data from Schools in London

- Linked PLASC/NPD Data for 7000 pupils in London
- **Outcome**: performance at age 16
- **Covariates**: FSM, gender, ENGF,IDACI, Prior ability
- Does performance at 16 depend on covariates ?
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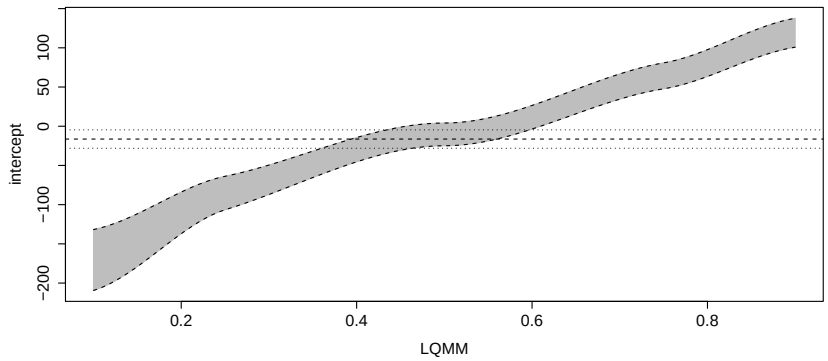
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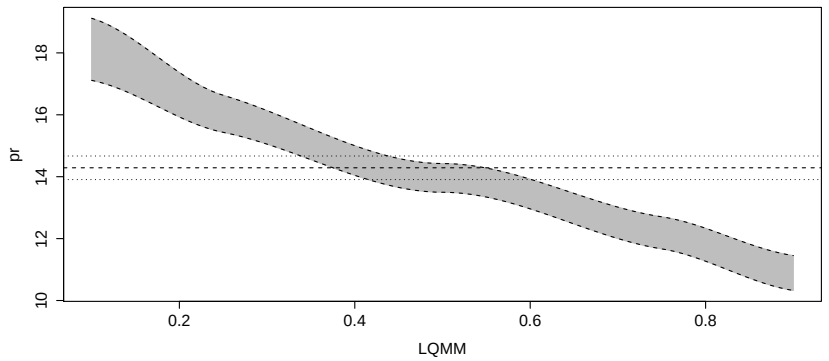
pr
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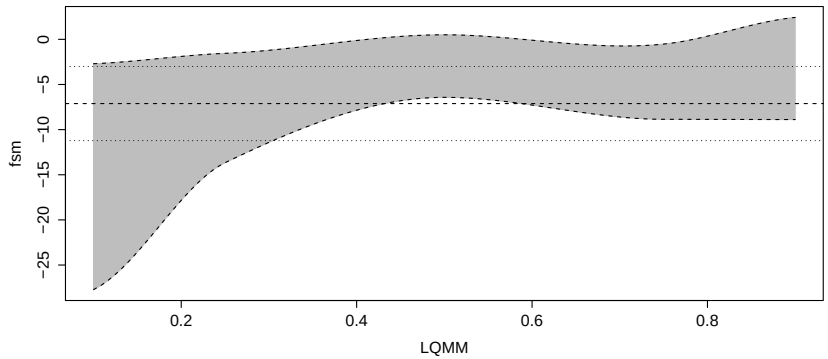
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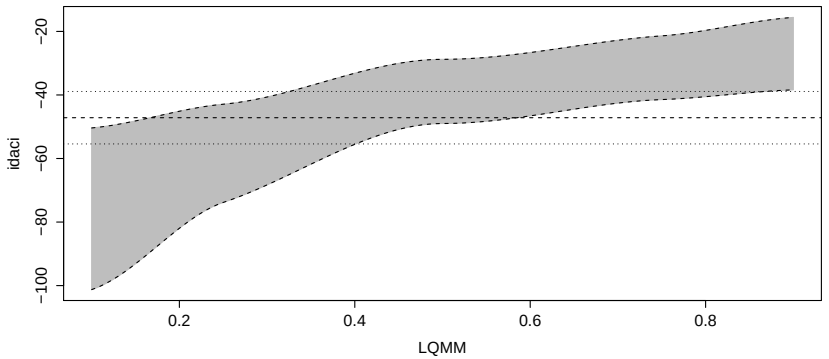
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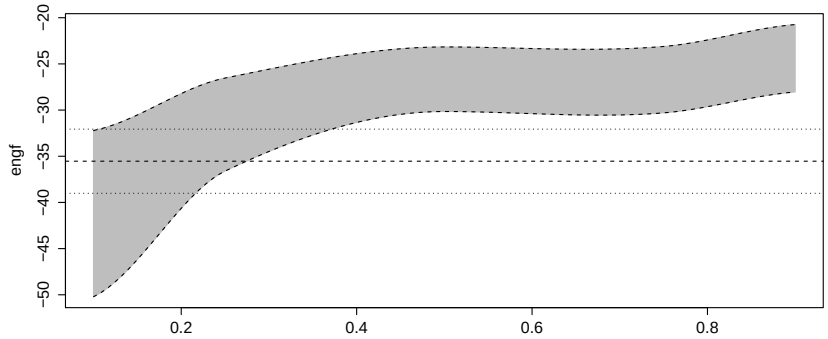
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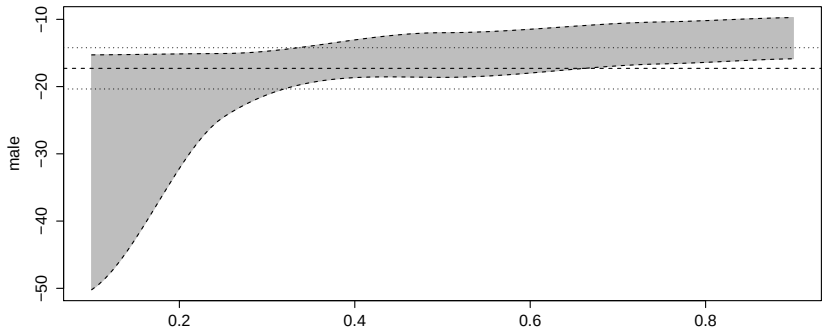
male

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What are Value Added (VA) and Contextual Value Models (CVA)?

- School performance: How well its pupils perform in exams
- Important to control for student prior ability
- Ideal Measure: Shows how much progress pupils have made
- This is the aim of a **Value Added** measure
- **Contextual Value Added**: accounts for contextual factors
- School performance is the value-added a pupil receives beyond what their own characteristics predict they should achieve

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A Simple Step by Step Illustration

- **Step 1**: Compute the predicted performance for a pupil (accounting for their prior ability) using data from all pupils
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A Measure of Contextual Value Added: A More Detailed Look

- Based on the use of a random intercepts multilevel model (Ray, 2006; Goldstein & Leckie, 2009)
- Outcome (y): Performance of pupils at age 16
- Covariates: Prior attainment at age 11(prior); free school meals(fsm); ethnicity; english as first language

$$y = \beta_0 + \beta_1 * prior + \beta_2 * fsm + ... + u_k + e_{ik}$$

- School performance defined by school level residual, u_k
  - $u_k > 0$ - **Above average school**
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- Propose a robust CVA measure using M-quantile regression
- Relaxes the assumption of normality of the school effects
- Allows for producing CVA measures for subgroups
- Accounts for the heteroscedastic nature of the data
- **School CVA**: The most representative quantile for the school
  - $q_k > 0.5$ - **Above average school**
  - $q_k = 0.5$ - **Average school**
  - $q_k < 0.5$ - **Below average school**

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An Application Using Data from the London Schools

- Linked NPD/PLASC Data (2007/08 cohort) from London schools
- Performance at age 11 (prior attainment) performance at age 16 (the outcome) - NPD
- Linked PLASC data to provide the background information
- Working model specification similar to the DfE CVA model (Ray, 2006)
- **Control variables**: Prior ability; fsm; gender; ethnicity; first language at home; SEN; change schools

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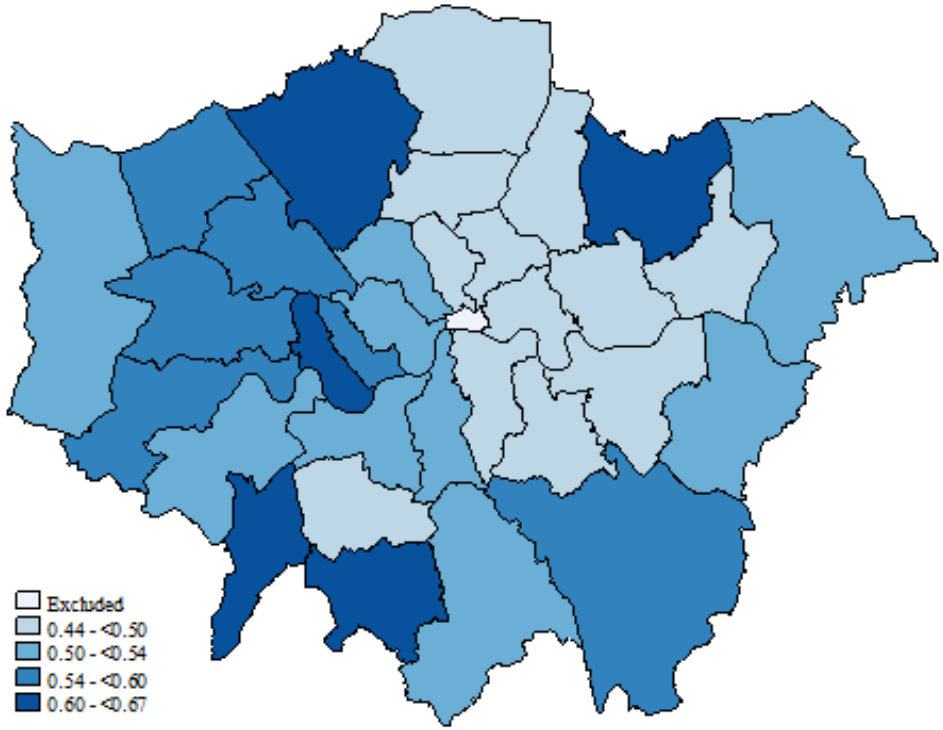
London LEAs - Marginal Performance Measures



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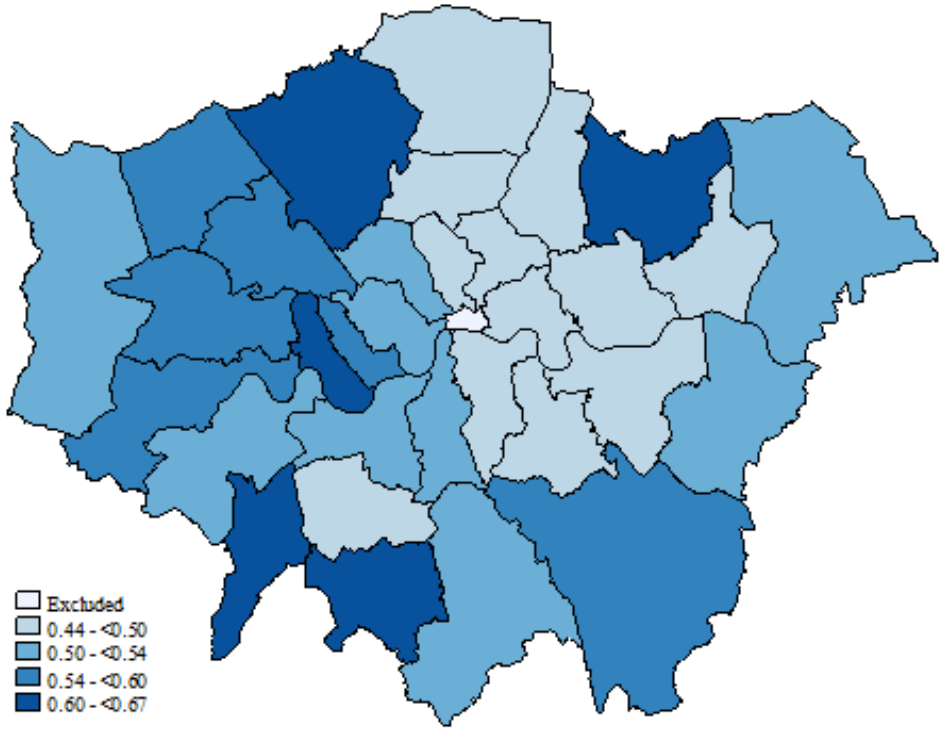

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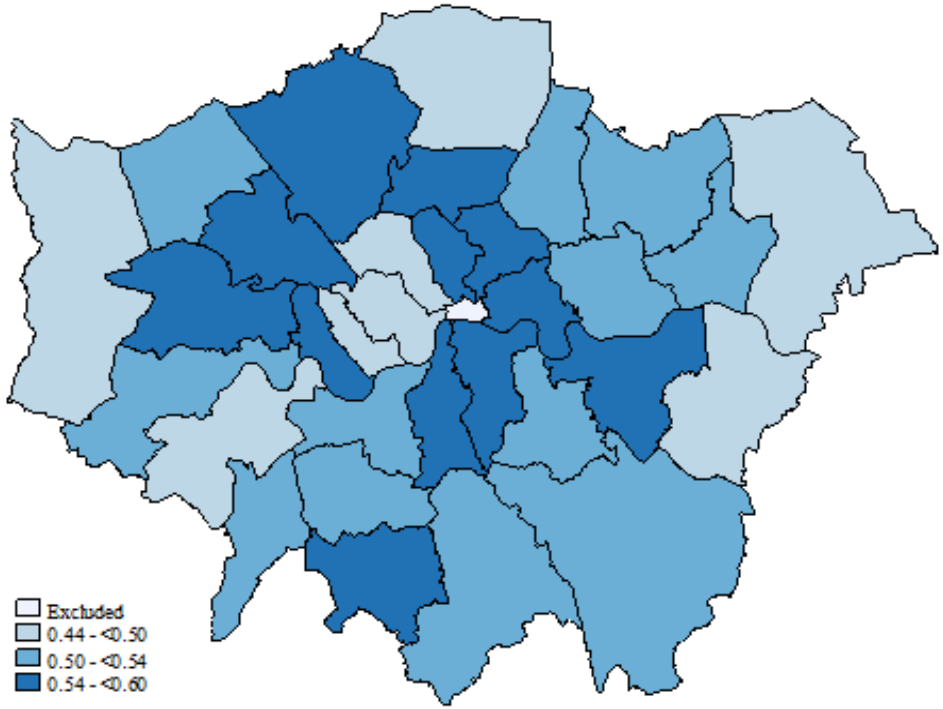
London LEAs - Conditional Performance Measures



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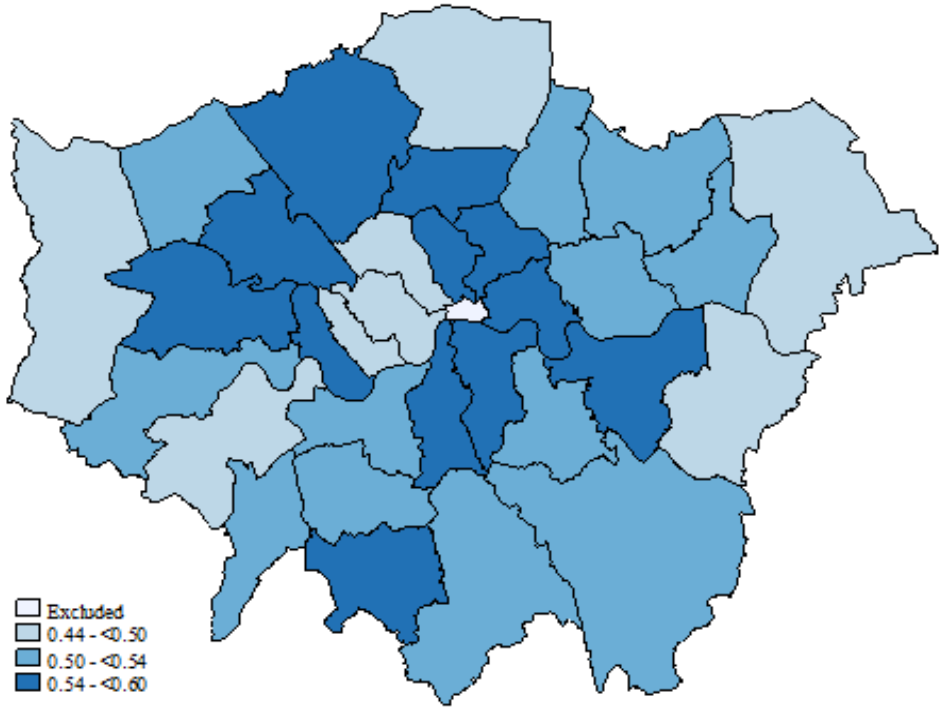

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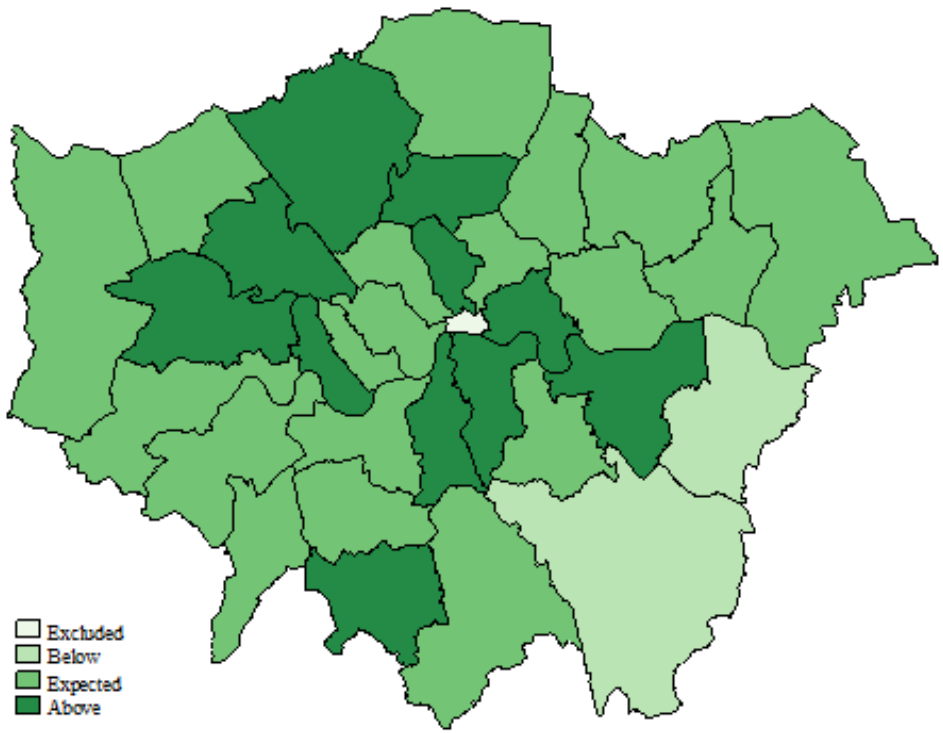
London LEAs - Conditional Performance Measures with Precision Estimates



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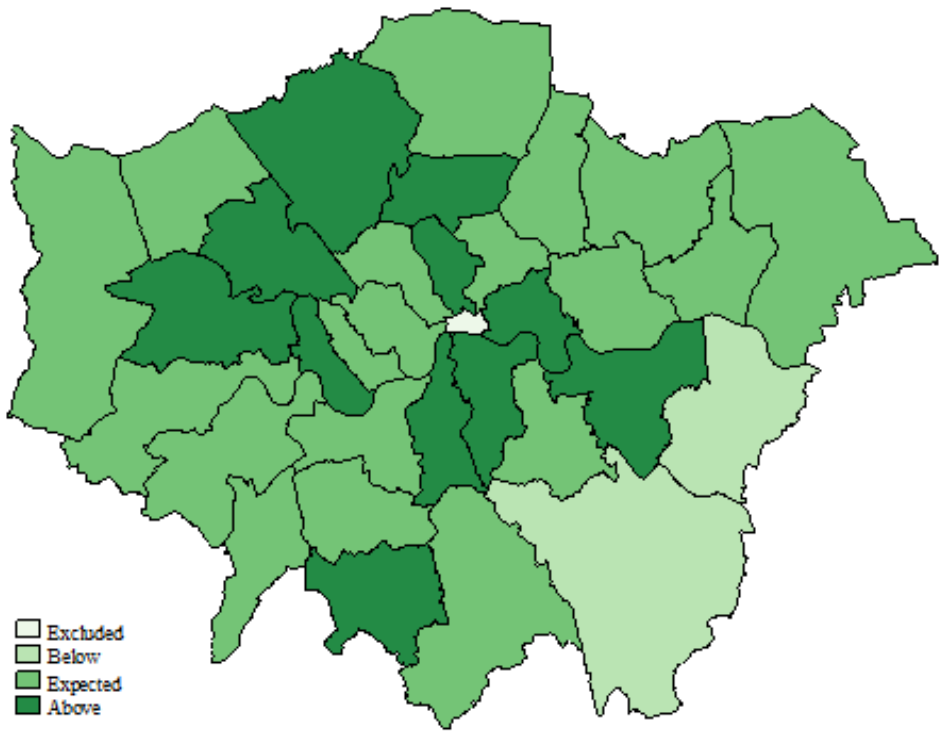

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Comments on CVA Analysis

- Conditional measure shows less variation than marginal measure
- Poor performing local authorities (Central-East London) improved when controls are introduced
- However, conditional performance measures subject to variability
- Two areas in south London that are significantly below the mean after accounting for variability

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Education and Culture DG

Lifelong Learning Programme

Early change

Promoting the Professional Development of Early Childhood Educators

Results of the Early childhood environment quality assessment (ECERS-R)

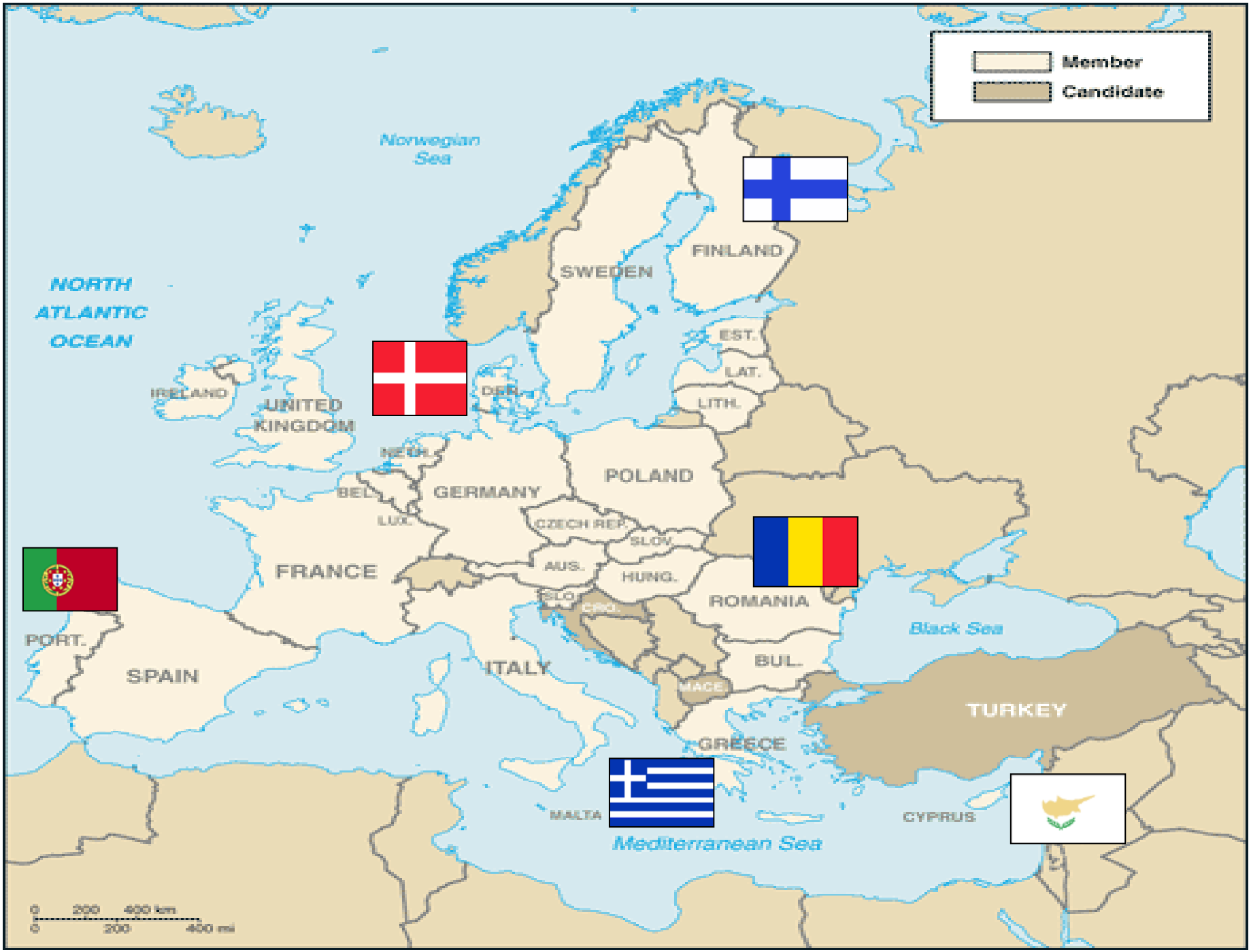
***Jarmo Liukkonen*, Professor**

University of Jyväskylä,

Finland

"With the support of the Lifelong Learning Programme of the European Union"

LLP, Comenius Multilateral Project 517999-LLP-2011-GR-COMENIUS-CMP


Member
Candidate
Norwegian Sea
NORTH ATLANTIC OCEAN
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IRELAND
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LUX.
GERMANY
POLAND
CZECH REP.
SLOV.
AUS.
HUNG.
FRANCE
ROMANIA
SLO.
CRO.
Black Sea
PORT.
SPAIN
ITALY
BUL.
MACE.
TURKEY
GREECE
MALTA
CYPRUS
Mediterranean Sea
0 200 400 km
0 200 400 mi

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EARLY Q
EARLY CHILDHOOD ENVIRONMENT QUALITY

Instruments

- ✓ Early Childhood Environmental Rating Scale – R (ECERS-R) (Harms, Clifford & Cryer, 2005)
- ✓ ECERS-R is considered by the majority of researchers as the most complete instrument for the evaluation of quality in ECE worldwide
- ✓ It is implemented throughout the USA, most of the European countries, Japan and other Asian nations

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Lifelong Learning Programme

EARLY Q
EARLY CHILDHOOD ENVIRONMENT QUALITY

Seven subscales

43 quality indicators

Instruments

1. Space & furnishing
2. Personal care routines
3. Language-reasoning thinking
4. Activities
5. Interaction
6. Programme structure
7. Parents and staff

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Means (sd) of the ECERS dimensions by country

ECERS-R Dimension (country deviation)	Greece N=126	Cyprus N=52	Finland N=98	Denmark N=70	Romania N=128	Portugal N=72	TOTAL N=546
Space & furnishings (1.20)	4.46 (1.16)	5.24 (.85)	5.61 (.91)	**5.66** (.83)	5.25 (.87)	5.28 (.77)	**5.19** (1.02)
Personal care routines (1.27)	5.18 (1.21)	5.50 (1.35)	**5.94** (.88)	5.56 (1.12)	4.89 (1.06)	4.67 (1.46)	**5.26** (1.23)
Language & Reasoning (1.25)	5.53 (1.13)	5.42 (1.27)	**5.79** (1.08)	5.63 (1.17)	4.54 (.69)	5.67 (1.05)	**5.36** (1.14)
Activities (0.73)	4.02 (1.03)	4.69 (1.12)	**4.75** (1.13)	4.12 (1.10)	4.67 (1.23)	4.21 (.99)	**4.40** (1.15)
Interaction (0.83)	6.35 (.80)	6.40 (.78)	**6.57** (.63)	6.35 (.71)	5.74 (.83)	6.33 (.74)	**6.25** (.81)
Program structure (2.07)	4.75 (1.40)	4.82 (1.40)	**6.42** (.99)	5.18 (1.29)	4.35 (.96)	5.20 (1.45)	**5.08** (1.41)
ECERS TOTAL (0.8)	**4.88** (.79)	**5.27** (.87)	**5.68** (.73)	**5.27** (.73)	**4.93** (.61)	**5.09** (.74)	**5.15** (.79)

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Means of the ECERS dimension Space & furnishings by country

	Greece N=126	Cyprus N=52	Finland N=98	Denmark N=70	Romania N=128	Portugal N=72	TOTAL N=544
Space & furnishings TOTAL	4.46	5.24	5.61	**5.66**	5.25	5.28	5.19
1. Indoor space	4.70	5.44	5.46	**6.43**	4.95	5.80	5.34
2. Furniture for care, play & learning	5.42	5.98	**6.11**	6.00	4.16	6.01	5.45
3. Furnishing for relaxation	3.87	3.78	4.67	4.97	**5.20**	4.46	**4.54**
4. Room arrangement	4.48	5.40	5.41	5.49	4.88	**6.17**	5.18
5. Space for privacy	4.32	4.60	5.59	5.90	**6.82**	4.64	5.44
6. Child-related display	5.38	5.46	5.07	4.28	**6.29**	5.85	5.47
7. Space for gross-motor	4.18	5.92	6.01	**6.30**	5.79	5.12	5.47
8. Gross-motor equipment	3.34	5.24	**6.55**	5.97	4.02	4.26	**4.74**

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Means of the ECERS dimension Personal care routines by country

	Greece N=126	Cyprus N=52	Finland N=98	Denmark N=70	Romania N=128	Portugal N=72	TOTAL N=542
Personal care routines TOTAL	5.18	5.50	**5.94**	5.56	4.89	4.67	5.26
9. Greeting/Departing	4.93	6.33	**6.57**	6.18	6.00	5.90	5.90
10. Meals/snacks	4.78	4.35	**5.72**	5.57	4.25	3.54	**4.72**
11. Nap/rest	4.44	4.58	5.45	**5.91**	3.52		**4.52**
12. Toileting/diapering	5.59	5.16	5.76	**5.81**	4.64	4.04	5.18
13. Health practices	5.68	5.96	6.14	4.99	**6.38**	5.10	5.79
14. Safety practices	5.37	**6.04**	5.97	5.46	4.47	4.90	5.28

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Means of the ECERS dimension Language & reasoning by country

	Greece N=126	Cyprus N=52	Finland N=98	Denmark N=70	Romania N=128	Portugal N=72	TOTAL N=542
Language & reasoning TOTAL	5.53	5.42	**5.79**	5.63	4.54	5.67	5.26
15. Books & pictures	4.84	4.56	**5.67**	4.81	3.31	4.83	**4.61**
16. Encouraging children to communicate	6.28	6.00	6.30	**6.39**	4.90	6.00	5.91
17. Using language to develop reasoning skills	6.12	5.50	4.99	5.38	3.99	**5.89**	5.23
18. Informal use of language	4.89	5.69	**6.18**	5.90	5.84	6.09	5.71

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Means of the ECERS dimension Activities by country

	Greece N=126	Cyprus N=52	Finland N=98	Denmark N=70	Romania N=128	Portugal N=72	TOTAL N=544
Activities TOTAL	4.02	4.69	**4.75**	4.12	4.67	4.21	**4.40**
19. Fine motor	5.15	5.52	**6.01**	5.60	4.63	5.74	5.35
20. Art	5.34	**5.48**	5.14	4.57	4.99	5.29	5.13
21. Music/movement	3.76	**5.27**	4.48	2.65	4.09	3.55	**3.94**
22. Blocks	4.53	4.71	4.76	**5.01**	4.94	3.00	**4.64**
23. Sand/water	1.97	4.86	5.29	4.91	**5.94**	2.91	**4.46**
24. Dramatic play	3.93	4.77	**5.07**	3.82	3.18	4.16	**4.08**
25. Nature/science	2.96	4.06	4.04	3.71	**4.18**	3.67	**3.73**
26. Math/number	3.93	4.63	4.80	3.60	**5.53**	5.51	**4.70**
27. Use of TV, video, and/or computers	4.19	4.31	4.50	**4.92**	4.68	4.61	**4.54**
28. Promoting acceptance of diversity	3.75	3.35	3.04	2.49	**3.87**	2.87	**3.34**

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Means of the ECERS dimension Interaction by country

	Greece N=126	Cyprus N=52	Finland N=98	Denmark N=70	Romania N=128	Portugal N=72	TOTAL N=542
Interaction TOTAL	6.35	6.40	**6.57**	6.35	5.74	6.33	**6.25**
29. Supervision of gross motor activities	6.09	6.12	6.15	5.87	**6.17**	5.78	**6.06**
30. General supervision of children	6.33	6.29	**6.41**	6.31	5.84	6.00	**6.18**
31. Discipline	6.00	6.44	**6.80**	6.51	4.98	6.58	**6.09**
32. Staff-child interactions	6.50	6.67	**6.76**	6.54	6.35	6.61	**6.55**
33. Interactions among children	**6.84**	6.56	6.72	6.54	5.36	6.66	**6.39**

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Means of the ECERS dimension Program structure by country

	Greece N=126	Cyprus N=52	Finland N=98	Denmark N=70	Romania N=128	Portugal N=72	TOTAL N=542
Program structure TOTAL	4.75	4.82	**6.42**	5.18	4.35	5.20	5.08
34. Schedule	4.03	3.77	**6.17**	3.71	3.19	3.86	**4.12**
35. Free play	5.93	6.02	**6.63**	5.49	4.89	5.75	5.74
36. Group time	4.33	4.65	**6.28**	5.91	5.13	5.89	5.31
37. Provisions for children with disabilities	4.67	4.88	**6.88**	6.43	4.30	5.42	5.23

Participants' evaluation of ECERS-R

(N=23 teachers from Jyväskylä/FINLAND)

1. How well does the ECERS-R give information about learning environments of early education?

poorly scarcely very well

1 2 3 4 5 6 7

mean=5.3, sd=.70

2. How useful is this kind of assessment from the point of view of developing early education?

not useful somewhat useful very useful

1 2 3 4 5 6 7

mean=6.0, sd=.90

3. How useful is this kind of assessment from the viewpoint of your own learning?

not useful somewhat useful very useful

1 2 3 4 5 6 7

mean=6.2, sd=.90

4. Is the number of assessment categories appropriate/good?

too little ok too many

1 2 3 4 5 6 7

mean=4.8, sd=1.33

5. How well does the ECERS-R assessment tool match with Finnish early education culture?

poorly scarcely very well

1 2 3 4 5 6 7

mean=4.3, sd=1.26

6. How satisfied are you with the education you have got in this project regarding running the assessment in kindergartens?

not satisfied ok very satisfied

1 2 3 4 5 6 7

mean=6.1, sd=.90

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Conclusions

1. The overall ECERS-R mean value was 5.15 (scale 1-7), showing high quality of early childhood care for EU countries
2. Minor country differences (deviation 0.8)
3. Highest score was for INTERACTION and lowest for ACTIVITIES
4. Good feedback from teachers

Further analyses needed:

- Representativeness to each country and EU
- Reliability and validity issues, e.g. kindergartens chosen to be evaluated, (inter)rater reliability

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Cultural differences

Cultural differences may explain country differences, e.g., in Finland the law regulates the limit for the number of educational and nursery staff/number of children as well as their educational level:

1-3 year-olds: 4 children/1 educator

4-5 year-olds: 7 children/1 educator

Preschool (6 year-olds): 13 children/ 1 educator

Average group size 20 children

Kuokkala Day-Care center

Nenäinniemi Day-Care Center

Quality of early childhood environments and child outcomes in Portugal

Teresa Leal
Sílvia Barros
Ana Madalena Gamelas
Manuela Pessanha

Thessaloniki
25 January 2014

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U.PORTO
FPCE FACULDADE DE PSICOLOGIA E DE CIÊNCIAS DA EDUCAÇÃO
UNIVERSIDADE DO PORTO

ESE POLITÉCNICO DO PORTO
ESCOLA SUPERIOR DE EDUCAÇÃO

Quality: two important dimensions

Process variables

- the actual experiences that occur in educational settings,
- the more directly experienced by children;
- e.g., adult-child interactions, interactions with peers, interactions with materials and interactions between adults.

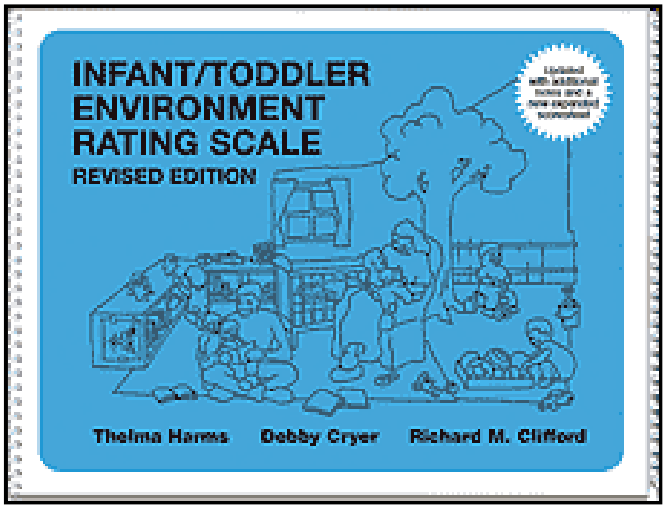
Structural variables

- frequently regulated characteristics (licensing requirements);
- include stable and physical characteristics of the settings and characteristics of the persons that act in those settings;
- e.g., adult-child ratios, group size, qualifications and compensation of teachers and staff, and space available per child (room size).

(e.g., Rossbach, Clifford, & Harms, 1991; Vandell & Wolfe, 2000)

How to assess quality of education and care? The Environment Rating Scales

- Infant/Toddler Environment Rating Scale – Revised (Harms, Cryer, & Clifford, 2003)
  - Escala de Avaliação do Ambiente de Creche (Trans. Sílvia Barros, Carla Peixoto, Manuela Pessanha, Ana Isabel Pinto)

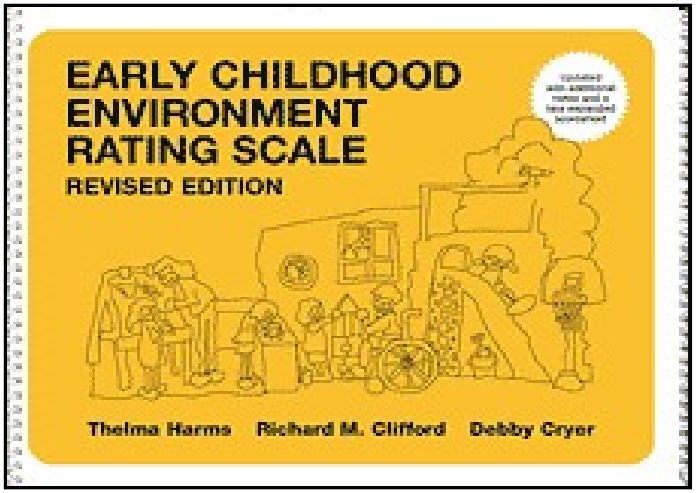


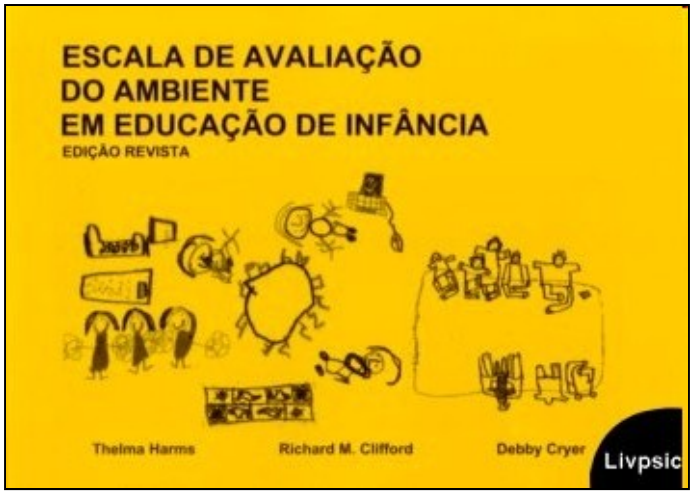
http://www.fpg.unc.edu/~ecers/

How to assess quality of education and care? The Environment Rating Scales

- Early Childhood Environment Rating Scale – Revised (Harms, Clifford, & Cryer, 1998)

  - Escala de Avaliação do Ambiente em Educação de Infância – Revista (Trans. I. Abreu-Lima, C. Aguiar, A. Gamelas, T. Leal, & A. Pinto, 2008)_





EARLY CHILDHOOD EDUCATION AND CARE IN PORTUGAL

A dual system of services:

0 - 3 years old **Ministry of <u>Labor and Welfare</u>**	**3 - 6 years old** **Ministry of <u>Education</u>**
***Crèche* (infants/toddlers)** **Official day care mothers / family day care** **Coverage rate:** 39.5 % (2011) Occupancy rate: 89% (Ministério do Trabalho e da Solidariedade Social, n/d)	**Preschool** Children attending preschool: 73.5% (INE, 2011)

Goals

Part I

- Describe quality features of **child care** classrooms (1 – 3 years old) using the ITERS-R
- Determine how quality assessed by the ITERS-R is related to children's developmental outcomes

Part II

- Describe quality features of **preschool** classrooms using ECERS-R
- Determine how quality assessed by the ECERS-R is related to children's developmental outcomes

Part I

Our research on the early years

- Data from two research projects

  - **2000 -2004**: The quality of child interactions in family and day care center and its impact in childcare socio-cognitive development (POCTI/PSI/35207/2000)

  - **2002-2007:** Child care quality: ideas and practices (FCT; BD10721/2002) (Barros, 2007)

Method: Participants
CLASSROOMS

	Study 1 *N*	Study 2 *N*
Child care classrooms	30	160
Nonprofit	11	80
For profit	4	80
1 – 2 years old	15	65
2 – 3 years old	15	80
1 – 3 years old		15

Method: Participants
CHILDREN & FAMILIES (Study 1)

	N	*M*	*SD*	Min. – Max.
Children	120			
Age (Months)		26	7.07	14 - 49
Families	120			
Mothers' education (years)		10.83	4.47	0 - 18
Family monthly income (€)		1362	738.00	324 - 2619

Measures and data reliability

	Cronbach's alpha
ITERS (Harms, Cryer, & Clifford, 1990) – Study 1	.80
ITERS-R (Harms, Cryer, & Clifford, 2003) – Study 2	.83
The Griffiths Mental Development Scales (Griffiths, 1984, 1986)	.98 (.84 - .94)
Home Observation for Measurement of the Environment Inventory (Bradley & Caldwell, 1984)	.90

Data collected by trained observers (external to the institutions).

Results: Quality (ITERS / ITERS-R)

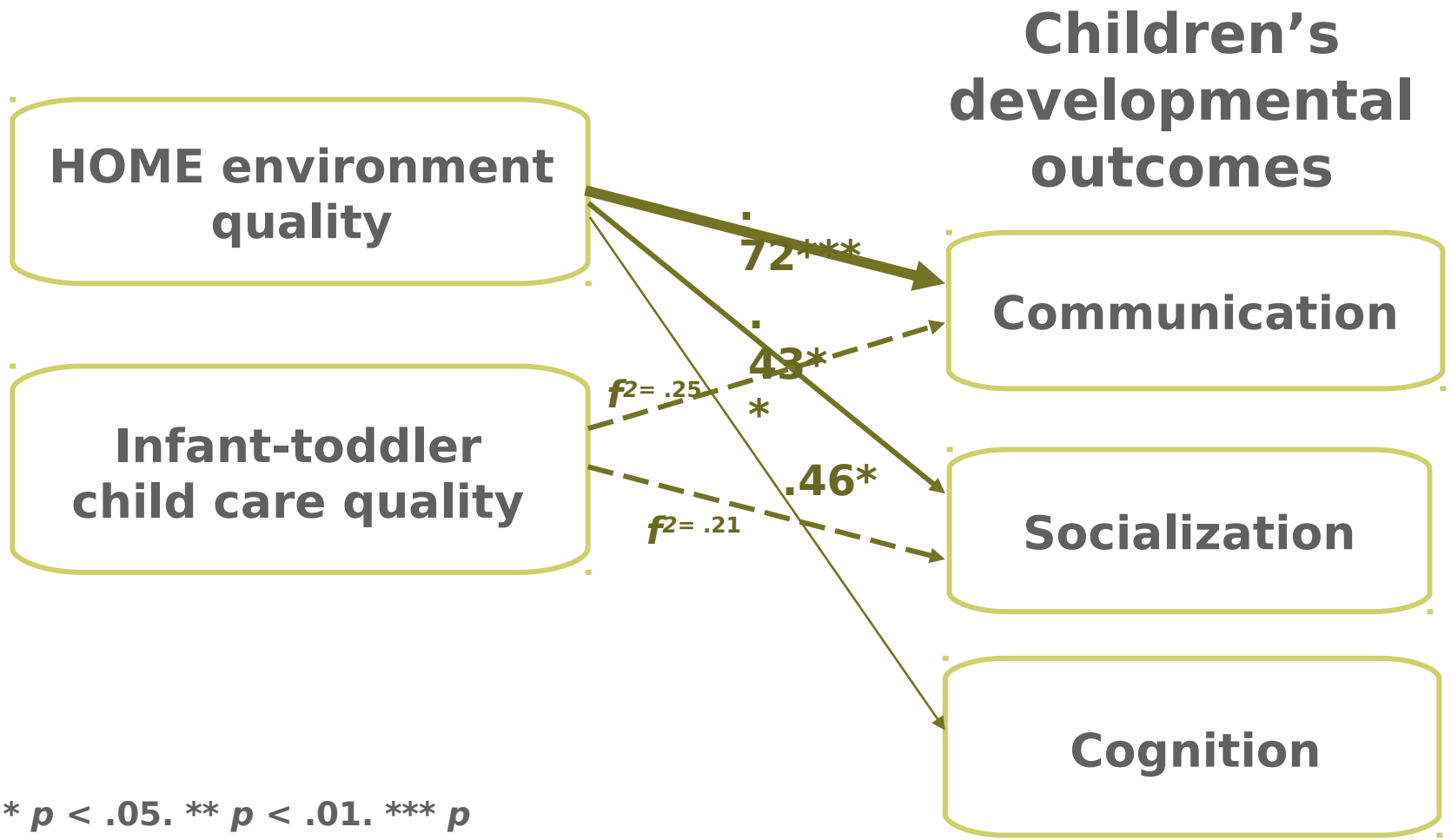
	N	*M*	*SD*	Min	Max
Study 1	30	**2.55**	0.42	1.76	3.47
Study 2	160	**2.84**	0.48	1.62	4.09

%

1 – 2.99 = low
3.00 – 4.99 = basic
5.00 – 7.00 = high

(Barros & Aguiar, 2010; Pessanha, Pinto & Barros, 2009)

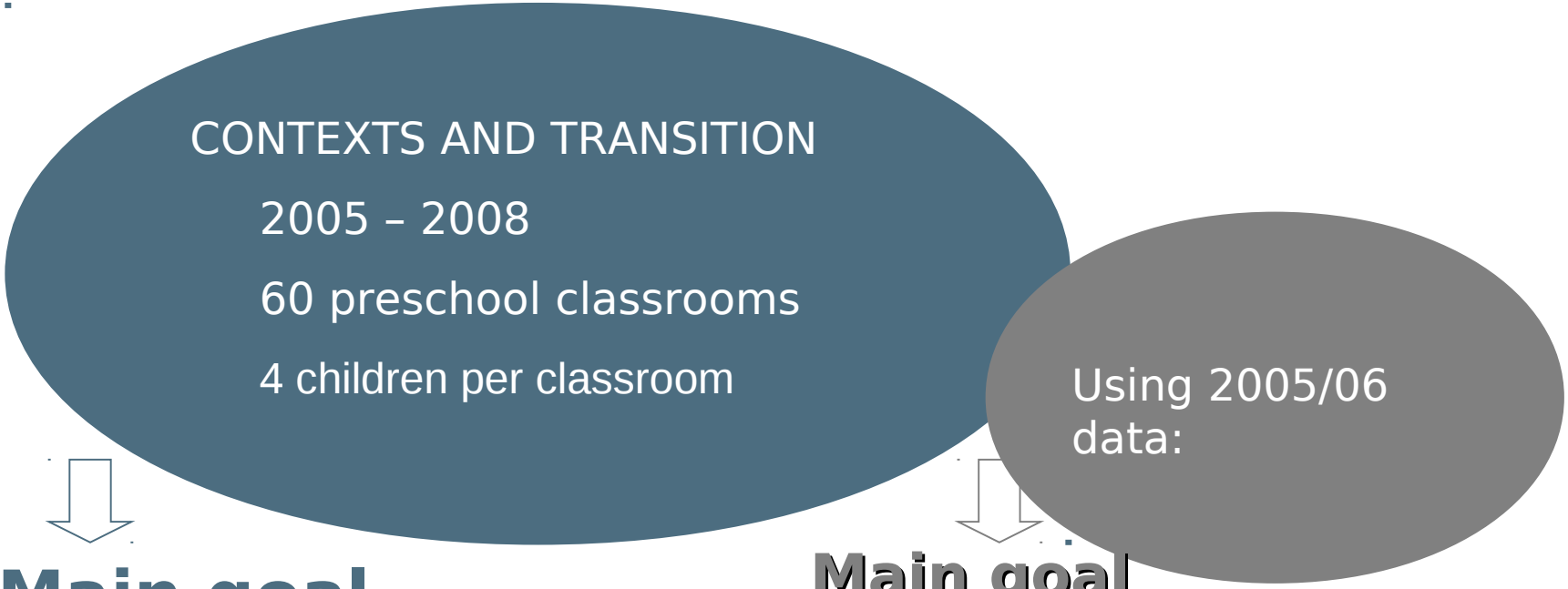
Infant-toddler child care quality and child development



(Pessanha, 2008; Pessanha et al., 2009)

Part II

Preschool settings



Main goal

To identify child and classroom factors that predict development trajectories

Main goal

To study the association between quality of preschool classroms and early childhood skills

(Abreu-lima, Leal, Cadima, & Gamelas, 2013)

Method: Participants

	N	%	M	SD	Range
Child Characteristics					
Age (months)	215		67	6.06	53-78
Sex					
Male	113	52.6%			
Female	102	47.4%			
Family Characteristics					
Mother's educational level	171		9.65	4.39	0-22
Elementary school (≤ 6 years)		22.1%			
Compulsory school (≤ 9 years)		35.5%			
High school (≤ 12 years)		22.6%			
College/University		19.8%			

Method: Participants

	N	%
Preschool classrooms	60	
Public	33	55%
Nonprofit	19	32%
Profit	8	13%
Mixed age group	32	53%
4 years- or 5 years-old group	28	47%

Method: Procedures

- Data collected during the school year 2005-06
  1. Classroom quality - Winter-Spring period
  2. Children data – Spring 2006

  - Trained observers assessed each classroom for one day
  - Children were individually assessed at the centers

  Questionnaires were given to teachers to obtain information on classroom behaviour and background characteristics

Method: Classroom measures

- ECERS-R
  - Alpha = .86
  - Interobserver agreement: 89.8% (within one)

Method: Child measures

	Skill	Instrument	alpha
Literacy skills	**Vocabulary**	*Peabody Picture Vocabulary Test-Revised (PPVT-R, Dunn, 1986)*	.95
	Print concepts	*Concepts about Print (CAP, Clay, 2003).*	.79
	Phonological awareness	*Phonological Awareness Test (PAT, Sucena & Castro, 2005)*	.90
	Letters identification	*Cross-Linguistic Assessment of Foundation Level (CLAFL, Castro, Cary, & Gomes, 1998).*	.98
Mathematics	**Arithmetic**	*The arithmetic sub-test of the WPPSI-R (Wechsler, 2003)*	
	Number identification	*Identification of numbers*	.93
	Counting	*Rote counting*	
Social -	**Attention/Cognitive**	*Classroom Behavior Inventory (CBI, Schaefer, Edgerton & Aaronson, 1978)*	.97
	Sociability		.93
	Considerateness		.90

Results

Descriptive data for the ECERS-R

	N	*M*	*SD*	*Min-Max*
ECERS-R (Total score)	60	3.44	*.72*	1.72 – 5.00

(Abreu-Lima et al., 2013)

Preschool classrooms'quality (*N* = 60)

ECERS subscales	***M***	***SD***	**Min-Max**
Space and Furnishings	3.67	1.08	1.63–6.00
Personal Care Routines	3.09	1.07	1.17–6.20
Language/reasoning	3.57	1.02	1.75-6.25
Activities	2.87	0.68	1.30–4.10
Interaction	4.56	1.22	1.60–6.60
Program Structure	3.73	1.10	1.50–6.75
Parents and Staff	3.03	0.54	2.00-4.50
Global	3.44	0.72	1.72 to 5.00

(Abreu-Lima et al., 2013)

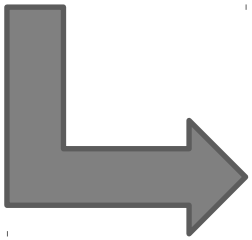
Results

Results from Hierarchical Linear Analyses predicting children's outcomes

		Vocab.	Print Conc.	Phon. Awar.	Letters	WPPSI-R	Number Id.	Count	Attent Cogni	Sociab	Consid
Intercept	B	42.02***	7.04***	3.09***	6.38***	7.92***	39.98***	36.50***	3.74***	4.01***	3.58***
	SE	1.05	0.26	0.13	0.53	0.22	1.66	1.41	0.06	0.06	0.06
Age	B	**0.76*****	**0.20*****	0.03	**0.39*****	0.01	**1.32*****	**1.45*****	**0.03*****	**0.02***	0.01
	SE	0.13	0.03	0.02	0.07	0.04	0.28	0.24	0.01	0.01	0.01
Sex [a]	B	-0.81	-0.46	-0.18	-0.42	**-0.72***	**-9.87*****	**-7.36*****	0.16[†]	0.03	**0.34****
	SE	1.59	0.33	0.20	0.74	0.33	2.51	2.44	0.09	0.11	0.11
Mother's education	B	**0.84*****	**0.15*****	**0.07****	**0.23***	**0.15****	**1.28****	**0.97****	**0.03***	0.02	0.01
	SE	0.21	0.05	0.02	0.09	0.05	0.34	0.32	0.01	0.01	0.01
ECERS-R	B	**2.37***	**1.29*****	**0.35***	0.92	0.32	4.57	4.06	0.06	0.07	**0.19***
	SE	1.17	0.34	0.17	0.67	0.25	2.62	2.13	0.08	0.06	0.07
Mot's ed. x ECERS-R	B	-0.18	0.09	0.01	0.15	0.06	0.94	0.32	0.01	0.01	0.00
	SE	0.32	0.08	0.03	0.12	0.09	0.47	0.50	0.01	0.01	0.01

Discussion

- Low overall quality of toddler child care
- Limited main effects of child care quality on children's development



Need to guarantee higher quality in child care classrooms for all children.

Discussion

- ECERS-R mean global score shows that no more than basic conditions are present in preschool classrooms
- Quality of preschool is important to promote early literacy skills
- The association between global quality and mathematics is not clear
  - More studies are needed
- Better quality is associated with children that relate better with others and who are more compliant

Recommendations should focus on the processes that occur at the classroom level and in-service professional development, when connected with the classroom context, could be an effective method to improve classroom quality.

(Mashburn et al., 2008)

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EARLY CHANGE

Good practices from six early childhood education systems

Athanasios Gregoriadis
Aristotle University of Thessaloniki, Greece

With the support of the LifeLong Learning Programme of the European Union

In a world witnessing rapid changes and massive transformations, urgent action is required if education is to maintain "its indispensable contribution to liberty, peace and the dignity of man…"

-UNESCO constitution

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The '**EU 2020 Strategy for Education**' acknowledges four pillars of learning for the 21st Century

learning to know

learning to do

learning to be

learning to live together

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Why good practices?

illustrate the benefits of globalization in support of quality education through national, regional and international networking

identifying good practices is part of ongoing monitoring and evaluative processes

distil innovative and validated approaches

contribute to teachers' professional development

Good Practices Map

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Good Practices
Collection Inventory

- Health & Safety
- Activities & Play
- Interactions
- Diversity/Inclusion
- Classroom management
- Other

6 categories

Good Practices Collection Inventory

Good Practice Collection Inventory

Good Practice Categories (check the category or categories of good practices described here)			
Health & Safety	☐	Classroom Management	☐
Activities/Play	☐	Diversity/Inclusion	☐
Interactions	☐	Other	☐

Country:.....	Phase of the daily schedule: .....
Duration of good practice:	Number of children involved (whole class, one group, individuals, etc.): .....

Purpose – goals (of the activity, behavior, action, incident)	
Teaching methods-strategies (if there are any used)	

Good Practices Collection Inventory

Materials: (equipment, materials, devices, room arrangement etc. if they are used)	
Good Practice Description (detailed description of dialogue, activity, lesson plan, behaviors, actions, etc. according to the type of good practice described here)	

Good Practices Collection Inventory

Teacher role: (instruction, behavior, action, question, expression, emotion, attitude, etc.)	
Children role: (action, behavior, answer, intention, movement, expression, emotion, engagement, etc.)	

Good Practices Collection Inventory

Highlights-Additional Comments:	

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The good practices were compiled by early childhood educators within the study consortium from each member country.

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Early Change Partners-6 EU countries

Approximately 150
Good Practices

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Good Practices CATEGORIES	%
Activities & Play	39.2
Interactions	21.7
Classroom management	13.5
Diversity / Inclusion	10.8
Health & Safety	10.1
Other	4.7
Total	100

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Health & Safety

Learning healthy oral practice through drama play

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Activities/Play

Organizing an "**Autumn Fair**". Children making jam from autumn fruits

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Interactions

Talk to a teddy bear game (increasing empathy)

-Calvin & Hobbes

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Activities/Play

Learning to take photos

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Classroom management

Creating rules for a snowball fight

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Diversity/Inclusion

Diversity and drama play

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Other

Parents and children redesigning their schoolyard

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Potential impact

Good practices to

shed some valuable light on how the European early educators strive to meet major educational challenges facing us today

exemplify good models of creative learning and innovative teaching

assist early childhood teachers' practices

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Creation of an open access E-book (Early Change website)

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Thank you

http://earlychange.teithe.gr/

University College SJÆLLAND

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Best Practice in Denmark

Associate professor Lise Sanders Olesen
Associate professor Claus Henriksen
University College Zealand

Recent History of Social Education in Denmark

- 1992
  - Early childhood education
    - Was divived into two directions
    - Changed to one general education
- 2007
  - Changed again
  - Possibility to specialise
- September 2014 the education takes a new direction

- Danish Social Education
  - Unique
  - More focused on practical education
  - Three internships totaling 1 year, 3 months
- Theory - Practice relationship

Theory / Practice

- Space for children with special needs.
  - Everyone is acknowledged
- Children can express themselves.
  - They are given sufficient challenges
- Develop themselves in their own time
  - Encouraged

Values in pedagogical work

- Everyone’s contributions are respected as constructive
- Being social is considered important for the child’s well-being and learning
- Win-win situations
- Solving social challenges using a puppet

Values in Pedagogical Work

Danish Kindergarten: Fieldtrip

Danish Kindergarten: Playground

Danish Kindergarten: Time for lunch, then play

- Example 1
- Puppet Juliane

Examples of Good Practice from Denmark

- Purpose
- Goal
- Outcome

Best Practice: Purpose and Desccription

- Example 2
- Where do you live?

Examples of Best Practise in Denmark

- Purpose
- Goal
- Outcome

Best Practise Purpose and Description

Music in Sofiehuset

- Ala jumbola ala jumbola we are central africa.
- Ala Jumbola, ala Jumbola we are central Africa.
- Singing la, la, la , lalala.
- Singing La, la, la, lalala.
- Singing La, la, la, singing La, la, la. Singing La, singing la, singing la

Activity and Thank You for Your Patience

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EARLY Q
EARLY CHILDHOOD ENVIRONMENT QUALITY

THALES Research Project – Early Q

EVALUATION OF EARLY CHILDHOOD EDUCATION QUALITY

Funded from the Operational Programme «Education and Lifelong Learning» and co-financed from the European Union (European Social Fund) and from national sources.

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«THALIS: Enhancement of the Interdisciplinary Research and Innovation with the potentiality to invite high profile researchers from abroad through the conduct of basic and applied research excellence»

Duration of the project

01/2012 – 09/2015
45 months

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Aim

The evaluation of the Early Childhood Education quality in Greece

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Lack of evaluation procedures for the quality of early childhood environment

Lack of valid and reliable instruments for the evaluation of ECE in the Greek educational setting

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OBJECTIVES

- Development of a training program for using the evaluation instruments ECERS-R & ECERS-E (Early Childhood Environment Rating Scales)
- Evaluation of the quality of 650 early childhood classrooms
- Creation of a data base about the quality of ECE in Greece
- Quality comparison of the provision of ECE among Greece and other countries that use the same scales

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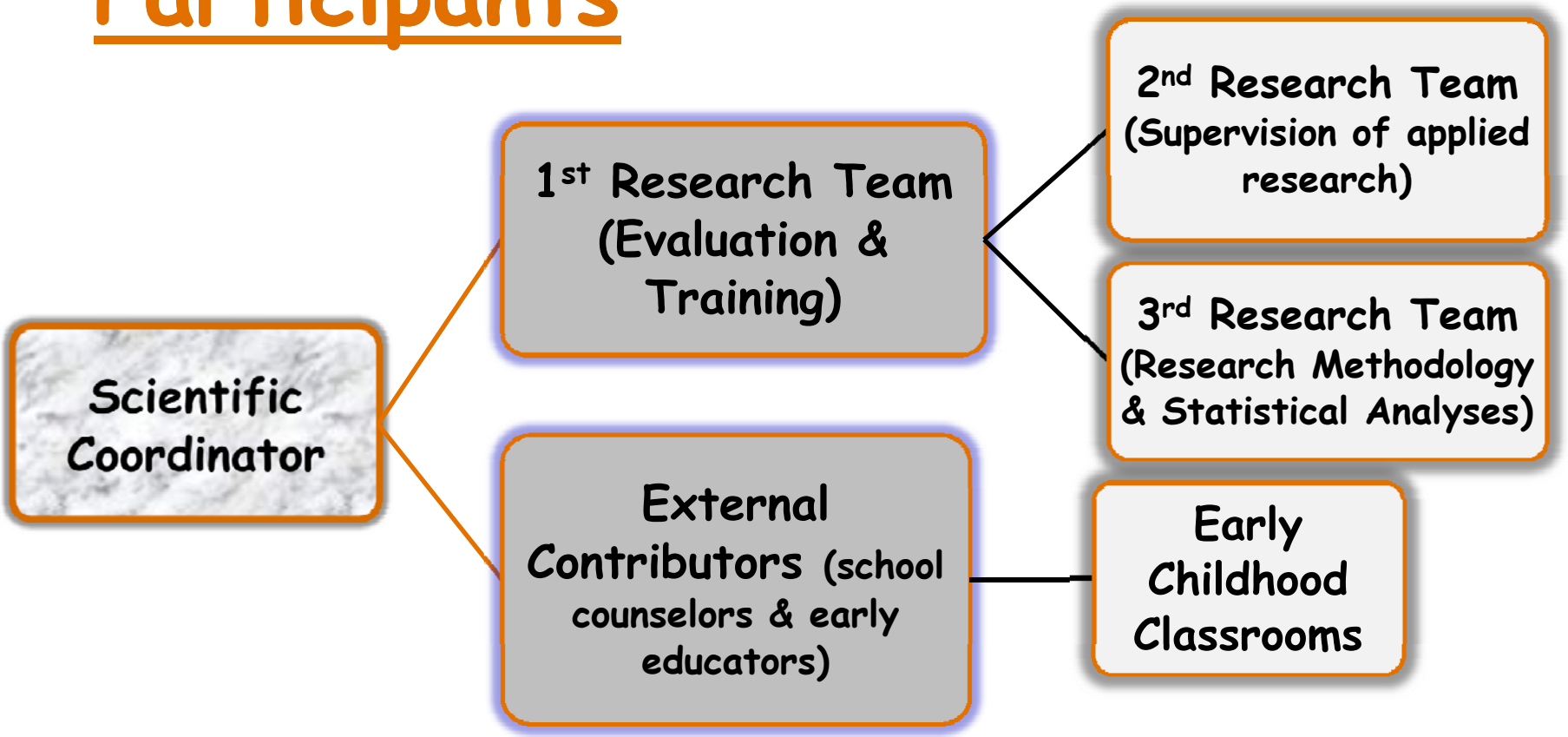
Participants



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Researchers

From 9 Universities

- Alexander Technological Educational Institute of Thessaloniki
- University of Crete
- Federal University of Rio de Janeiro (Brazil)
- University of Southampton (UK)
- Aristotle University of Thessaloniki
- University of Bielefeld (Germany)
- University of Cyprus
- University of Western Macedonia
- University of Ioannina

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4 Invited Researchers

1. Federal University of Rio de Janeiro (Brazil)
2. University of Southampton (UK)
3. University of Bielefeld (Germany)
4. University of Cyprus (Cyprus)

Municipalities & Educational Districts

20 assessors

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Evaluation Instruments

ECERS-R (FPG Child Development Institute, University of North Carolina, Chapel Hill, NC, USA)

ECERS-E (University of Oxford & Institute of Education – University of London, UK)

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Instruments

- ✓ Early Childhood Environmental Rating Scale – R (ECERS-R) (Harms, Clifford & Cryer, 2005)
- ✓ ECERS-R is considered by the majority of researchers as the most complete instrument for the evaluation of quality in ECE worldwide
- ✓ It is implemented throughout the USA, most of the European countries, Japan and other Asian nations

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Seven subscales

43 quality indicators

Instruments

1. Space & furnishing
2. Personal care routines
3. Language-reasoning thinking
4. Activities
5. Interaction
6. Programme structure
7. Parents and staff

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ECERS-E

- an extension to ECERS-R

Consisted of four subscales:

(a) Literacy (six items)

(b) Mathematics (three items)

(c) Science & environment (three items)

(d) Diversity (three items)

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20 assessors

Training the assessors

1st Training Seminar

22nd - 24th of February 2013 (Thessaloniki)

Age, M = 42.4 years

Professional experience

M = 19.4 years

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Training the assessors

- ✓ Was based on the Environment Rating Scales Institute

Trainers

- 4 researchers
- They had previously received a full training by the founders of the ECERS

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Training the assessors

1st Training Seminar

- Theoretical background of the evaluation instruments
- Analyze the subscales, the items and the indicators of the evaluation instruments
- Practice on videotaped observation
- Rating the evaluation indicators

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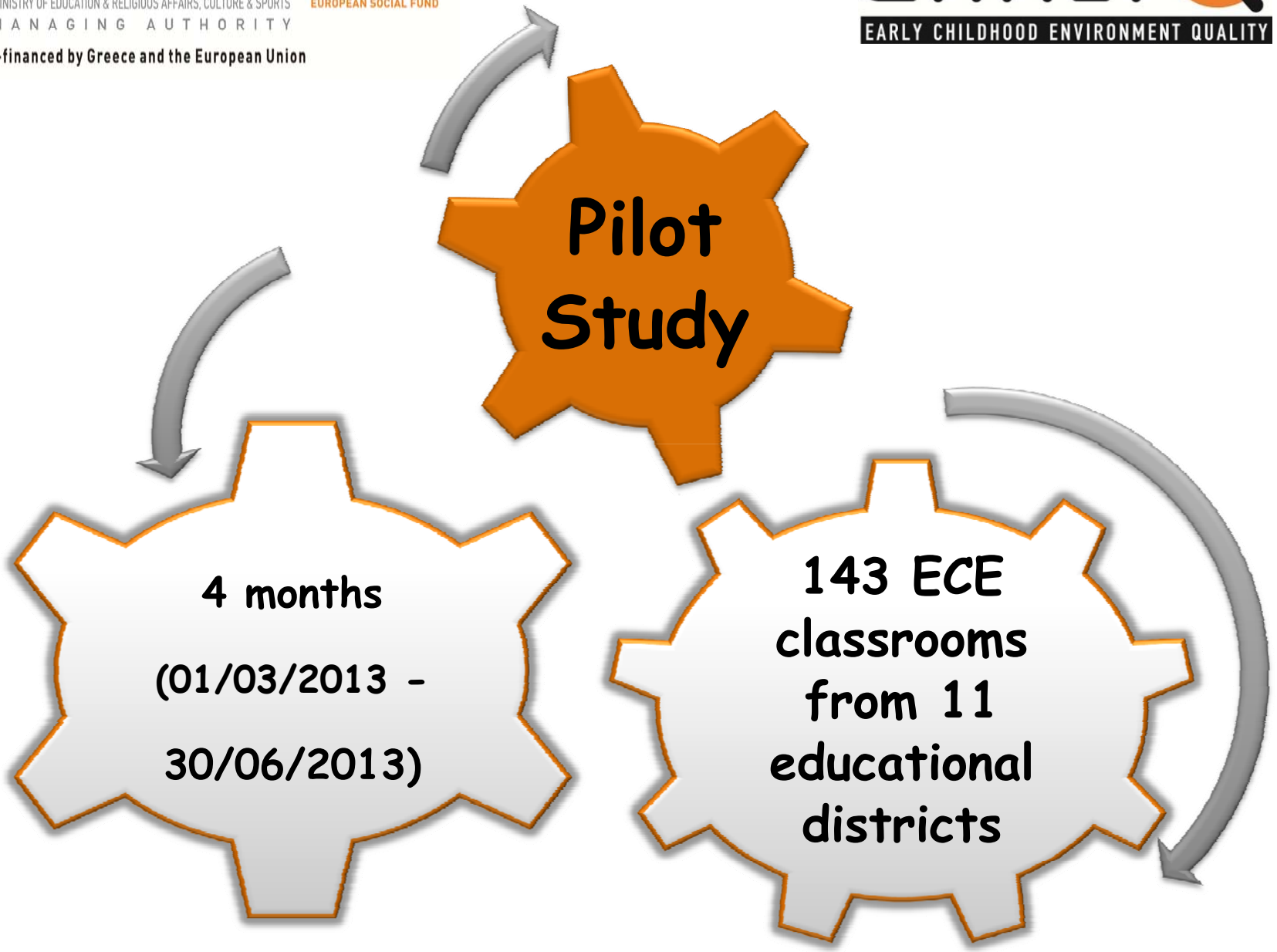

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EUROPEAN SOCIAL FUND
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EARLY CHILDHOOD ENVIRONMENT QUALITY

Forthcoming actions

- 2nd Training Seminar for assessors (26th & 27th of January 2014, Thessaloniki)

- Main study - 15 months (01/02/2014 - 30/04/2015)

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Envisaged main outcomes

A well-documented evaluation for the Quality of Early Childhood Education in Greece

Comparable data for the quality of ECE among Greece and other countries

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We have a long way to go.....

Thanks to.....

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