Early Childhood BMI Trajectories and Weight Status Lability: Leveraging ECHO's Longitudinal Data to Identify Critical Developmental Patterns

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ECHO Discovery Presentation

Sep 10th, 2025

Presentation Outline

- ECHO's methodological advantages over conventional study designs
- Study 1: Early-Life Factors and Body Mass Index (BMI) Trajectories
- Study 2: Early-Life Factors Associated with BMI Z-score Lability
- Future research directions

ECHO's Longitudinal Advantages

Multi-Wave Design Enabling New Discoveries

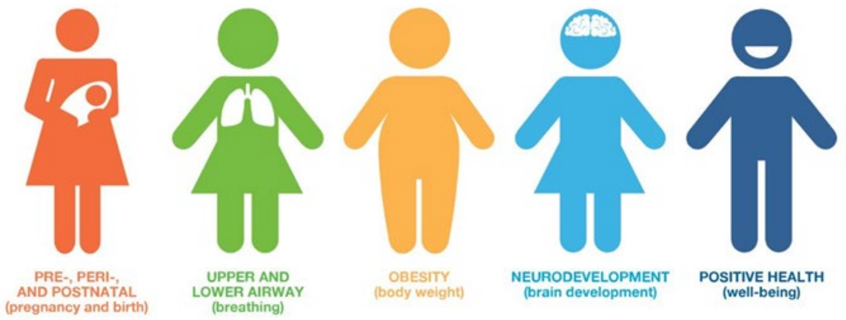
ECHO's Unique Capability

- Follows children from birth through adolescence and adulthood
- Multiple assessments per child
- Multiple cohorts providing geographically and socioeconomically diverse data

ECHO's Longitudinal Advantages

Multi-Wave Design Enabling New Discoveries

ECHO's Unique Capability



Previous Research Design Limitations

- **Cross-sectional:** Single time point, different children at each age

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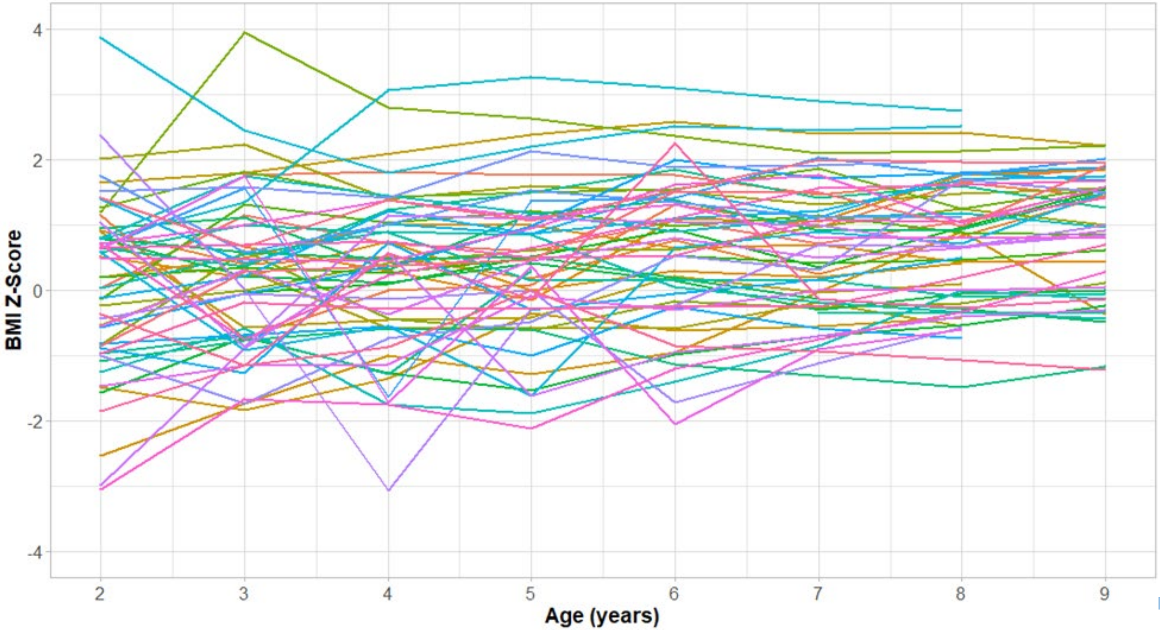
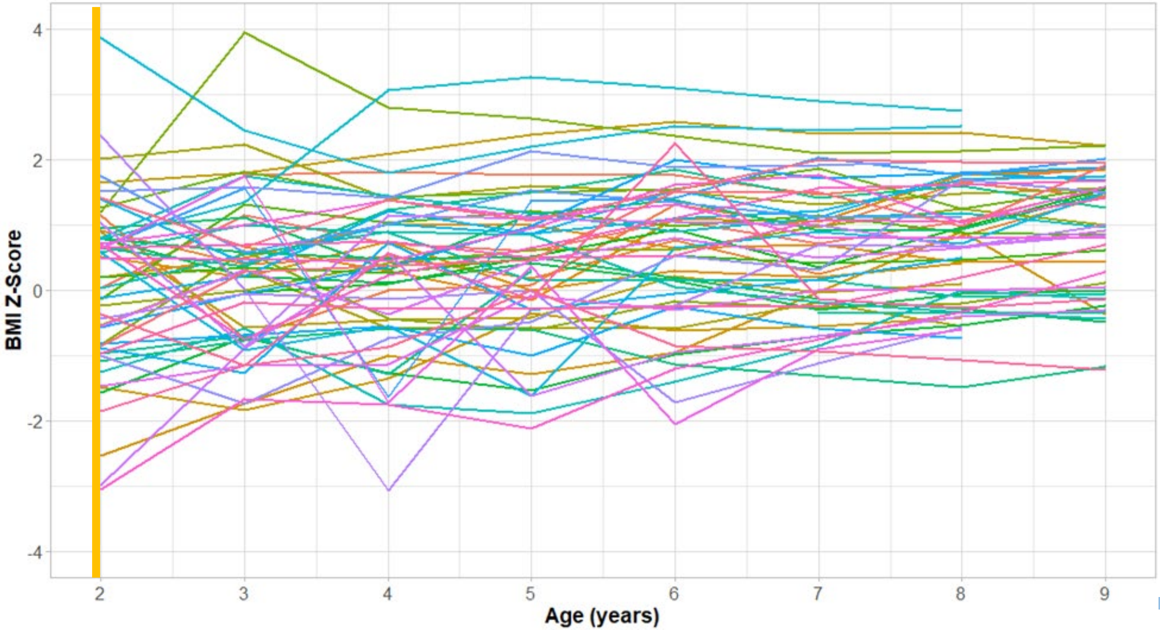


Previous Research Design Limitations

- **Cross-sectional:** Single time point, different children at each age (e.g., age 2)



Previous Research Design Limitations

- **Cross-sectional:** Single time point, different children at each age
  - **Measurement Timing**
  - **Individual Differences**: ***Between-person variation*** (e.g., why some children are heavier than others) conflated with ***within-person change*** (e.g., how individual children's weight changes over time)

Previous Research Design Limitations

- **Cross-sectional:** Single time point, different children at each age
  - **Measurement Timing**
  - **Individual Differences**: ***Between-person variation*** (e.g., why some children are heavier than others) conflated with ***within-person change*** (e.g., how individual children's weight changes over time)
    - Heart rate and physical activity:
      - At the within-person level, engaging in physical activity immediately leads to increased heart rate
      - While at the between-person level, more physically active individuals typically show lower resting heart rates.

Previous Research Design Limitations

- **Cross-sectional:** Single time point, different children at each age
- **Two-wave longitudinal**: Limited to simple change detection
- **Three-wave longitudinal**: Cannot model complex developmental patterns

ECHO's Multi-Wave Advantages

Methodological Capabilities

- **Individual trajectory estimation**: Map each child's unique developmental trajectory
- **Change point detection**: Identify when growth patterns shift (e.g., adiposity rebound timing)
- **Complex pattern modeling**: Non-linear, multiphase developmental processes
- **Minority pattern detection**: Statistical power to identify small but high-risk subgroups

Clinical Applications

- Early identification of concerning developmental patterns

Research Examples Using ECHO Data

Study 1: Multi-Phase BMI Trajectories

- **Question**: How are early-life factors associated with BMI trajectories from toddlerhood to pre-adolescence?

Study 2: BMI Z-Score Lability

- **Question**: Are early-life factors associated with BMI z-score lability from ages 2 to 9 years?

Study 1[1]

- Early-Life Factors and BMI Trajectories Among Children in the ECHO Cohort

JAMA Network Open

Original Investigation | Pediatrics

Early-Life Factors and Body Mass Index Trajectories Among Children in the ECHO Cohort

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Abstract

IMPORTANCE Identifying atypical body mass index (BMI) trajectories in children and understanding associated, modifiable early-life factors may help prevent childhood obesity.

OBJECTIVE To characterize multiphase BMI trajectories in children and identify associated modifiable early-life factors.

DESIGN, SETTING, AND PARTICIPANTS This cohort study included longitudinal data obtained from January 1997 to June 2024, from the Environmental influences on Child Health Outcomes (ECHO) cohort, which included children aged 1 to 9 years with 4 or more weight and height assessments. Analyses were conducted from January to June 2024.

EXPOSURES Prenatal exposure to substances and stress (smoking, alcohol, depression, anxiety)

Key Points

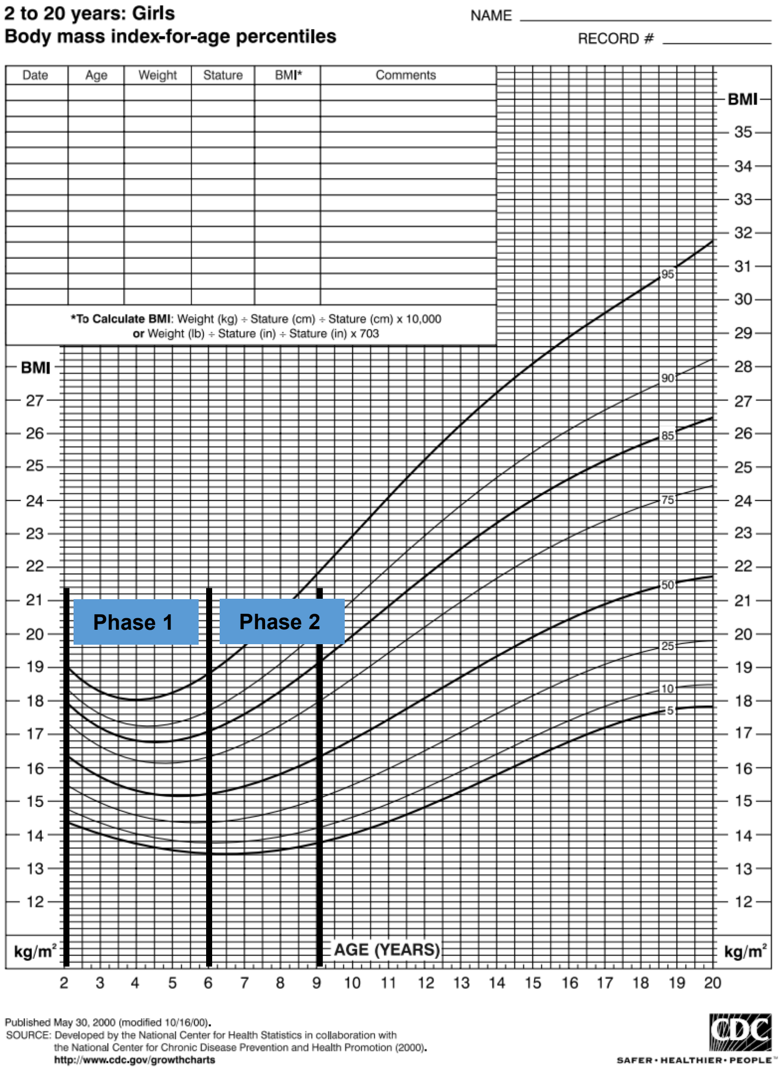
Question How are early-life factors associated with body mass index (BMI) trajectories in children?

Findings In this cohort study of 9483 children, there were 2 distinct BMI trajectories: a typical trajectory (89% of children) and an atypical trajectory with an earlier BMI increase (11% of children). Prenatal smoking, high maternal prepregnancy BMI, high gestational weight gain, and high birth weight were associated with the atypical trajectory.

Study 1: Background

Multiphase Trajectories:[2]

Phase 0: BMI rapidly increases during the first year of life
Phase 1: BMI declines during early childhood, reaching a nadir between ages 5 to 7 years
Phase 2: Increasing BMI, i.e. adiposity rebound



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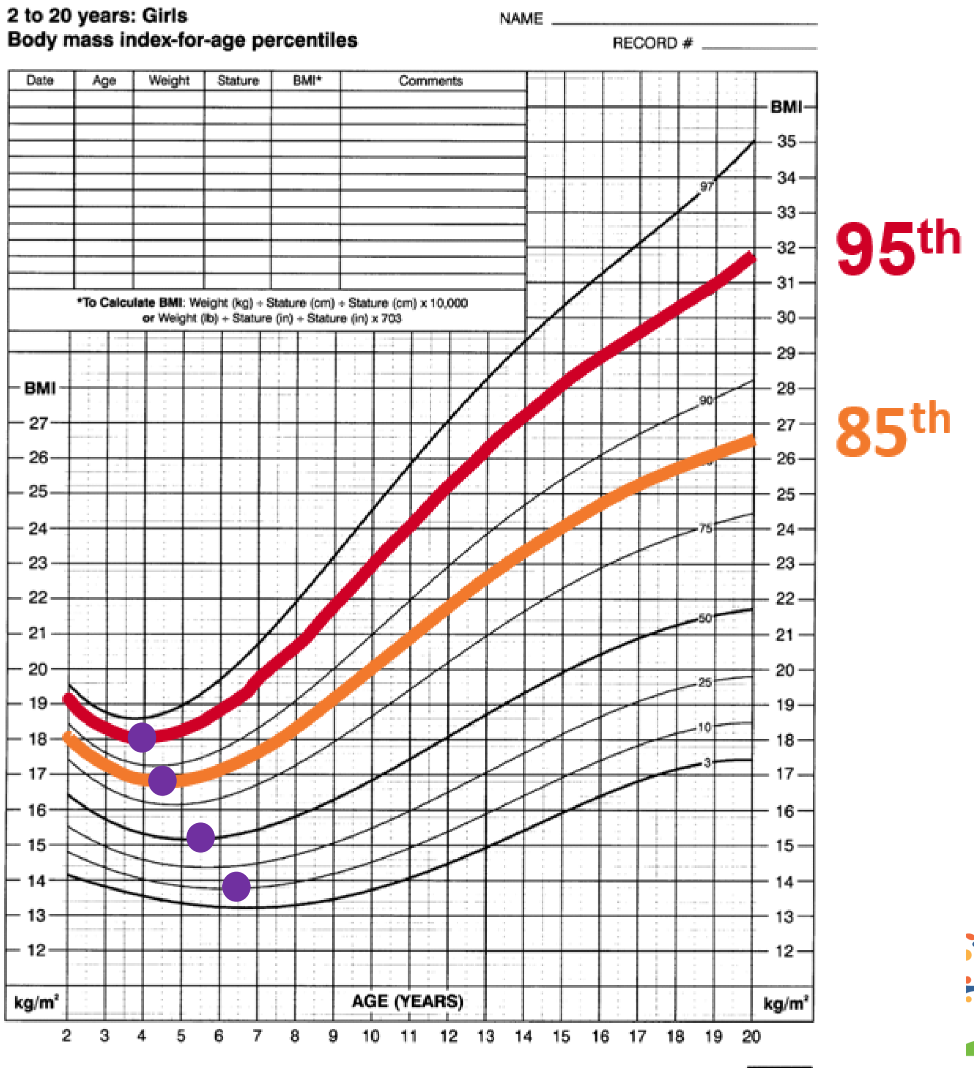

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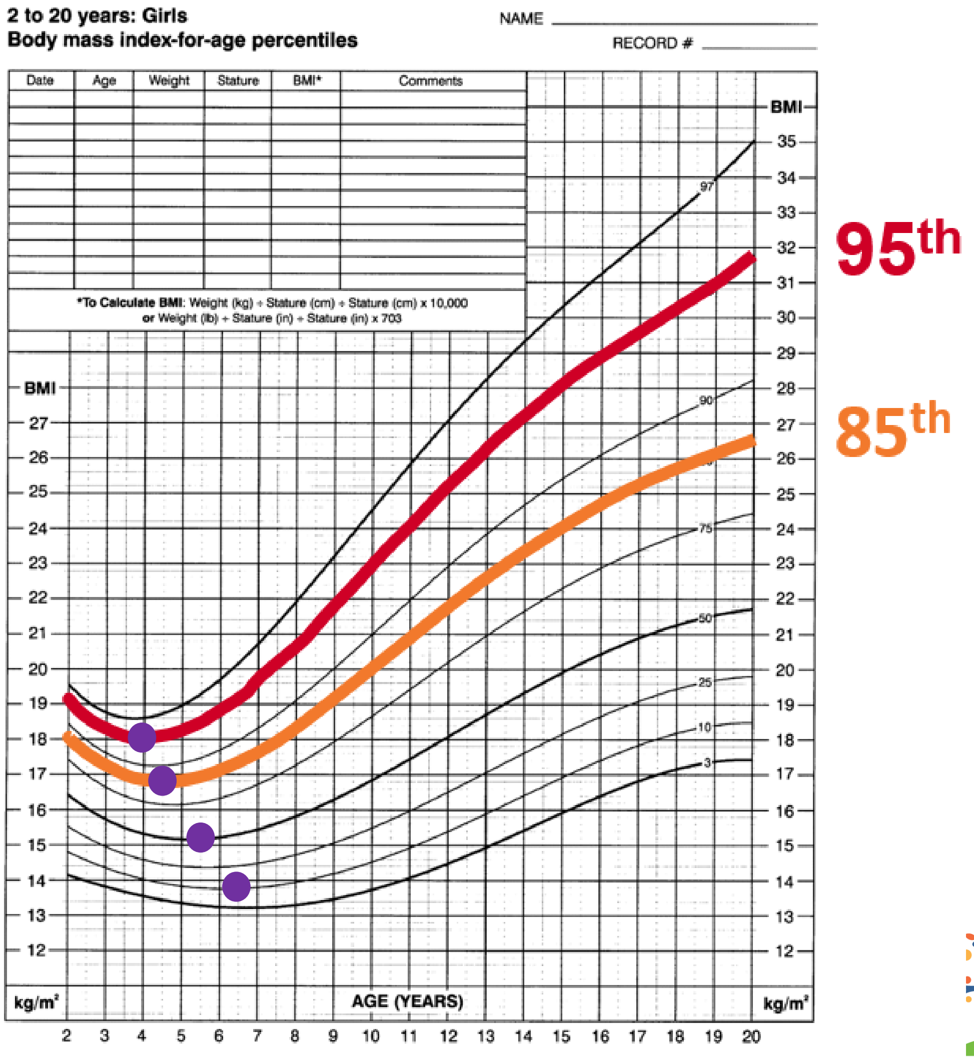
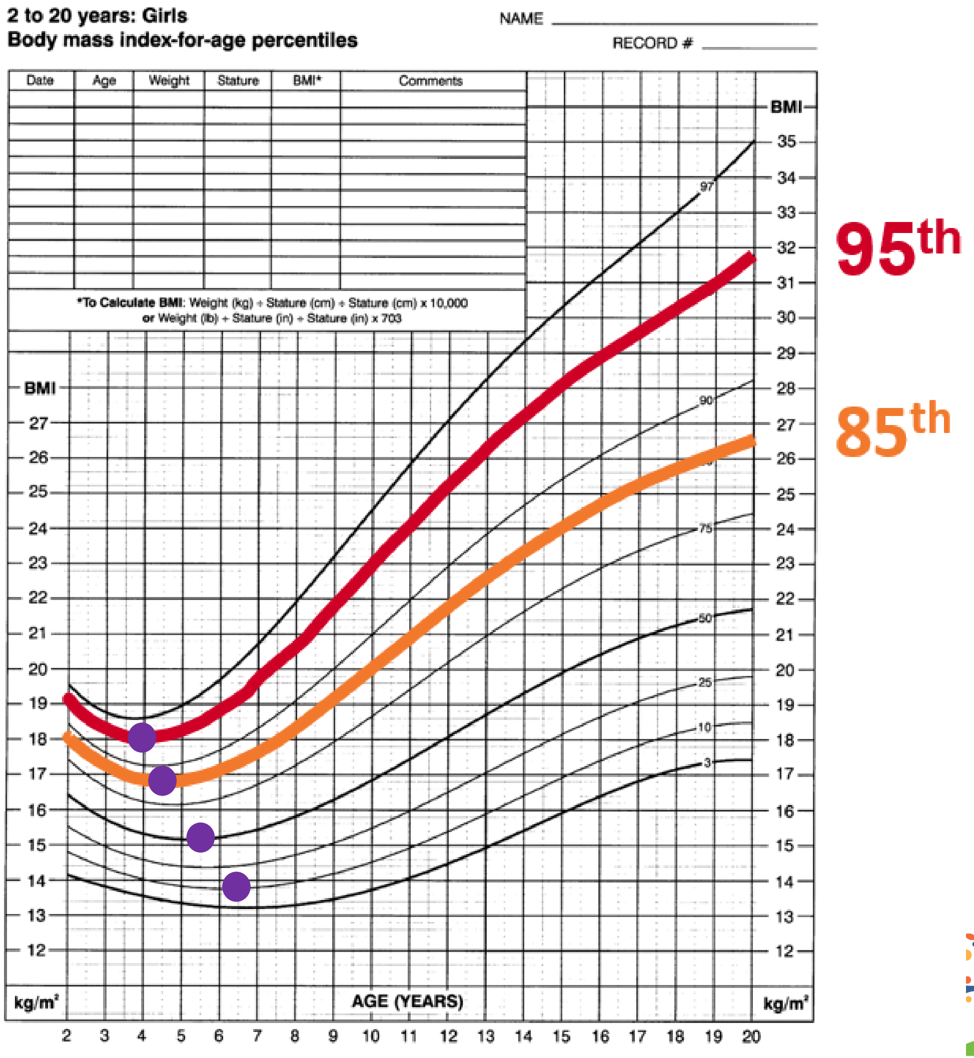


Study 1: Why Multiphase Modeling?

- **Limitations in Traditional Methods[3] → Our Solution**
- Inability to assess individual transitions → Multiphase models estimate personal change points
- Cannot detect atypical transition patterns → Mixture modeling identifies distinct trajectory groups
- Result: Early identification of children on high-risk developmental pathways

Study 1: Background



Study 1: Current Study

- **Objective**: To characterize multiphase BMI trajectories in children and identify associated modifiable early-life factors.
- **Inclusion Criteria**: Children with 4 or more weight and height assessments from ages 1–9 years.
- **Sample**: *N* = 9,483 children from 23 ECHO cohorts
- **Analytical Model**: Multiphase Latent Growth Mixture Modeling
    - Identifies when children's growth patterns shift direction (e.g., from decreasing to increasing BMI) and estimates individual timing of these transitions.

Study 1: Analytical Approach

- Analytical Approach:
  - Step 1: Single-phase growth mixture model → identified typical vs. atypical groups
  - Step 2: Two-phase, two-group model allowing different rates within each phase
- Unlike traditional models assuming same timeline for all children, this approach recognizes **unique individual developmental patterns.**
- The power of this approach is that it moves beyond population averages to capture **individual heterogeneity in both the timing of developmental transitions and the rates of change within each phase**.

Study 1: Current Study

- **Innovation**:
  - **Qualitatively different developmental pathways**: Typical vs. Atypical
  - **Individual Change Points:** Personal adiposity rebound timing estimated for each child
  - **Phase-Specific Growth:** Different rates within each developmental phase (e.g., linear, quadratic, or exponential changes)
  - **Complete flexibility:** Children within same group can have very early or very late change points
  - **Individual-level estimation:** Each child's change point and growth rates estimated separately

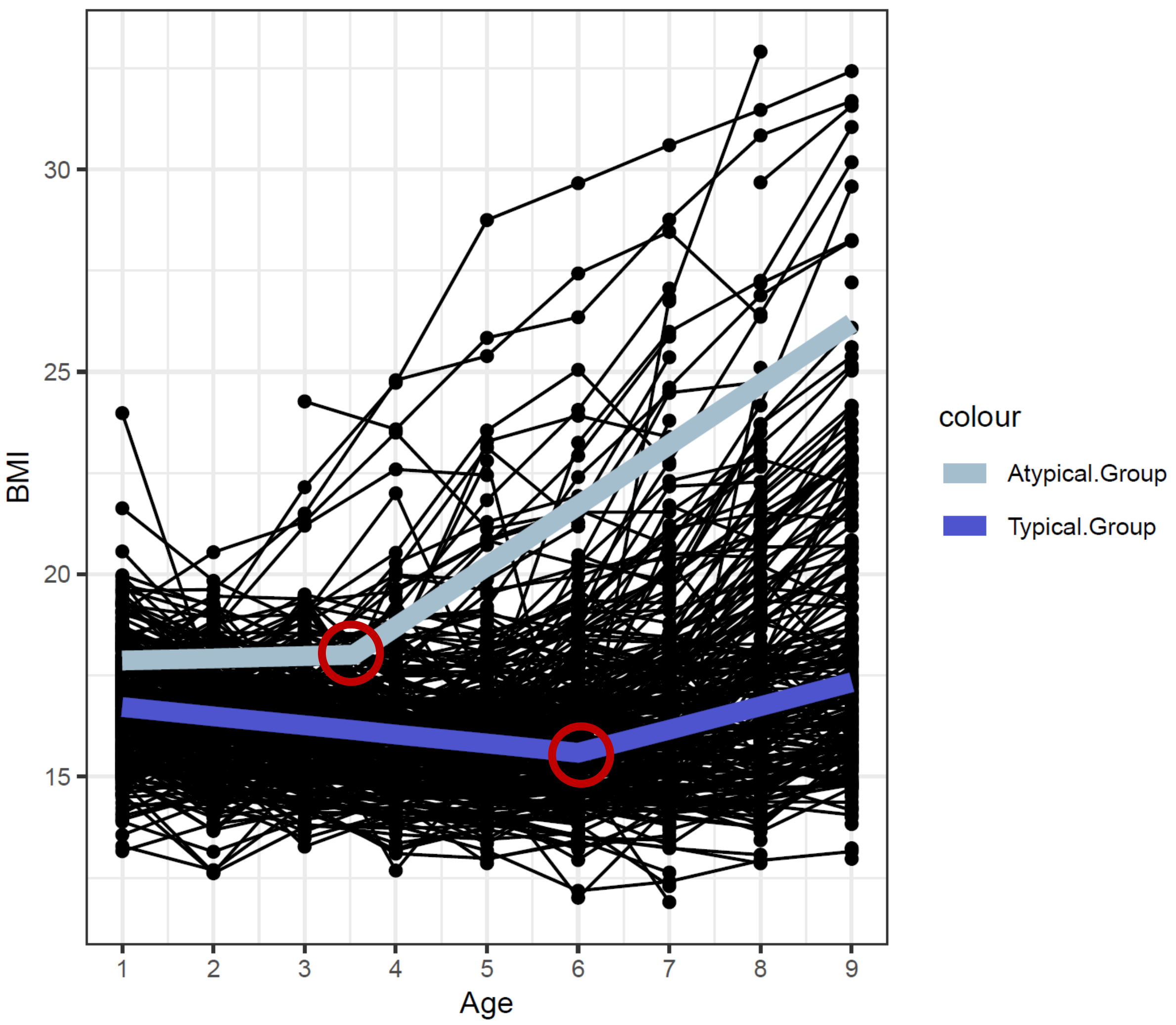
Study 1: Results

Typical Trajectory (89.4%, *n*=8,477)

- Ages 1-6: Linear decline (-0.23 kg/m²/year)
- Change point: 6.0 years
- Ages 6-9: Gradual increase (+0.58 kg/m²/year)
- Age 9 BMI: 17.33 kg/m² (~69th percentile)

Atypical Trajectory (10.6%, *n*=1,006)

- Ages 1-3.5: Stable BMI (+0.06 kg/m²/year)
- Change point: 3.5 years
- Ages 3.5-9: Rapid increase (+1.50 kg/m²/year)
- Age 9 BMI: 26.2 kg/m² (~99th percenti

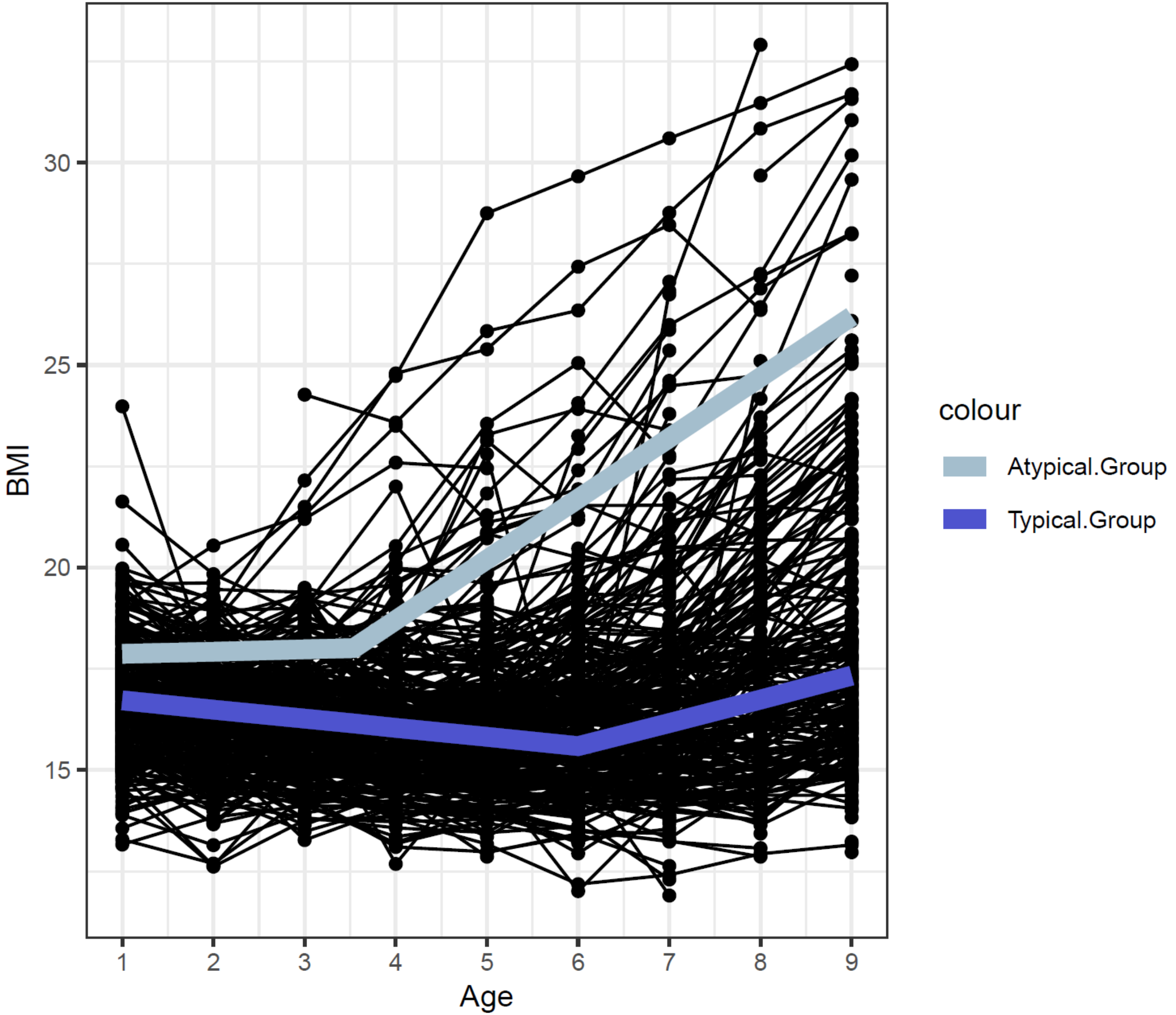


Study 1: Results

Typical Trajectory (89.4%, *n*=8,477)

Atypical Trajectory (10.6%, *n*=1,006)

- Prenatal smoking
- High pre-pregnancy BMI
- Greater gestational weight gain
- High birthweight



Study 1: Implications

Distinguished children on an early path to obesity from those with normative development as early as age 3.5 years

Modifiable factors could be targeted for early prevention and intervention programs aimed at reducing childhood obesity.

Study 1: Future Directions

- **Follow-up research**: Gyeyoon Yim, Xuan Li, & Joseph M. Braun et al., examined the associations of prenatal PFAS exposures with BMI trajectories (i.e., change point, growth parameters) derived from this study.
- The multiphase growth mixture model is well-suited for research **where timing of individual-specific change points and phase transitions are key interests** (e.g., the onset of anxiety for children).

Study 2

- Early-Life Factors Associated with BMI Z-score Lability in Children in the ECHO Cohort

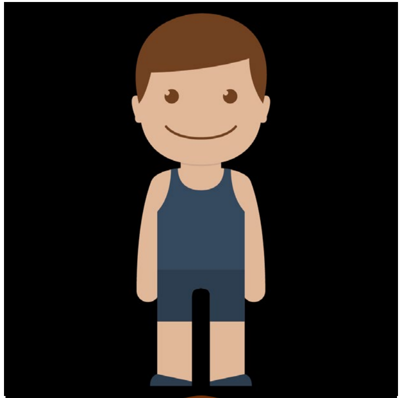
Early-Life Factors Associated with Body Mass Index Z-score Lability in Children in the ECHO Cohort

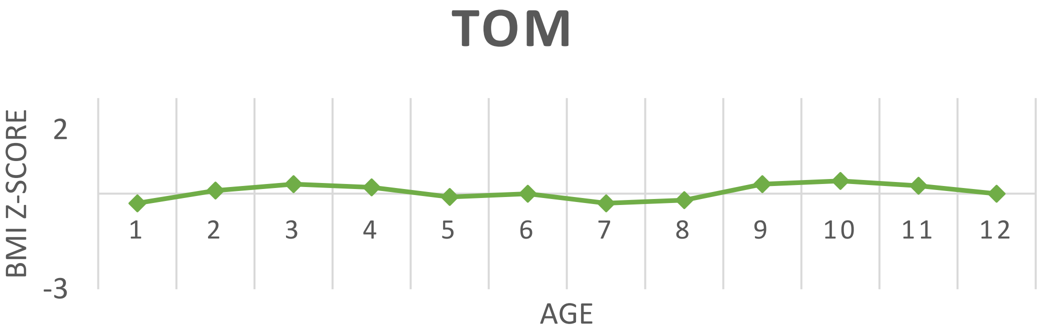
Chang Liu, PhD,[1] Sy-Miin Chow, PhD,[2] Izzuddin M. Aris, PhD,[3] Dana Dabelea, MD, PhD,[4,5,6] Jenae M. Neiderhiser, PhD,[7] Leslie D. Leve, PhD,[8] Diane J. Catellier, DrPH,[9] Wei Perng, PhD, MPH,[4,5] Carlos A. Camargo, Jr., MD, DrPH,[10] Thomas G. O'Connor, PhD,[11] Qi Zhao, MD, PhD,[12] Cindy T. McEvoy, MD, MCR,[13] Hooman Mirzakhani, MD, MMSc, PhD,[14] Assiamira Ferrara, MD, PhD,[15] Alicia K. Peterson, PhD,[15] Yeyi Zhu, PhD,[15] Lihua Yao, PhD,[16] Griffith Gao, MS,[17] Jennifer K. Straughen, PhD,[18,19] Sarah S. Comstock, PhD,[20] Andrea E. Cassidy-Bushrow, PhD,[18,21] Andrew Rundle, DrPH,[22] Eliza W. Kinsey, PhD,[23] Debra Mackenzie, PhD,[24] Amrik Singh Khalsa, MD, MSc,[25] Akram N. Alshawabkeh, PhD,[17] Emily Zimmerman, PhD,[26] T. Michael O'Shea, MD, MPH,[27] Carrie Breton, ScD, MPH,[28] Theresa M. Bastain, PhD, MPH,[28] Rachel K. Conlon, PhD,[29] Daphne Koinis-Mitchell, PhD,[30,31,32] Viren D'Sa, MD,[31] Grace Cushman, PhD,[30,32] Lacey McCormack, PhD, MPH, RD,[33,34] Nicole L. Mihalopoulos, MD, MPH,[35] Sarah D. Geiger, PhD,[36,37] and Jody M. Ganiban, PhD[38]; on behalf of program collaborators for Environmental influences on Child Health Outcomes (ECHO)*

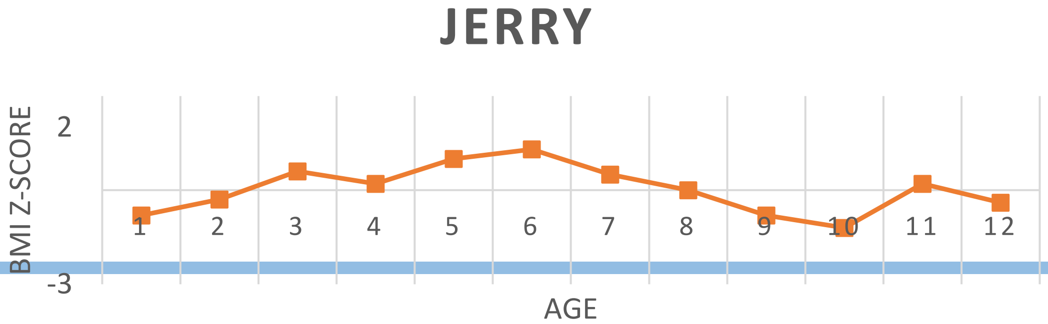
*See Acknowledgments for full listing of collaborators

Child BMI Z-score Lability

- BMI = weight in kilograms divided by height in meters squared
- BMI z-score: adjusted for child sex and age







Child BMI Z-score Lability

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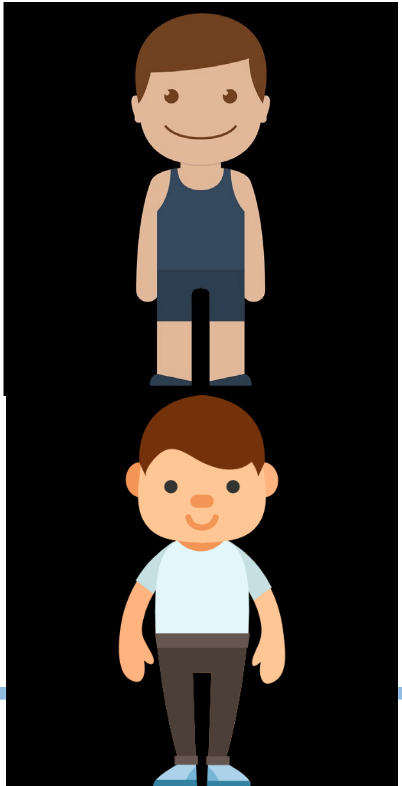
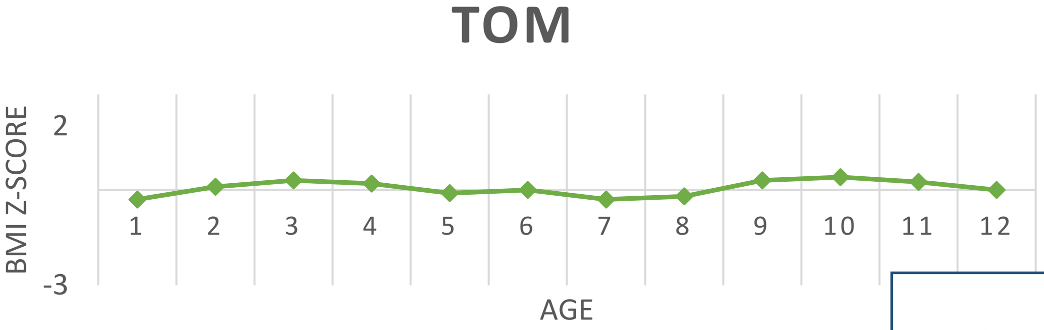
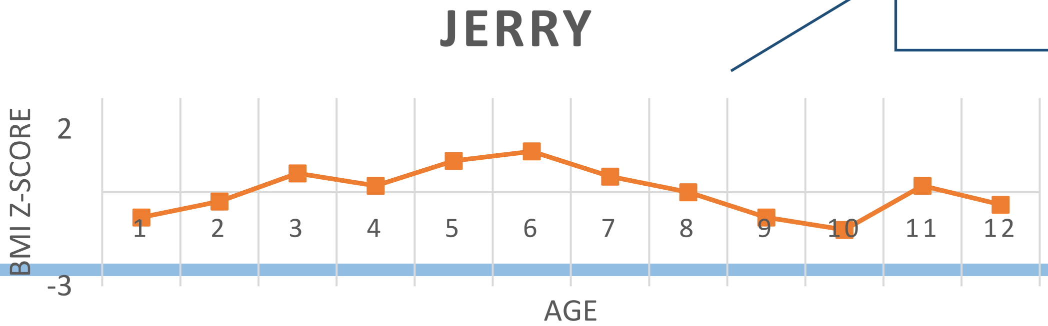




Risk factor for long-term weight control problem



Study 2: Background

- Previous research focused on ***absolute weight status*** (i.e., BMI z-scores);
- Emerging evidence: ***Weight status lability*** independently predicts adverse health outcomes
  - Weight status lability: fluctuations above and below each child's expected age-related growth patterns over time[4]

Study 2: Background

Adult Research Evidence

- Weight lability predicts adverse outcomes **independent of absolute weight level**
  - Weight loss program: Higher early weight lability → lower long-term weight loss success[5]
  - Coronary patients: Highest weight lability group had:[6]
    - 64% higher coronary events
    - 85% higher cardiovascular events
    - 124% higher mortality risk

Pediatric Evidence[7]

- Girls with higher BMI lability (ages 2-6) → increased adult obesity risk
- Association persists after controlling for overall BMI developmental trajectory

Study 2: BMI Z-Score Lability in Children

- **BMI z-score lability**: Intraindividual variability around expected BMI z-score developmental patterns
  - Accounts for normative age-related growth patterns
  - Describes fluctuations that deviate from expected development
- **What Lability May Indicate**[4,8]
  - Disrupted homeostatic weight regulation
  - Heightened sensitivity to environmental factors
  - Compensatory growth processes

Study 2: Research Gap and Objective

- **No systematic examination** of early-life factors associated with BMI z-score lability in children
  - Critical gap given potential for **informing prevention efforts**

- **Objective**: To identify associated early-life factors
  - Examine differential associations between early-life factors and BMI z-score lability across weight status groups:
    - Overweight/obesity
    - Healthy weight
    - Underweight

Study 2: Current Study

- **Inclusion Criteria**: Children with 4 or more weight and height assessments from ages 2–9 years
- **Sample**: N = 7,800 children from 20 ECHO cohorts
- **Analytical Model**: Multilevel Location-Scale Model

Study 2: Multilevel Location-Scale Model

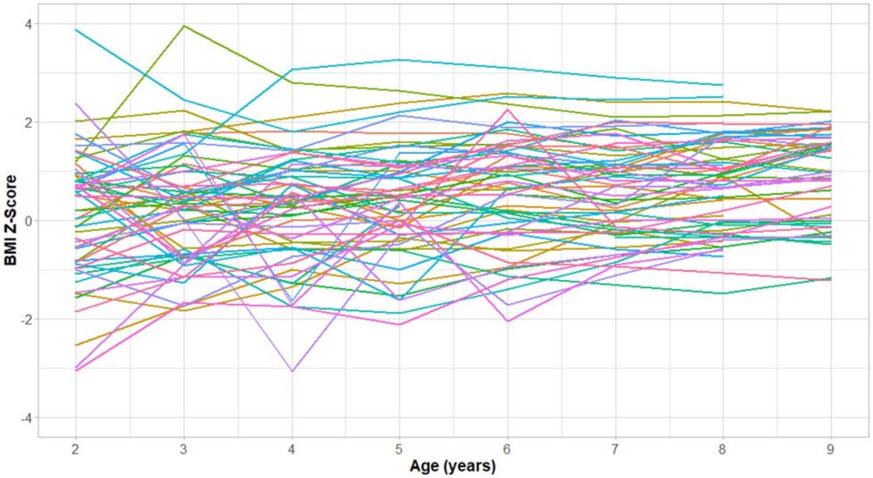
Innovation: Simultaneous modeling of **mean trajectory** (level) and **intraindividual variability** (lability)[9]

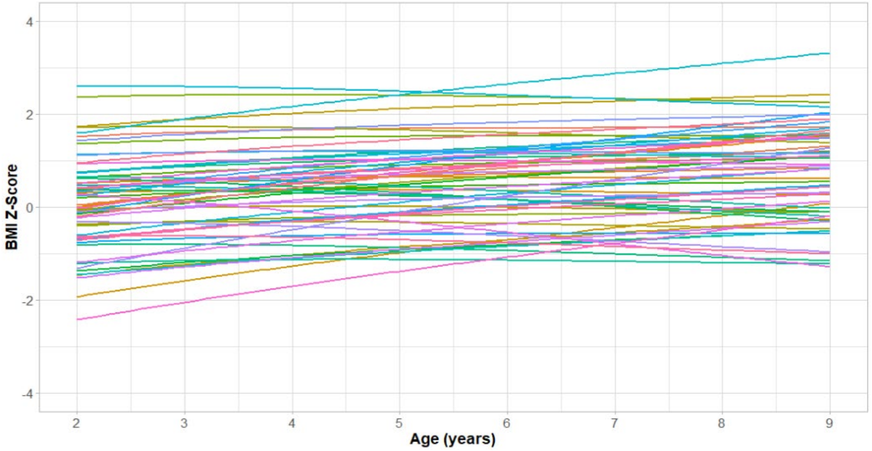
Model Components

- **Location model**: Expected BMI z-score trajectories
- **Scale model**: Intraindividual variability around individual trajectory
- Full sample analysis, then **group-specific** analysis

Study 2: RAW vs. Model-Predicted BMI Z-Score Trajectories

BMI Z-Score





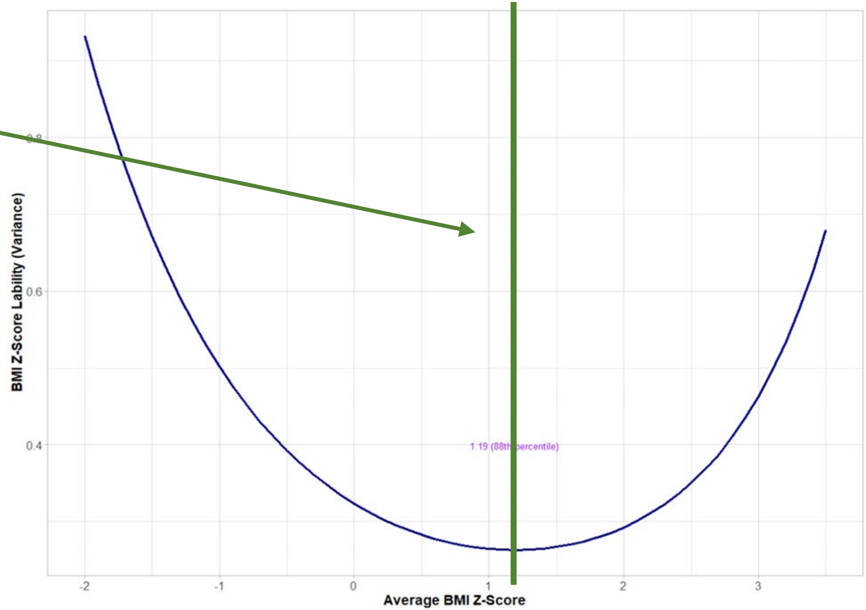
Age (years)

Age (years)

Study 2: Cubic Association Between Children's Average BMI Z-Score and BMI Z-Score Lability

The estimated cutoff score is 88th percent

BMI Z-Score Lability



Average BMI Z-Score

Study 2: Findings – Full Sample (*N* = 7,800)

Lower Lability (More Stable)
- Female sex, Hispanic (vs. White)
- Higher maternal education
- Higher birthweight
- Higher neighborhood resources (i.e., child opportunity index)

Higher Lability (Less Stable)
- Preterm birth
- Higher maternal pre-pregnancy BMI

Non-Significant
- Breastfeeding, Gestational weight gain

Study 2: Group-Specific Lability Effects

Universal Patterns (Across Groups)

- Female sex → Lower lability
- Preterm birth → Higher lability

Overweight/Obesity Group (*n* = 1,844)

- Breastfeeding → Lower lability
- Higher neighborhood resources → Lower lability
- Higher gestational weight gain, higher birthweight → Lower lability

Healthy Weight Group (*n* = 5,790)

- Higher maternal education → Lower lability
- Higher maternal pre-pregnancy BMI → Higher lability

Underweight Group (*n* = 166)

- Limited significant findings (small sample size)

Study 2: Clinical and Public Health Implications

Prevention Programs

- Target early-life factors to promote **healthy and stable** BMI z-score trajectories

Monitoring

- Children born preterm
- Children with family history of high BMI

Policy Implications

- Breastfeeding support (particularly for obesity-risk populations)
- Neighborhood resource improvements (particularly for obesity-risk populations)

Study 2: Future Directions

Ongoing Projects

- Prospective examination of early BMI z-score lability as predictor of subsequent obesity, cardiometabolic, and behavioral health outcomes during middle childhood, early adolescence, and middle adolescence

Key Takeaways

ECHO's Multi-Wave Longitudinal Design Enables Novel Discoveries

- Individual trajectory mapping reveals critical developmental patterns
- Early identification possible: Atypical BMI trajectories detected by age 3.5 years
- Early-life factors influence both BMI trajectory patterns and weight status stability/lability in group-specific ways

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Key Collaborators

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Any Questions?

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ECHO

Environmental influences
on Child Health Outcomes

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