

Introducing the Healthy Start to Life Project: economic modelling using epidemiological evidence

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Centre of Research Excellence

**National Research
Centre for Growth
and Development**

Fundamental
processes in
developmental
plasticity

Gene-environment
interactions in early
life: Molecular &
cellular mechanisms

Determinants of
environmentally
induced
developmental
mismatch

Later life effects of
developmental
mismatch

Applications to
agriculture and
human health

**Translation of our
research and its
impact on policy
and practice**

Liggins Institute, AgResearch, Landcorp, Massey University,
University of Auckland. Canterbury University, Otago University

Theoretical

Translational

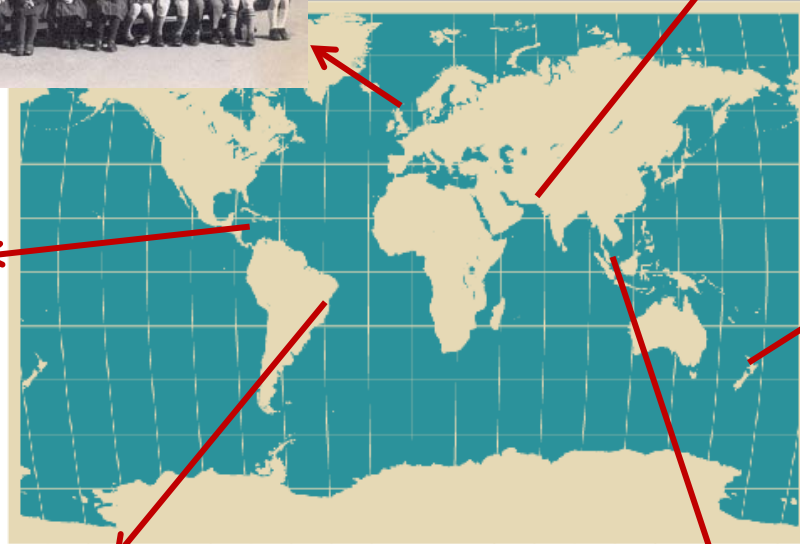
Theme 6: Translational Research

- Focussed on translating NRCGD research into effective policy interventions and educational practice.
- Key issue is the economic justification for a policy shift from later life interventions to early interventions.
- Must be defined in population-specific manner.
- Currently two studies as a part of this theme:
 - International Healthy Start to Life Project (currently in phase II)
 - A healthy start to life – adolescent education for preparedness

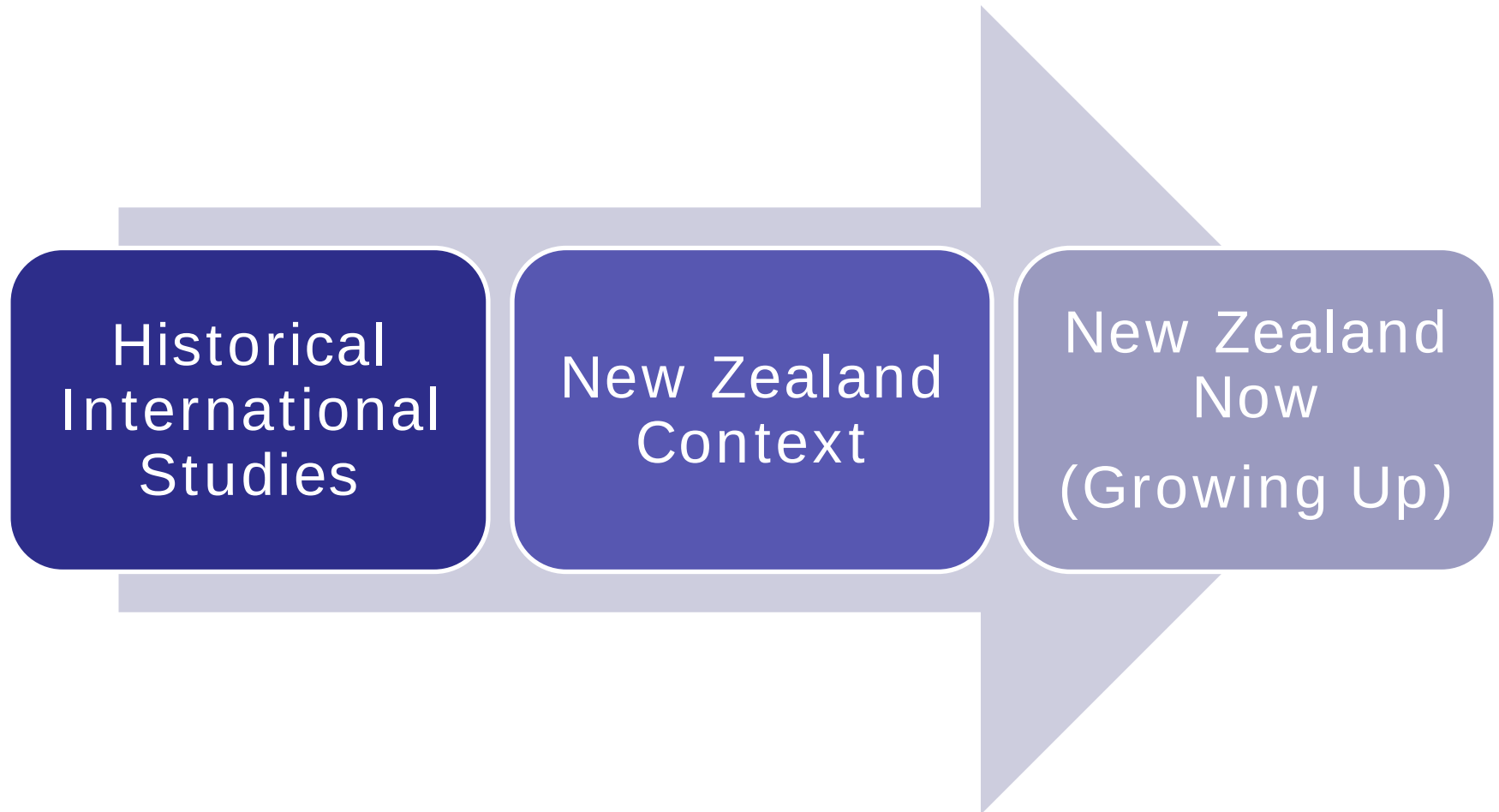
IHSLP

- Population based study that aims to:
 - provide context-relevant evidence to policy makers in order to ...
 - improve population health and ...
 - recognise the importance of cost-effectiveness of investment early in life.
- Collaborative study between economists and medical researchers from...
- developed and developing countries.

International Datasets



New Zealand Benefit



Modelling Approach

Cross Disciplinary

- Combining health, economic, educational and environment variables ...
- from different life periods (life course modelling).

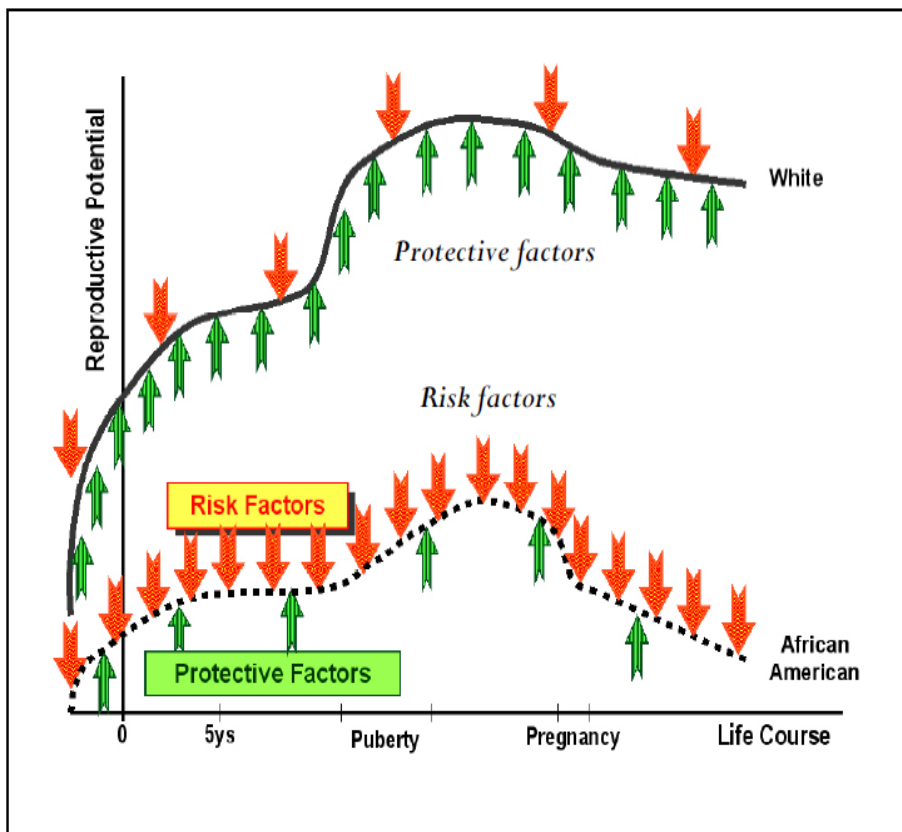
Parametrize

- Each dataset will be used to establish benchmark parameters of key dependent variables.
- Comparisons between these parameters will be analysed based on contextual differences between the countries.

Micro- simulation

- Parameters most similar to New Zealand will be used to parametrize the micro-simulation model of life course effects
- Used to allocate agents to attribute constants that can then be varied according to individual decisions and/or interventions.

Life Course Modelling



Examples of Protective & Risk Factors

- Socioeconomic status
- Race and racism
- Health care
- Disease status
- Stress
- Nutrition
- Weight status
- Birth weight
- Various health behaviors

Scaling up and scaling down!



SCORM – A first step

- Singapore Cohort Study of the Risk factors of Myopia
- Longitudinal data set collected from 1999 that includes a wealth of demographic, socioeconomic, pre-natal and childhood characteristics.
- Short life course – pre-natal to 11 years of age
- We know that low levels of cognitive ability as a child are associated with numerous health and social outcomes later in life.
- Dependent variable childhood IQ
- Can early life environment influence outcomes?

Sample

- Half of the sample from schools:
 - ranked in the bottom 20 in Singapore
 - ranked in the top 20 in Singapore
 - based on prior National Examination results
- Data included:
 - comprehensive peri-natal data
 - socio-economic data at both birth and aged 11
 - parent educational levels
 - one of the top 20 schools had additional peri-natal data on included:
 - birth order, breast fed & mother's work status.

Analysis - 3 stages

1. Initially IQ, measured at age 11, was regressed against a range of individual, household/socio-economic and school determinants consistent with study undertaken by Cesur & Kelly (2010)
2. Logistic regression of IQ groups was then run to identify the possible impact of interventions such as schooling
3. Multinomial logit models were then used to investigate the likelihood of moving across IQ groups and whether these movements were greater than or less than the average.

IQ Regression Analysis

- OLS regression with 662 individuals
- Dependent variable IQ at age 11
- Re-run using half the sample that had additional peri-natal data
 - school omitted from this as all individuals were from the same school
- Mother's education was the only determinant significant across samples
- School was also significant in the full sample
- Weakly significant results for income and ethnicity
- While others not significant they were signed as expected

IQ Regression Results

Variables	IQ Full Sample	IQ Half Sample
Individual characteristics		
Birth weight	-0.006 (0.007)	-0.003 (0.008)
Birth weight squared	0.000 (0.000)	0.000 (0.000)
Male	-0.300 (0.872)	-1.205 (1.161)
Breast fed	-	1.007 (1.197)
Birth order	-	-0.936 (0.907)
Chinese	2.546 (1.697)	3.676* (2.185)
Malay	-2.771 (1.88)	-1.156 (2.644)
Household characteristics		
Total combined income	1.391* (0.784)	0.504 (1.069)
Father education	0.84 (0.596)	0.594 (0.803)
Mother education	2.078*** (0.637)	2.709*** (0.882)
Mother age	-0.372 (0.872)	-0.197 (1.387)
Mother age squared	0.005 (0.014)	0.004 (0.023)
Number of children	-	-1.147 (0.807)
Mother working	-	0.999 (1.34)
School characteristics		
School dummy	5.878*** (0.982)	-
Observations	662	320
R squared	0.233	0.178

***, **, and * denotes significance at 1%, 5%, and 10% levels, respectively.

Logistic Regression of IQ Groups

- Really interested in the transition between life stages
- IQ only collected at age 11 for children but given earlier results that Mother's education strongly and consistently significant it motivated us to use this as a proxy for cognition at birth.
- Mother' education split into five categories
 - no formal, primary, secondary, pre-degree/diploma, university
- Made sense to split IQ into five categories as well based on standard interpretations of IQ

IQ Categories

- 1 if $IQ < 90$ (below average)
- 2 if $90 \leq IQ \leq 99$ (low normal or average)
- 3 if $100 \leq IQ \leq 109$ (high normal or average)
- 4 if $110 \leq IQ \leq 119$ (superior)
- 5 if $IQ \geq 120$ (very superior)
- First applied an ordered logistic regression
 - appropriate given the constructed ordinal and categorical nature of our dependent variable
- Allowed for 'odds ratios' to be calculated
 - 'odds ratios' are a way of comparing whether the probability of a certain event or outcome is the same for two groups.
 - An odds ratio of 1 indicates an event is equally likely in both groups/circumstances.

Ordered Logit Model

- The ordered response model is:

$$\Pr(Y = j|X, \alpha, \beta) = F_j(\alpha_j - X' \beta) - F_{j-1}(\alpha_{j-1} - X' \beta)$$

- Where $j=1,2,\dots,5$, $\alpha_0 = -\infty$, $\alpha_{j-1} \leq \alpha_j$, $\alpha_m = \infty$ and F is the cumulative distribution function of the logistic distribution $F_j = 1/(1 + \exp(-(\alpha_j - X' \beta)))$.
- The underlying IQ function is given by:

$$\begin{aligned} IQ = & \alpha + \beta * \text{Birth weight} + \beta * \text{Birth weight squared} + \beta * \text{Male} + \beta * \text{Chinese} \\ & + \beta * \text{Malay} + \beta * \text{Income} + \beta * \text{Father education} + \beta * \text{Mother education} \\ & + \beta * \text{Mother age} + \beta * \text{Mother age squared} + \beta * \text{School dummy} + u \end{aligned}$$

$$\begin{aligned} IQ = & \alpha + \beta * \text{Birth weight} + \beta * \text{Birth weight squared} + \beta * \text{Male} + \beta * \text{Breast fed} \\ & + \beta * \text{Birth order} + \beta * \text{Chinese} + \beta * \text{Malay} + \beta * \text{Income} \\ & + \beta * \text{Father education} + \beta * \text{Mother education} + \beta * \text{Mother age} + \beta * \text{Mother age squared} \\ & + \beta * \text{Number of children} + \beta * \text{Mother working} + \beta * \text{School dummy} + u \end{aligned}$$

Logistic Regression Results

Cuts		
When IQ group = 1	-1.158 (2.704)	-2.200 (4.555)
= 2	0.027 (2.700)	-0.766 (4.539)
= 3	1.085 (2.700)	-0.019 (4.535)
= 4	3.277 (2.700)	2.285 (4.538)

Variables	Coefficients (Full sample)	Odds-Ratio	Coefficients (Half Sample)	Odds-Ratio (Half Sample)
Individual characteristics				
Birth weight	-0.001 (0.001)	1.000	-0.000 (0.001)	1.000
Birth weight squared	0.000 (0.000)	1.000	0.000 (0.000)	1.000
Male	0.087 (0.150)	1.091	0.012 (0.227)	1.012
Breast fed	-	-	0.274 (0.232)	1.316
Birth order	-	-	-0.252 (0.176)	0.778
Chinese	0.331 (0.283)	1.393	0.602 (0.416)	1.827
Malay	-0.373 (0.313)	0.689	-0.172 (0.505)	0.842
Household characteristics				
Total combined income	0.189 (0.135)	1.208	0.158 (0.204)	1.171
Father education	0.098 (0.102)	1.102	-0.008 (0.156)	0.992
Mother education	0.458*** (0.114)	1.581***	0.619*** (0.179)	1.857***
Mother age	-0.010 (0.146)	0.989	-0.072 (0.268)	0.931
Mother age squared	0.000 (0.002)	1.000	0.002 (0.004)	1.002
Number of children	-	-	-0.180 (0.157)	0.835
Mother working	-	-	0.021 (0.259)	1.021
School characteristics				
School dummy	1.102*** (0.171)	3.011***	-	-
Observations	662	662	320	320
Pseudo R squared	0.102	0.102	0.081	0.081

Multinomial Logit Model

- This model investigates the likelihood of moving across IQ groups between birth and age 11.
- We seek to isolate the impact of environment & proxy cognition at birth by mother's education.
- Allows us to infer,, for a given level of mothers education, how environmental factors influence the development of cognition.
- preliminary inspection shows most children are in 1 IQ group higher than their mother's education level.
- We then focus on movements greater than or less than average movements.

Multinomial Logit Results (Above avg)

	Mother education = 2	Mother education =3
Above average		
Individual characteristics		
Birth weight	-0.001 (0.002)	0.001 (0.003)
Birth weight squared	0.000 (0.000)	-0.000 (0.000)
Male	-0.136 (0.484)	0.192 (0.256)
Chinese	-0.332 (0.873)	0.413 (0.553)
Malay	-0.536 (0.910)	-0.198 (0.641)
Household characteristics		
Total combined income	0.568 (0.599)	-0.036 (0.215)
Father education	0.930 (0.423)**	-0.110 (0.163)
Mother age	-0.205 (0.452)	-0.011 (0.285)
Mother age squared	0.004 (0.008)	0.000 (0.005)
School characteristics		
School dummy	1.157 (0.555)**	1.027 (0.318)***
Observations	171	331
Pseudo R squared	0.154	0.106

***, **, and * denotes significance at 1%, 5%, and 10% levels, respectively.

Multinomial Logit Results (Below avg)

Below average	Mother education = 2	Mother education =3
Individual characteristics		
Birth weight	0.016 (0.008)**	0.001 (0.004)
Birth weight squared	-0.000 (0.000)**	-0.000 (0.000)
Male	0.425 (0.571)	0.225 (0.333)
Chinese	-0.586 (1.138)	-0.449 (0.600)
Malay	0.819 (1.137)	-0.313 (0.657)
Household characteristics		
Total combined income	0.184 (0.726)	-0.460 (0.300)
Father education	0.342 (0.516)	-0.360 (0.223)*
Mother age	-0.139 (0.528)	0.018 (0.341)
Mother age squared	0.003 (0.009)	0.000 (0.006)
School characteristics		
School dummy	0.723 (0.671)	-1.270 (0.358)***
Observations	171	331
Pseudo R squared	0.154	0.106

***, **, and * denotes significance at 1%, 5%, and 10% levels, respectively.

Conclusions

- Firstly, these results are largely consistent with previous studies.
- Given the Singaporean context there are only 3 drivers of childhood cognitive ability:
 - parental education
 - school attended
 - birth weight (small impact & u-shape)
- Important to note that we investigated **CHANGES** in childhood cognitive ability rather than actual ability
 - why other peri-natal variables were not found to be significant.

Translating the research to policy

- In research, we typically scale down to pinpoint cause and effect:
 - Identify individual relationships
 - Account for explanatory variables
 - Minimise the variation in other variables to focus on the key driving factors
- For policy, we need to
 - 1) scale up
 - What does the research imply for an entire population?
 - 2) look long term
 - Quantify the lifetime benefits of a healthy start to life

Scaling up: modelling at a population level

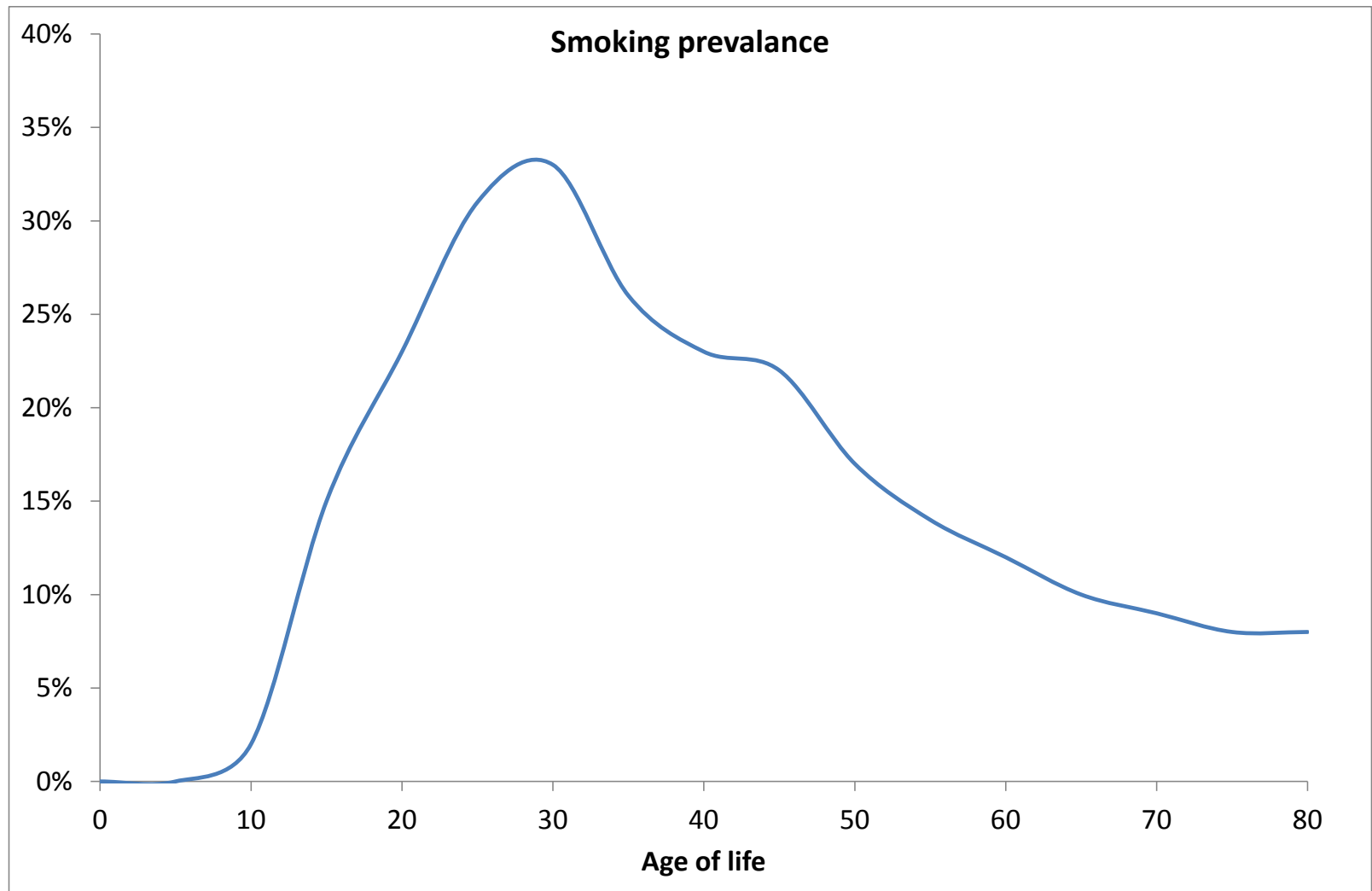
- People are different!
- Populations change



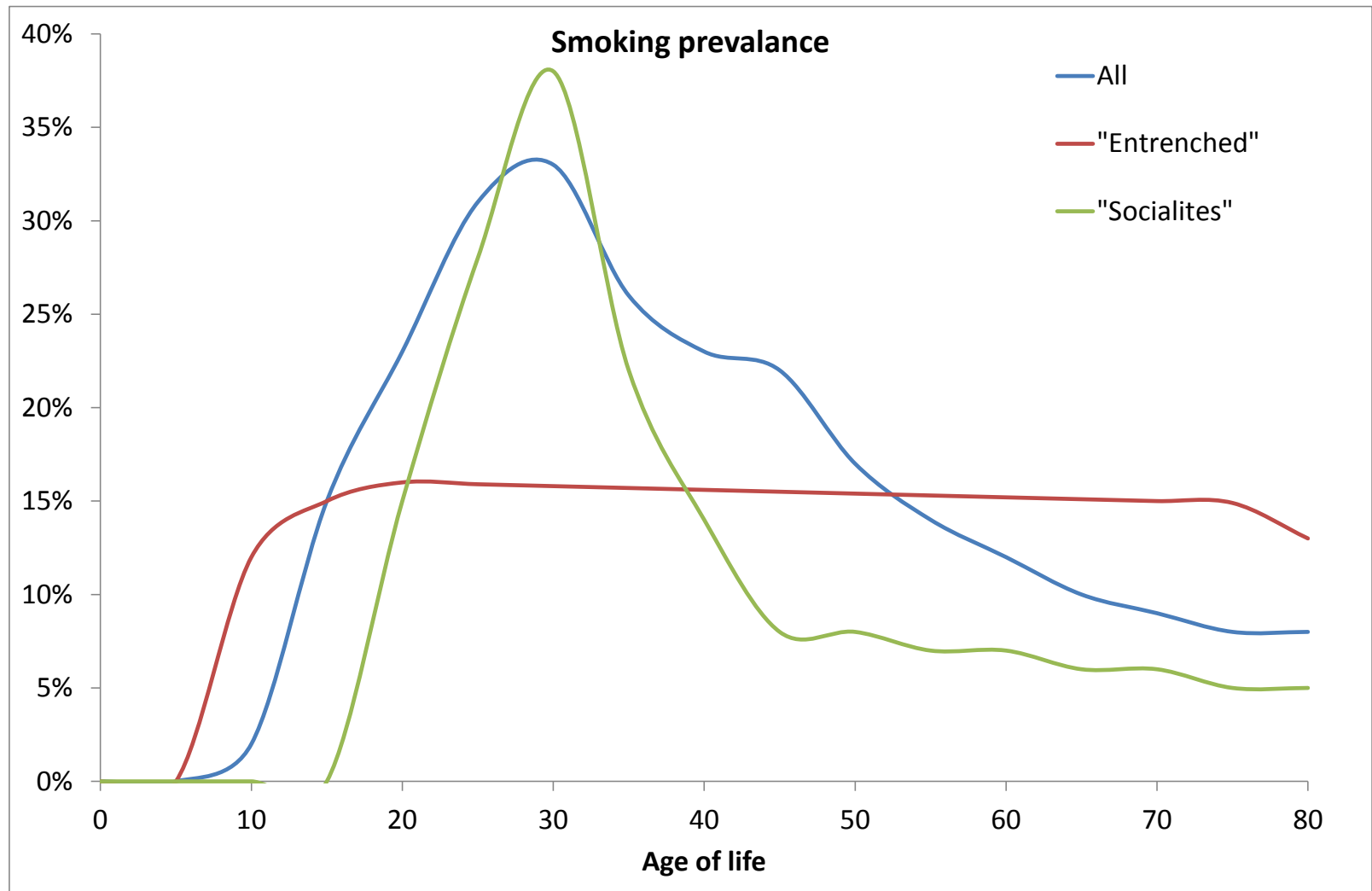
Impacts of interventions are different across cohorts

- Modelling needs to include population heterogeneity

Example: tobacco control

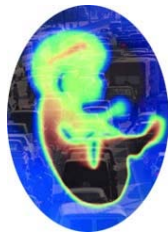


Example: tobacco control



Looking long term: modelling over time

- Epidemiology tells us that early life matters



Benefits of an intervention today may accrue over 50 years or more

- Critical periods in health development
- Modelling needs to capture lifetime benefits and costs and sum into today's money

A microsimulation framework (1)

- 'Agent' based
- Model 4 million agents rather than 1, 10 or even 10,000
- Each agent is modelled individually
 - Has an ethnicity, an income, a gender
 - Experiences different life events (e.g. birth, pregnancy, death)
 - Is exposed to risk factors (e.g. smoking initiation and cessation)
- Population is representative of wider New Zealand

See how impacts of interventions vary

A microsimulation framework (2)

- Based on Statistics NZ demographic data
 - Projects out to 2061
- Models the lifepath of each agent out for 50+ years
 - Include key health paths of interest e.g. smoking and cancer
 - Parameterise using relative risk ratios (or odds ratios)

Models each stage of life, including long term impacts

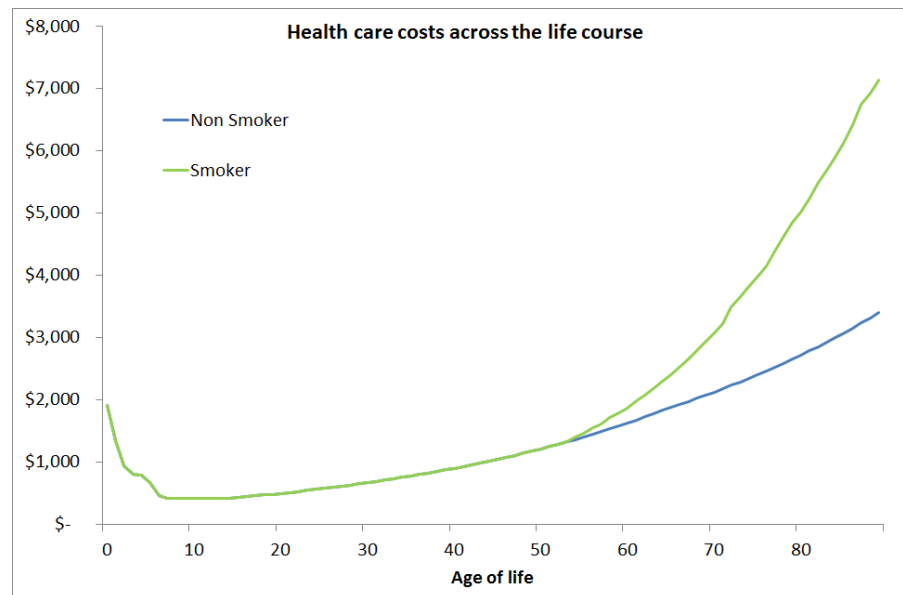
Populating the model

- Longitudinal studies:
 - International datasets (e.g. SCORM analysis)
 - Growing up in NZ
- Ministry of Health data
- Census and health surveys
- International literature
- Statistics NZ

An on-going process – “scaleable”

Valuing a healthy start to life

- Consider
 - Health care costs
 - Labour productivity impacts
 - Value of statistical life (VOSL)



Scenario modelling

- Scenario modelling used to estimate economic costs of intervention
 - Baseline scenario (without intervention) compared to Policy scenario (with intervention)
- Sensitivity testing of key parameters
 - Discount rates
 - Econometric coefficients
 - Economic valuation numbers

What it delivers?

- An ability to make policy trade-offs
- Highlight the long term benefits of early interventions
- A framework for international comparisons
- Evidence

The evidence for policy makers to make decisions

Promoting a healthy start to life

- The epidemiology is generally accepted...
- But yet translation to policy is still difficult
- IHSLP is a cross disciplinary team with a focus on policy
- Our aim to promote a healthy start to life by:
 - Understanding epidemiological relationships
 - Quantifying the implications of early life on later life
 - Scaling up our findings using population modelling

Robust evidence to promote a healthy start to life