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Determinants and disparities: A simulation approach to the case of child health care

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ABSTRACT

Though there is much agreement on the importance of the social determinants of health, debate continues on suitable empirically-based models to underpin efforts to tackle health and health care disparities. We demonstrate an approach that uses a dynamic micro-simulation model of the early life course, based on longitudinal data from a New Zealand cohort of children born in 1977, and counterfactual reasoning applied to a range of outcomes. The focus is on health service use with a comparison to outcomes in non-health domains, namely educational attainment and antisocial behaviour. We show an application of the model to test scenarios based on modifying key determinants and assessing the impact on putative outcomes. We found that appreciable improvement was only effected by modifying multiple determinants; structural determinants were relatively more important than intermediary ones as potential policy levers; there was a social gradient of effect; and interventions bestowed the greatest benefit to the most disadvantaged groups with a corresponding reduction in disparities between the worst-off and the best-off. Our findings provide evidence on how public policy initiatives might be more effective acting broadly across sectors and across social groups, and thus make a real difference to the most disadvantaged.

Keywords: New Zealand; children; health care; social determinants; disparities; micro-simulation.

INTRODUCTION

Complex policy issues across a range of domains affecting children require thought and action based on the best evidence available and responsive to rapidly changing social conditions. We adopt a conceptual approach combining the social determinants of health framework with a life course perspective, and apply a methodological approach based on counterfactual modelling using a form of simulation. We construct a dynamic micro-simulation model of health service use and other outcomes in early childhood to assess the relative effects of altering social conditions at different levels of influence. Testing counterfactual scenarios in this way may illuminate the effectiveness of potential policy interventions.

Social determinants

There is much agreement on the importance of the social determinants of health (CSDH, 2008; The Marmot Review, 2010) and similar constructs such as ‘circumstances’ that give rise to ‘inequality of opportunity in health’ (Rosa Dias, 2009). However, debate continues on suitable empirically-based models to underpin efforts to tackle health and health care disparities (Batty, 2011; Harper & Strumpf, 2012).

Large-scale social experiments are not practicable or affordable but even so there is no guarantee that a particular policy intervention will be effective and make a difference. We propose and demonstrate an approach that uses a simulation model based on real data to test the differential impact of changing selected social determinants for disadvantaged groups on outcomes in a range of domains. The focus is on children’s health service use with a comparison to outcomes in non-health domains - educational attainment and antisocial behaviour - as an indication of where policy initiatives might be the most effective.

Reducing inequity in health outcomes for children is a central concern of a fair society and raises a serious challenge to public policy (Asthana & Halliday, 2006; Hallam, 2008). Inequity refers to inequalities or disparities that are avoidable, amenable or unjust. Inequity in health arises because of differences among social groups such that they have different health status and associated need (Scambler, 2012). Inequity in health care may arise because children with the same need do not have access to the same care or those with more need do not receive more care (Starfield, 2011). Thus higher social class is associated with both better health and better access to health care (Starfield, Robertson, & Riley, 2002). These disparities then are rooted in social determinants that confer differential vulnerability to poor health or exposure to conditions that produce poor health (Frohlich & Potvin 2008). To reduce disparities, public policy must find ways to address social determinants.

A key aim of the social determinants of health framework is 'to highlight the difference between levels of causation, distinguishing between the mechanisms by which social hierarchies are created, and the conditions of daily life which then result' (Solar & Irwin, 2010, p. 4). Thus the former 'structural' determinants (of health inequities) produce the latter 'intermediary' determinants, and together they comprise the social determinants of health. From a policy perspective, 'objectives are defined quite differently, depending on whether the aim is to address determinants of health or determinants of health inequities' (Solar & Irwin, 2010, p. 5).

There is debate as to the specific social determinants that play crucial roles in patterning health and health care, and to the relative importance, as effective policy levers, of those determinants upstream (distal) or downstream (proximal) to the outcome (Chokshi &Farley, 2012). We must put aside the structural determinants that are fixed or not modifiable at an individual level, such as family socio-economic position at the birth of the child. However there are proxy indicators, such as income source, that can be characterised as upstream and modifiable (Solar & Irwin, 2010). Downstream determinants are intermediary and may be modifiable at the individual level, such as family functioning and behaviour. In the social determinants of health framework, these intermediary ones are shaped by and are mediating the effects of underlying structural determinants. Furthermore, the social determinants that give rise to poor health in a particular group tend to cluster and accumulate over the life course (Larson, 2008; Stevens, 2006). Thus disadvantage is associated with the 'intersectionality' of multiple related determinants rather than independent single ones, tending to persist and become entrenched over time (Hankivsky 2011).

In the rest of this paper we will use the term 'factor', meaning 'potential determinant', instead of 'determinant', to remove the connotation of social processes being completely deterministic.

The life course

The broad framework of the life course is especially relevant to the modeling of dynamic processes and their implications for public policy (Hunt, 2005; Policy Research Initiative, 2004). We draw conceptually on a range of relevant perspectives including human development (Keating & Hertzmann, 1999), life course epidemiology (Ben-Shlomo & Kuh, 2002), and risk or resilience (Luthar, 2003). Using longitudinal data on a birth cohort, we focus on the influence of a range of key social determinants on health service use and other outcomes across the years of early childhood (Dearden, Sibieta, & Sylva, 2011; Holmes & Kiernan, 2013; Pearce, Lewis, & Law, 2013). The temporal aspect is especially crucial to understanding the impact of potential policy interventions to promote health equity (Braveman, 2013). Here we focus on shorter term effects of social determinants within the early life course (to age 13) though there is extensive evidence that these effects accumulate and persist into adulthood (for example, see Conti, Heckman, & Urzua, 2010).

Counterfactual modelling

We adopt a counterfactual approach to causal inference (Davis, 2014; Glass, Goodman, Hernan, & Samet, 2013). Using observational data to mimic an experiment, we compare what is actually observed with what might be observed in a counterfactual scenario. The focus is not to establish cause, though this may be indicative, but to evaluate the effects on social outcomes of different sets of circumstances (theoretical purpose) or competing intervention options (policy purpose).

Complex policy issues require methods that enable research synthesis and utilise systems thinking (Lobb & Colditz, 2013; Milne et al., 2014). Micro-simulation modeling has been used to represent systems and processes in health care and to test their functioning for policy purposes (Glied & Tilipman, 2010; Ringel, Eibner, Girosi, Cordova, & McGlynn, 2010; Rutter, Zaslavsky, & Feuer, 2011; Zucchelli & Rice, 2012). Micro-simulation sits within a continuum of social simulation methodologies with more aggregated approaches (for example, system dynamics) on the one hand and more behavioural ones (for example, agent-based modelling) on the other (Gilbert & Troitzsch, 2005).

The dynamic micro-simulation model, based on empirical individual-level data over time, can account for social complexity, heterogeneity, and change (Orcutt, 1957; Spielauer, 2011). This is the technical approach we adopt in this paper with an application focussing on health service use in early childhood, with comparison to two other non-health outcomes. It relies on data from the real world to create an artificial one that mimics the original but upon which virtual experiments can be performed (Gilbert & Troitzsch, 2005). It operates at the level of individual units, in our case children from a representative, real-world sample. Each child has a set of associated attributes as a starting point, for example age, gender, ethnicity and health state. A set of rules, here equations derived from statistical analysis of real longitudinal data, is then applied in a stochastic manner to this sample to simulate changes in state or behaviour over time. This model essentially generates a set of diverse synthetic health histories for our starting sample of children. Based on a form of counterfactual reasoning, modifications of influential factors can then be undertaken to test hypothetical 'what if' scenarios on a key outcome of policy interest such as health service use (Davis, Lay-Yee, & Pearson, 2010; Dubay & Kenney, 2003).

We used micro-simulation because it could integrate, and accommodate the manipulation of, the effects of variables across multiple model equations in one simulation run. Thus each otherwise separate equation is given its social context and influence among the other equations, representing a system of inter-dependent social processes.

AIMS

The overall aim of this paper is to apply a computer-based model in a New Zealand setting designed to (1) represent health service use (and other comparative outcomes) in early childhood, and (2) enable experimentation on the impact of changing social determinants (Milne et al., 2014). Note that, in New Zealand, primary care is provided by private family physicians who receive a government subsidy per patient as well as patient co-payments. The family doctor has traditionally provided the majority of prevention and treatment services. For children, doctor visits are even more so the prime mode of contact with health services.

The construction of the model followed a framework (Figure 1) based on the social determinants of health where structural factors related to social advantage or disadvantage fundamentally influence intermediary parental and family factors and final health outcomes (Solar & Irwin, 2010). Any specific factor may have a direct or an indirect effect, through a mediating factor, on the outcome.

FIGURE ONE ABOUT HERE

We employed a dynamic micro-simulation model to reflect a life course perspective (Appendix, Figure A1). In order to build an empirically realistic model, we used longitudinal data on children from a New Zealand birth cohort - the Christchurch Health and Development Study (CHDS) (Gibb, Fergusson, & Horwood, 2012). We applied statistically-derived rules to age the cohort from birth to 13 years and so create a virtual cohort composed of representative synthetic health histories around the original sample data. The model could then be interrogated to assess the likely health service effects of changing various social factors and their pattern across groups defined by advantage or disadvantage.

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Research questions

Our analysis was focussed around a set of guiding questions:

1. What is the effect of improving various factors – single or multiple - on the levels of health service use in children?
2. Are structural or intermediary factors more influential on the level of health service use in children?
3. Is there a greater impact on socially disadvantaged groups?
4. Do the same mechanisms operate for other outcomes, in other domains, such as educational attainment or antisocial behaviour?

DATA AND METHODS

We constructed a dynamic micro-simulation model of the early life course where salient factors were embedded and cast as structural or intermediary, that is, upstream or downstream to the child outcomes.

Study design

The model was founded on data from a New Zealand longitudinal study (CHDS). The CHDS data were used for three purposes: (1) to establish a starting sample to provide initial conditions for simulation, (2) to generate statistically-based simulation rules, and (3) to provide benchmarks with which to compare simulated results. Data manipulation and analysis were carried out using SAS (SAS Institute, 2013) and R (R Development Core Team, 2013). Model implementation used JAVA and R (Mannion, Lay-Yee, Wrapson, Davis, & Pearson, 2012).

The steps in constructing and implementing the model were:

1. Design simulation processes to mimic social pathways.
2. Establish the starting sample.
3. Undertake statistical analysis on available data to derive equations related to time-variant health and other outcomes of interest.
4. Beginning with the starting sample, apply equations to stochastic simulation processes to drive change in individual states and behaviour.
5. Validate the results of simulation processes and outcomes against benchmarks.
6. Design and test various scenarios by varying relevant factors.

Data sources

We used individual-level longitudinal data (from the CHDS) on a cohort of 1,017 children born in Christchurch, New Zealand in 1977 and followed to age 13 (Gibb, Fergusson, & Horwood, 2012). Ethical approval was not required as the study used an existing data set with the permission of the data-owners. As well as the child's demographic and perinatal characteristics, health service use, educational attainment, and antisocial behaviour, information was available on parental and family characteristics (Figure 1). The original data were mostly gathered from interviews with mothers. A description of model variables can be found in Table 1.

TABLE ONE ABOUT HERE

Statistical analysis

To run statistical sub-models, we used pooled CHDS data where there were no missing data on any variables of interest over up to 13 annual time-points. Data were available for all years from birth (where relevant) except for the final outcome variables: family doctor visits (years 1-10), reading ability (years 8-13), and conduct problems (years 6-10) (Table 1).

We undertook statistical analyses to give us results fit for the purpose of dynamic micro-simulation (Milne et al., 2014) accounting for effects of time-variant (e.g. number of children in the household) and time-invariant (e.g. family's socioeconomic status at child's birth) attributes. We developed regression models of relevant modifiable (time-variant) factors and outcomes to estimate coefficients for significant observed predictors (Appendix, Table A1 lists equations). Different variable selection methods were used for different types of statistical sub-model (e.g. logistic or linear regression). For each sub-model, the full set of potential predictors was defined by our conceptual framework as those variables situated upstream to the outcome (Figure 1). In addition, lagged dependent variables were generally included as predictors for count or continuous outcomes. Interactions between age and each potential predictor were considered as well as quadratic terms for continuous predictors. Only statistically significant terms were included in the final equation to avoid non-significant variables with large effects producing spurious impacts during scenario testing.

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These statistically-derived parameters were then used to inform the probabilistic rules that drove the simulation process. A variety of statistical sub-models (summarised by a set of equations) underpinned the overall simulation model. To test the appropriateness of each sub-model, we compared simulated results against actual data with reproducibility as the pragmatic criterion. For a categorical outcome variable in the current year, separate regressions were run depending on last year's state, e.g. 0 or 1 in the binary case. For a continuous outcome variable, a lagged dependent variable was included as a predictor in an ordinary least squares model (OLS-LDV) which – while possibly resulting in biased estimates - we found performed best for simulation purposes compared to other techniques (further information available from authors on request) including: a random effects model to account for individual effects where present; a dynamic panel model (Blundell & Bond 1998); and a hybrid model (Allison 2005). Since our approach was pragmatic - geared towards ease of implementation, and reproducing actual data - we accepted that statistical assumptions could have been violated (Rephann et al., 2004). The OLS-LDV technique has been widely used for parameter estimation in micro-simulation models (e.g. Baekgaard 2000; Toder et al., 2002; Wolfson 1995).

The simulation model required a critical sequencing of steps within an annual cycle and dynamism across years. Each time-variant factor had to be predicted and in turn was a potential predictor to a successive time-variant outcome in the cycle. Successive sub-models had to include both time-variant and time-invariant predictors from preceding sub-models. For any given individual, a persistent link from year to year enabled generating a coherent trajectory. This dynamic transition was achieved by the use of time-variant predictors, including a lagged dependent variable where substantively justified, such that the state in the current year depended on that in the previous year.

Implementing the simulation

Our discrete-time model used a starting sample comprising data on a cohort of 1,017 children where there were complete data across all birth and year one variables. The simulation process for each subsequent year followed a sequence of steps from structural through intermediary factors to the final outcomes. Each time-variant attribute (in turn) for an individual child was updated each year using a statistically-derived probability and Monte Carlo simulation. For a dichotomous time-variant attribute, a random number was drawn from a binomial distribution with probability of a positive value derived from say a logistic regression model. In the case of a continuous time-variant attribute, coefficients were applied to the observed predictor values in the current year. A random number - drawn from a normal distribution with mean equal to the predicted mean and standard deviation equal to the residual standard error - was then assigned as the current value of the attribute. The simulated estimates were the average results of 100 runs with a different random seed specified for each run. Our experience showed that 100 runs was more than sufficient to generate a stable average estimate with a tight 95% confidence interval (calculated by taking the 2.5 and 97.5 percentiles) on the distribution of the means from the 100 runs). Larger numbers of runs were also constrained by computing and time resource considerations.

Validation

Validation of the simulated results was carried out by comparison to the actual real-world CHDS data as borne out over the first thirteen years of the life course. The test was whether the simulation model was able to reproduce a similar distribution of outcomes in the original longitudinal data.

Scenario testing

What if there was a policy intervention – without specifying its precise form - that could change social determinants for the better and what would be its impact on outcomes down the line? We attempted to answer this 'what if' question by testing various scenarios.

We focussed on health service use as the main domain of interest with comparison to two other domains. The domains and their observed measures were:

- Health service use (years 1-10)
    - Family doctor visits: number.
- Educational attainment (years 8-13)
    - Reading ability: BURT score (Gilmore , Croft, & Reid, 1981)
- Antisocial behaviour (years 6-10)
    - Conduct problems: number.

We used scenario testing as a form of counterfactual reasoning. This was carried out by simulating a potential outcome via varying relevant factors of interest in the starting sample, while holding other initial factors constant, and observing change to the outcome. In particular, we tested the effect of changing a combination of specific factors on child visits to the family doctor and other outcomes. Note that the changes made - for example, a family not needing to depend on welfare - were considered to be permanent throughout the period of the life course studied.

For our scenarios, we defined opposing social categories, e.g. single- or two- parent family, as likely to be associated with lower or higher levels of the outcome variable. In the case of family doctor visits, this relationship is potentially muddied by the divergent effects of health need and access. Our baseline data showed that more advantaged groups enjoyed higher levels of doctor visits. Thus, we felt justified to interpret the impact of improvement scenarios, i.e. improving determining factors, as increasing access to services (more doctor visits).

For each scenario, we improved time-variant structural and intermediary factors - modifiable in the context of the model - singly and in combination at every year.

For the purposes of scenario testing, the set of modifiable proxy indicators (for **structural** factors) was as follows:

- o single parent family (yes/no)
- o number of children (high: >2/low: <=2)
- o father employed (no/yes)
- o welfare dependence (yes/no)

And the set of modifiable **intermediary** factors was as follows:

- o accommodation type (other/house)
- o housing tenure (rented/owned)
- o overcrowding (= household size/bedrooms) (high: >2, low:<=2)
- o change of parents – due to partnership change or death of parent (yes/no)
- o change of residence (yes/no)
- o parental smoking – mother and/or father (yes/no)

For all scenarios, we assessed if there were differential impacts of change between advantaged and disadvantaged groups as defined by the following fixed structural factors (at birth of the child):

- family's socioeconomic status (1. unskilled, semi-skilled, unemployed; 2. skilled, clerical, technical; 3. professional, managerial) - based on the Elley-Irving scale (Elley & Irving, 1976).
- maternal education level (no formal qualifications; secondary qualifications; tertiary qualifications)
- maternal age (<20, 20-24, 25-29, 30+)
- child's ethnicity (European/other, Maori, Pacific) - this was derived from parents' ethnicity with prioritization of Maori (the indigenous people) and Pacific.

Scenario testing procedure

Family doctor visits

1. We distinguished two sets of modifiable factors as structural or intermediary in nature.
2. Within each set, in the starting sample, we improved single factors in turn to an extreme counterfactual while keeping the other factors the same, and then assessed the degree of impact of single factors.
3. Within each set, in the starting sample, we improved multiple factors simultaneously to extreme counterfactuals, and then assessed the degree of impact of multiple factors.
4. We compared the relative effects of improving structural and intermediary factors respectively.
5. We posed best case scenarios on the levels of health service use by improving structural and intermediary factors simultaneously.

Means and their 95% confidence intervals were calculated from the results of 100 simulation runs. Non-overlapping intervals were taken as a measure of significance in any change in outcome between the base case simulation and the scenario tested.

Reading ability; Conduct problems (comparative outcomes)

Similarly, we posed better and best case scenarios on these outcomes by improving structural and intermediary factors respectively, and compared the pattern of effects to that on the health service outcome.

RESULTS

Validation

Simulated output on mean numbers per year of family doctor visits was compared to corresponding values from the real cohort (Appendix, Table A2). The virtual (simulated) cohort followed the pattern of health service use for the real cohort. The average level of family doctor visits was highest in the first year of life and then decreased to a steady level. Similarly simulated means of reading score and number of conduct problems, both increasing with age, matched well to actual data (Appendix, Table A2).

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Scenario testing

Base case simulation

The distribution of time-variant social determinants, both structural and intermediary, in the starting sample shows sizeable levels of disadvantage (Appendix, Table A3). We used the simulated results for the virtual cohort – with no changes made - as the base case scenario. We then examined the breakdown of family doctor visits according to whether children belonged to families characterized by various time-invariant fixed structural factors representing degrees of social disadvantage (Table 2, Figure 2: base scenario). It can be seen that the average annual level of family doctor visits over the simulated years differs clearly by degree of social disadvantage.

Thus over ten years, the mean number of family doctor visits was lower for children from families of lower socioeconomic status, of mothers with less education, of younger mothers, and of Maori and Pacific ethnicity.

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TABLE TWO ABOUT HERE

FIGURE TWO ABOUT HERE

Improvement scenarios

<u>Family doctor visits</u>

We posed improvement scenarios for the outcome family doctor visits. What if all children enjoyed low social risk of poor health according to various modifiable structural and intermediary factors, singly or in combination? The simulated results showed an increase in family doctor visits (averaged over ten years) between base case and improvement scenarios (Tables 2, 3: improvement scenarios, last column 'All families'). Thus improving factors tended to increase family doctor visits. The strongest influences were 'fewer children' (3.4% increase in doctor visits) of the structural factors, and 'home ownership' (1.9% increase) of the intermediary factors, with others in the respective blocks having minimal effect (Table 2). All structural factors combined (4.1% increase, $p<0.05$) had a greater effect than all intermediary factors combined (2.5% increase) (Table 2). When both structural and intermediary factors were improved together over ten years ('best case scenario'), the average number of family doctor visits per year increased by 6.6% ($p<0.05$) (Table 3).

TABLE THREE ABOUT HERE

We then examined the breakdown of family doctor visits according to whether children belonged to families characterized by various fixed structural factors representing degrees of social disadvantage (Tables 2, 3). Was there a greater impact on socially disadvantaged groups? For example, taking the 'best case scenario' – i.e. improvement of all structural and all intermediary factors together – the more disadvantaged groups across each of the fixed structural factors showed greater increases in family doctor visits): un/semi-skilled +8.7% ($p<0.05$) versus skilled/clerical/technical +6.4% ($p<0.05$) versus professional/managerial +5.1%; mother with no formal education +7.7% ($p<0.05$) versus mother with secondary education +5.8% versus mother with tertiary qualification +5.6%; mother aged <20 years +10.1% ranging down to 25-29 years +5.8% ($p<0.05$); Pacific ethnicity +9.7% versus Maori +9.2% versus European/other +6.5% ($p<0.05$) (Table 3).

FIGURE TWO ABOUT HERE

Thus social gradients were apparent with differential effects on outcome according to disadvantage (shown graphically in Figures 2, 3). These greater benefits to the more disadvantaged accumulated as more modifiable factors were improved so that the proportional gap from the worst-off to the best-off groups was gradually closed though not eliminated. The largest gap related to ethnicity (initially 25.5%) which closed on improvement of structural factors (down to 25.2%) and further of intermediary factors (down to 21.8%). There was a consistent pattern across the fixed structural determinants (ethnicity and so on) of intermediary factors closing the gap to a greater extent than modifiable structural factors.

FIGURE THREE ABOUT HERE

<u>Reading ability</u>

Improving factors tended to increase reading score (Appendix, Tables A4, A5, top panel, last column 'All families'). All structural factors combined (+1.7%) seemed to have a greater effect on reading score than all intermediary factors combined (+0.9%). Improving all structural and intermediary factors combined increased reading score for children 8-13 years by an average 2.1%. There was generally a gradient of greater improvement related to greater degree of disadvantage (Appendix, Tables A4, A5, top panel). The gap between the worst-off and the best-off gradually closed as more modifiable factors were improved (shown graphically in Appendix, Figure A2). The largest gap related to maternal education (initially 18.7%), closing as structural factors were improved (down to 16.9%) and further as intermediary factors were also improved (down to 15.8%). Across the fixed structural determinants (maternal education and so on), modifiable structural factors consistently closed the gap to a greater extent than intermediary factors.

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Midconduct problems

Improving factors tended to decrease the number of instances of conduct problems (Appendix, Tables A4, A5, bottom panel, last column 'All families'). All structural factors combined (-1.3%) had a similar size of effect on conduct problems as all intermediary factors combined (-1.3%). Improving all structural and intermediary factors combined decreased conduct problems for children 6-10 years by an average 2.2% ($p<0.05$). There was generally a gradient of greater improvement related to greater degree of disadvantage (Appendix, Tables A4, A5, bottom panel). For example, in the 'best case scenario' – improvement of all structural and all intermediary factors - the most disadvantaged groups showed the greatest decreases in conduct problems: un/semi-skilled -3.9% ($p<0.05$); mother no formal education -3.1% ($p<0.05$); mother <20 years -5.5% ($p<0.05$). The gap between the worst-off and the best-off gradually closed as more modifiable factors were improved (shown graphically in Appendix, Figure A3). The largest gap related to maternal age (initially 8.5%) which closed on improvement of structural factors (down to 5.3%) and further of intermediary factors (down to 4.5%). A consistent pattern emerged across the fixed structural determinants (maternal age and so on) of modifiable structural factors being more effective in closing the gap than intermediary factors.

DISCUSSION

We focused on the influence of key determinants on health service use in early childhood (Chen & Escarce, 2006; Guendelman, Wyn, & Tsai, 2000; Heck & Parker, 2002). We posed the following research questions, and outline the principal findings.

Research questions and findings

Question 1: What is the effect of improving various factors – single or multiple - on the levels of health service use in children?

Findings: Changing single factors generally had a slight effect on the outcome though some factors were more influential than others. Improving factors tended to increase family doctor visits, even for the most advantaged groups which we took to be the desirable benchmarks. Therefore, increased family doctor visits likely reflected better access (rather than increased need due to worsening health). Appreciable change in outcome could only be effected by simultaneously changing multiple factors in combination.

Question 2: Are structural or intermediary factors more influential on the level of health service use in children?

Findings: For family doctor visits, modifiable structural factors (principally 'fewer children') exerted a greater influence than intermediary factors (principally 'home ownership').

Question 3: Is there a greater impact on socially disadvantaged groups?

Answering question 3: Social gradients of effect existed. There were differential effects by the fixed structural factors even where effects were slight overall. Generally, improvements in outcome, in this case better access to primary care, were greater for more disadvantaged groups.

Beneficial effects accumulated as more factors were modified so that gaps between the most disadvantaged (worst-off) and the most advantaged (best-off) were gradually closed.

Question 4: Do the same mechanisms operate for other outcomes, in other domains, such as educational attainment or antisocial behaviour?

Findings: Similar results applied to the improvement of outcomes in other domains, i.e. educational attainment and antisocial behaviour: multiple factors were important, structural factors were more influential than intermediary ones, and there was greater impact on more disadvantaged groups with cumulative benefits serving to close the gap with the most advantaged. The best case scenarios showed that greater improvements could be made to family doctor visits (+6.6% aggregate increase) than to either reading ability (+2.1% aggregate increase) or to anti-social behaviour (-2.2% aggregate decrease). However, while improving modifiable structural factors for family doctor visits closed the gap (between worst-off and best-off groups) to a greater extent than further improving intermediary factors, this pattern was reversed for the other two outcomes.

In summary, the counterfactual was to improve a set of 'modifiable' structural and intermediate factors so that the disadvantaged group resembled the advantaged group in this regard. Further the resulting improved outcomes were then analysed against a set of 'fixed' structural factors (for example, socioeconomic status (SES)) which consisted of multiple ordered categories (except ethnicity). We were able to show that the improvement in outcome differed along a social gradient formed by the ordered categories (for example, low SES, medium SES, and high SES) so that the impact increased as disadvantage increased, that is, the more disadvantaged groups benefitted more, and the most advantaged group benefitted most.

Implications

Policy efforts to tackle health, and other, disparities need to be based on the best evidence as to what interventions might work for vulnerable social groups particularly those with multiple disadvantage (Asthana & Halliday, 2006). Thus calls to action, that assume health disparities can be reduced and enough is known on which to act, have implicit research imperatives aimed at strengthening the evidence base (Marmot, Goldblatt, & Allen, 2010). We see our simulation model as contributing to this 'social movement' by indicating that changing social settings through the early life course, across multiple determinants of disadvantage, has a clear effect on child outcomes according to a social gradient with greater impacts on the most disadvantaged groups (Engle et al., 2007).

The Commission on the Social Determinants of Health sets out three broad approaches to reducing health inequities: '(1) targeted programmes for disadvantaged populations; (2) closing health gaps between worse-off and better-off groups; and (3) addressing the social health gradient across the whole population' (Solar & Irwin, 2010, p 7). Our study findings provide evidence to support each of these approaches as being potentially effective with the greatest population gain perhaps coming from a form of progressive universalism that would act along the full social gradient of disadvantage with selective measures to assist the worst-off. (Whitehead & Popay, 2010). Furthermore, it is evident that both structural determinants (which are more influential), and intermediary determinants need to be tackled for maximum impact (Lonnroth, Jaramillo, Williams, Dye, & Raviglione, 2009), indicating that wide-ranging and inter-sectoral policies are warranted (Solar & Irwin, 2010).

Many unanswered questions remain regarding the adequacy of evidence on efficacy and effectiveness that policy makers need to underpin interventions (Kawachi , Adler, & Dow, 2010; Lynch, Law, Brinkman, Chittleborough, & Sawyer, 2010). Nevertheless, our empirical model supports a concerted (across domains) and sustained (over the life course) strategy to reducing disparities.

Strengths and limitations

There are serious challenges to implementing the counterfactual framework (Glass, Goodman, Hernan, & Samet, 2013). The dynamic microsimulation approach has many advantages bundled in one package: it has an empirical basis using real or realistic synthetic data; data are at the micro individual level and longitudinal , and so can capture social complexity, heterogeneity, and change over time; mechanisms are contextualised in a model of the social system; 'causal' processes or pathways are modelled that may be amenable to policy influence; and virtual experiments, e.g. counterfactual scenarios, can be undertaken. However, this approach also has limitations: it relies on adequate data; the most important factors and processes must have been taken into account; and statistical estimates are assumed to be accurate and precise. The CHDS data had the advantage of being longitudinal but the disadvantages of having a small sample size, and being regional and historical.

We focussed on clear research questions and scenarios to guide the construction of our simulation model, given the available data. Our model needed to be robust with a sound link between lever and outcome where change in the former would effect change in the latter. This assumed social pathway underpins the model's responsiveness to counterfactual analysis or scenario testing. Ultimately, the model should provide indicative results while recognizing its simplifications and limitations.

In testing various scenarios by manipulating specific factors of interest in the starting sample, other initial conditions were assumed to remain the same including inherent relationships between factors. While this is not entirely realistic, our substantive findings from scenario testing were plausible and interpretable. Testing of single factors showed modest impact on outcomes. There appeared to be a degree of inertia in the model perhaps due to not only small effect sizes but also the dampening effect of interconnected factors and processes. It may be the case that this is a reflection of social reality, difficult to change because of its complexity. Given the stability of the model, the scenarios tested were based on counterfactuals of extreme improvement in the social determinants to amplify any changes and to draw attention to differences from the base scenario. These broad-brush scenarios could be deemed to have no realistic implications for actual policy making but they serve to indicate the limits of possible impact of any intervention.

Our model is a simplification of reality but is nevertheless a powerful source of information that can be used alongside other evidence for policy. Its ability to integrate and contextualise information can address problems perhaps unable to be studied by conventional means. This approach also lends itself to better model useability by policy analysts who wish to test relevant scenarios.

CONCLUSIONS

Adopting a social determinants framework, we developed a dynamic micro-simulation model, based on real data, that could potentially inform policy initiatives to tackle disparities in health and health care as well as other domains. Using counterfactual reasoning across a range of child outcomes, we were able to show that: appreciable change was only effected by modifying multiple determinants; structural determinants were more influential than intermediary ones as potential policy levers; and more socially disadvantaged groups derived greater benefits from intervention with a reduction in disparities between the worst-off and the best-off. Our findings provide evidence on how public policy initiatives might be more effective acting broadly across sectors and across social groups. In these ways, public policy can make a real difference to the most disadvantaged.

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Table 1. Description of variables in the model

Structural - Fixed

Child

Age: 0 to 13 years.
Gender: male, female.
Ethnicity: Maori, Pacific Island, European-and-other - derived from parents' ethnicity with prioritization of Maori (the indigenous people) and Pacific Island.

Parental and familial (at birth of child)

Mother's age: years.
Father's age: <20, 20-24, 25-29, 30-34, 35-39, 40+ years.
Mother's ethnicity: Maori, Pacific Island, European-and-other.
Father's ethnicity: Maori, Pacific Island, European-and-other.
Mother's education: (1) no formal qualifications, (2) secondary quals., (3) tertiary quals.
Father's education: (1) no formal qualifications, (2) secondary quals., (3) tertiary quals.
Family's socio-economic position: (1) semi-skilled, unskilled, unemployed; (2) clerical, technical, skilled; (3) professional, managerial - based on the Elley-Irving scale (Elley and Irving 1976).
Single-parent status at birth: single-parent, two-parent.

Structural – Modifiable (proxy indicators)

Parental and familial

Single-parent status: single-parent, two-parent.
Number of children in family/household.
Mother's hours worked.
Father's hours worked.
Welfare dependence: family receiving benefit, not receiving benefit.

Intermediary level

Parental and familial

Household size.
Number of bedrooms.
Accommodation type: detached house, other.
Home ownership: owned, rented.
Change of parents: change, no change.
Change of residence: number.
Mother's smoking: number of cigarettes per day.
Father's smoking: number of cigarettes per day.

Other (time-invariant)

Breast-feeding: duration in months.
Birthweight: kilograms.
Gestational age: weeks.
Smoking in pregnancy: average number of cigarettes smoked per day by natural mother.
Drinking in pregnancy: average number of alcoholic drinks per week consumed by natural mother.
Maternal receptiveness: score.
Maternal punitiveness: score.

Child outcomes

Family doctor visits: number (years 1-10).
Reading ability: BURT score (years 8-13)
Conduct problems: number (years 6-10).

Table 2. Family doctor visits: Base and improvement scenarios by fixed structural factors

	Fixed structural factors [b]													
	Socioeconomic status (%)			Maternal education (%)			Maternal age (%)				Ethnicity (%)			All families (n=1017)
Scenarios	Un/semi -skilled	Skilled/ clerical/ technical	Professional/ managerial	No formal quals.	Secondary quals.	Tertiary quals.	<20	20-24	25-29	30+	Pacific	Maori	Euro/ Other	
	26.1	53.0	20.9	51.4	29.2	19.4	8.6	30.3	40.3	20.8	3.2	9.8	86.9	100%
(Years 1-10)	Family doctor visits (mean)													
Base [a]	2.99	3.26	3.31	3.11	3.25	3.37	2.98	3.14	3.27	3.24	2.59	2.93	3.25	3.20
Improve modifiable structural factors (only)														
Fewer children	3.11	3.37	3.42	3.23	3.35	3.48	3.07	3.25	3.38	3.36	2.69	3.03	3.37	3.31
ALL	3.12	3.39	3.43	3.24	3.37	3.50	3.11	3.28	3.39	3.37	2.70	3.05	3.38*	3.33*
Improve intermediary factors (only)														
Own home	3.10	3.30	3.33	3.19	3.29	3.39	3.10	3.22	3.30	3.27	2.72	3.03	3.30	3.26
ALL	3.13	3.34	3.35	3.22	3.31	3.41	3.16	3.26	3.33	3.29	2.76	3.08	3.33	3.28
Best scenario: Improve ALL structural and intermediary factors (both)														
ALL	3.25*	3.47*	3.48	3.35*	3.44	3.56	3.28	3.37*	3.46*	3.44	2.84	3.20	3.46*	3.41*

a. Base case scenario: status quo for the virtual cohort; b. At birth of child; * p<0.05 (difference between base and scenario)

Table 3. Family doctor visits. Base and cumulative improvement scenarios by fixed structural factors: Relative change (percentage)

	Fixed structural factors [b]													
	Socioeconomic status			Maternal education			Maternal age				Ethnicity			All families (n=1017)
Scenarios	Un/semi -skilled	Skilled/ clerical/ technical	Professional/ managerial	No formal quals.	Secondary quals.	Tertiary quals.	<20	20-24	25-29	30+	Pacific	Maori	Euro/ Other	
(Years 1-10)	**Family doctor visits**													
Base [a] *(mean)*	2.99	3.26	3.31	3.11	3.25	3.37	2.98	3.14	3.27	3.24	2.59	2.93	3.25	3.20
Improve all modifiable structural factors														
% change	*+4.3*	*+4.0*	*+3.6*	*+4.2*	*+3.7*	*+3.9*	*+4.4*	*+4.5*	*+3.7*	*+4.0*	*+4.2*	*+4.1*	*+4.0 **	*+4.1**
Best scenario: Improve all structural and intermediary factors														
% change	*+8.7**	*+6.4 **	*+5.1*	*+7.7 **	*+5.8*	*+5.6*	*+10.1*	*+7.3**	*+5.8**	*+6.2*	*+9.7*	*+9.2*	*+6.5**	*+6.6**

a. Base case scenario: status quo for the virtual cohort; b. At birth of child; * p<0.05 (difference between base and scenario)

Figure 1. Model of structural and intermediary influences on child outcomes

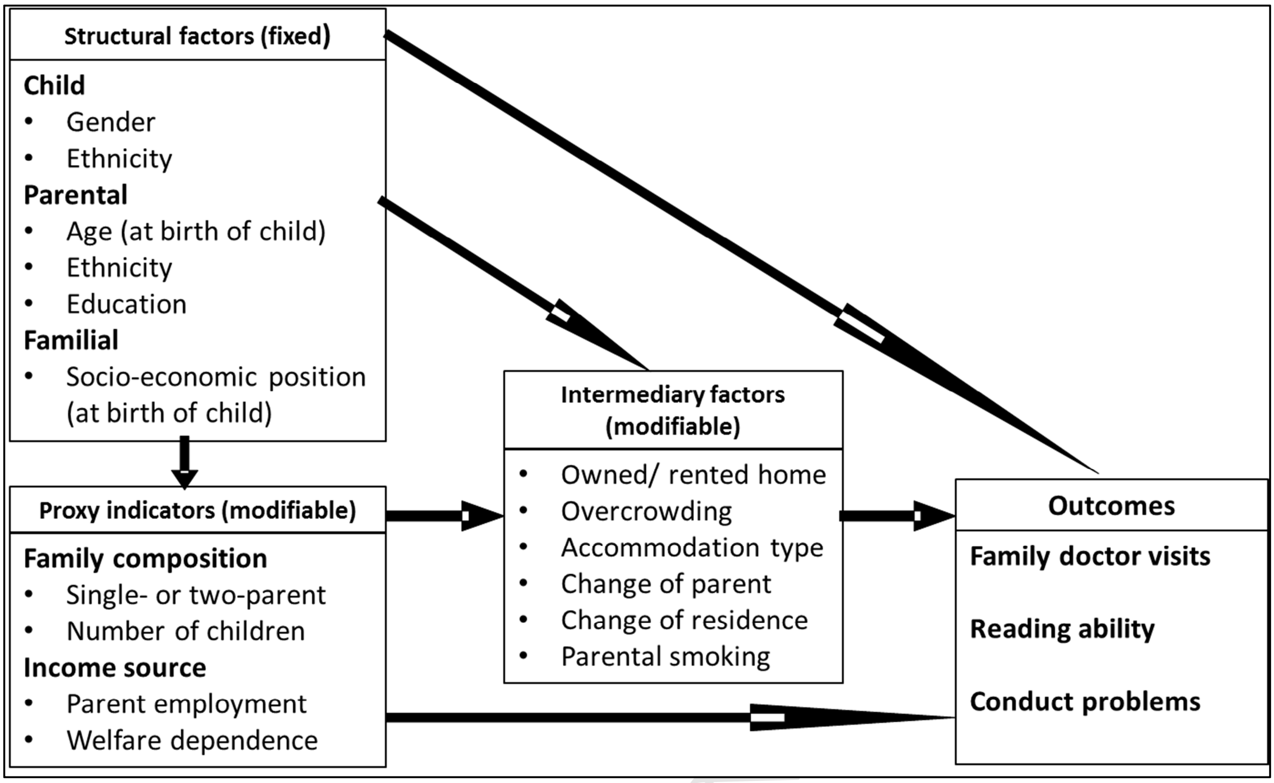


Figure 2. Family doctor visits. Disparities: absolute change

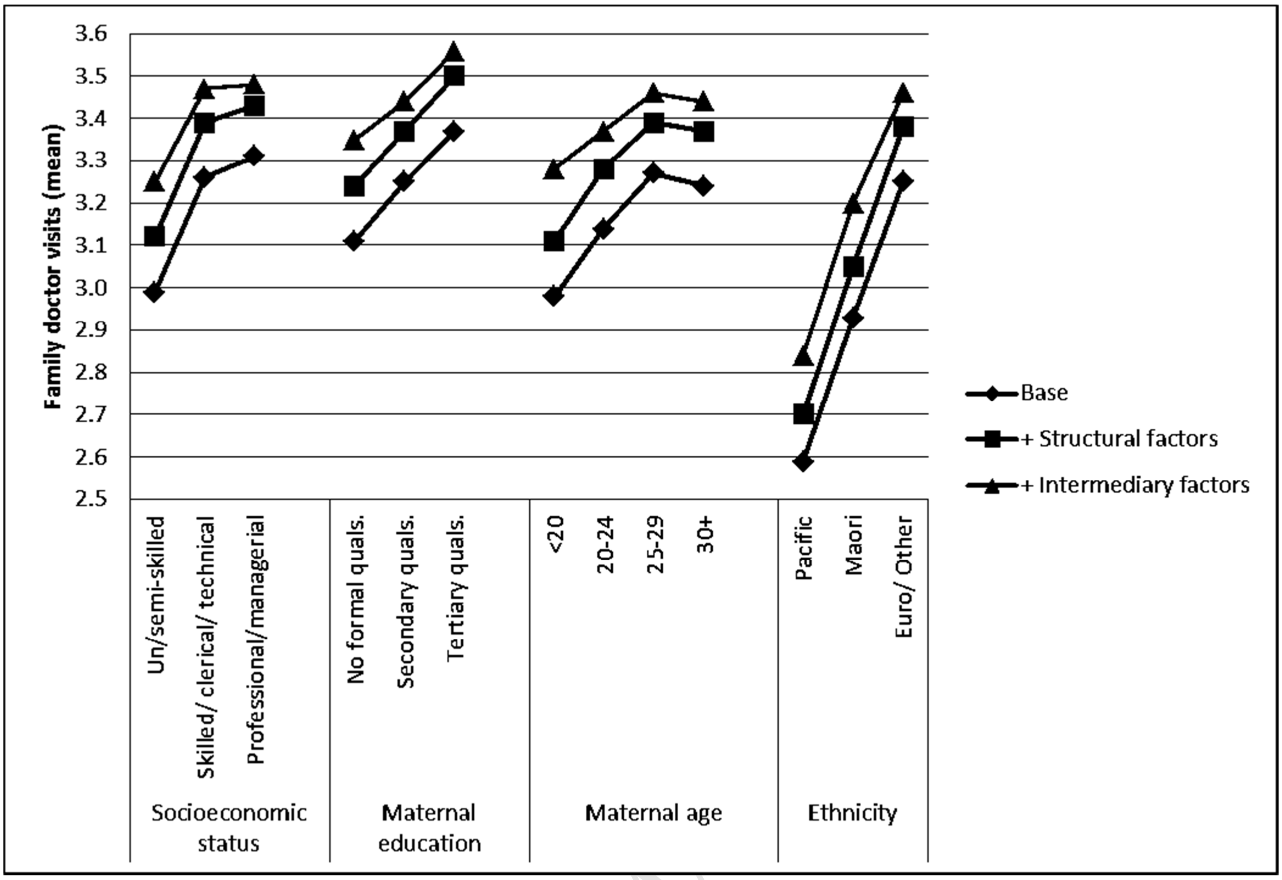
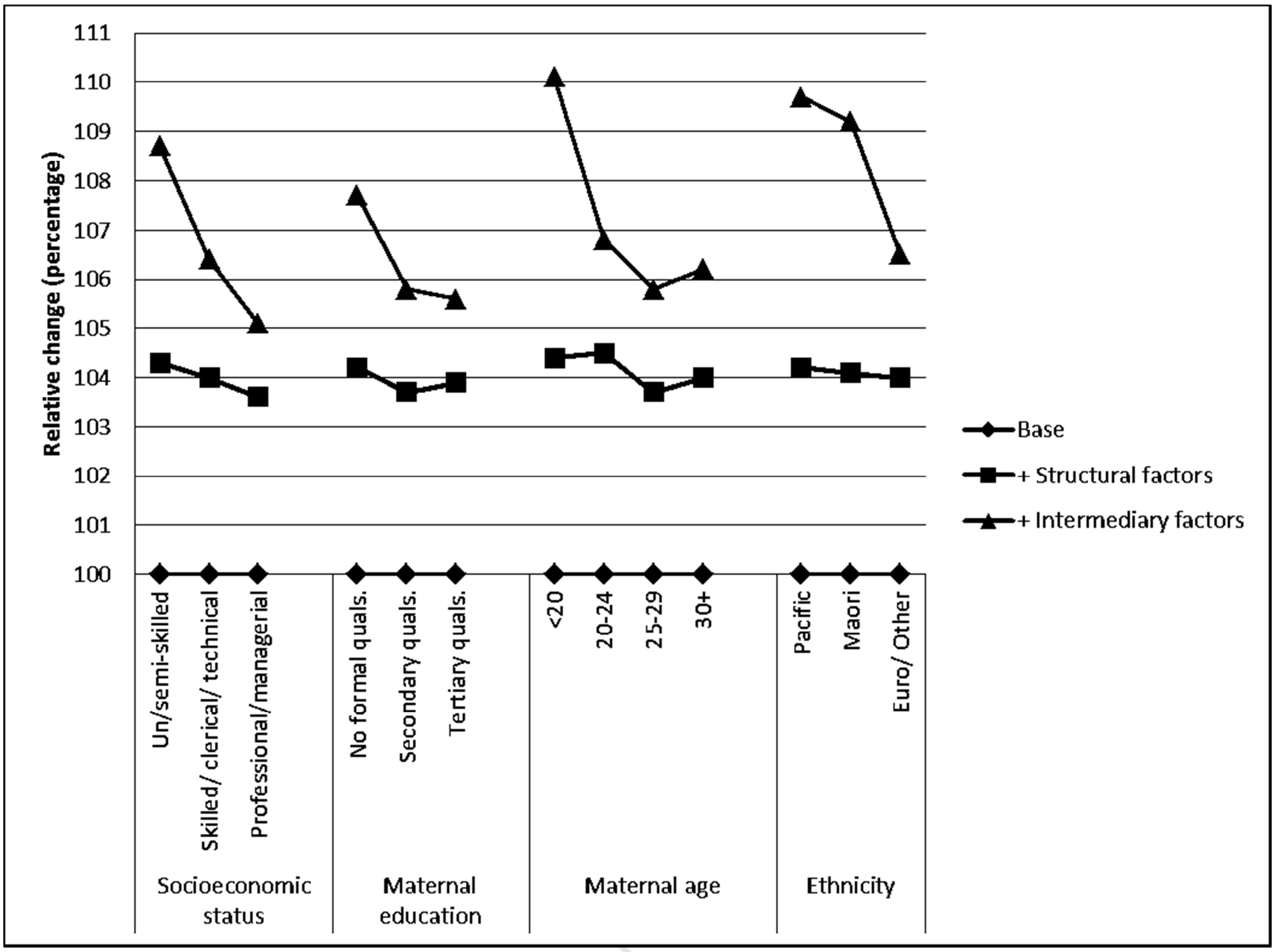


Figure 3. **Family doctor visits. Disparities: relative change**



Highlights

- Modifying social determinants of health is the key to reduction of disparities.
- We use a dynamic micro-simulation model of a New Zealand 1977 birth cohort.
- Positive impact is gained by improving multiple especially structural determinants.
- Social gradients exist with the most disadvantaged groups gaining most benefit.
- Findings support broad public policies that work across sectors and social groups.

Figure A1: The dynamic micro-simulation model

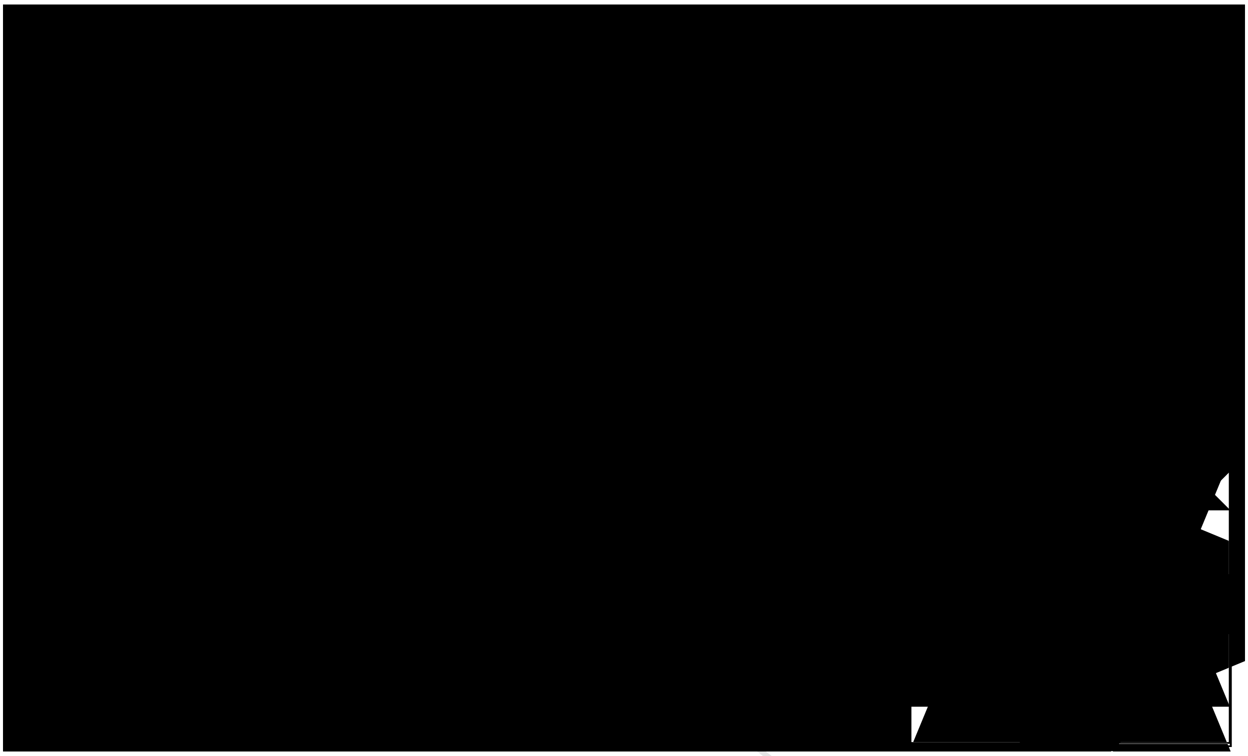


Figure A2. Reading ability. Disparities: absolute and relative change

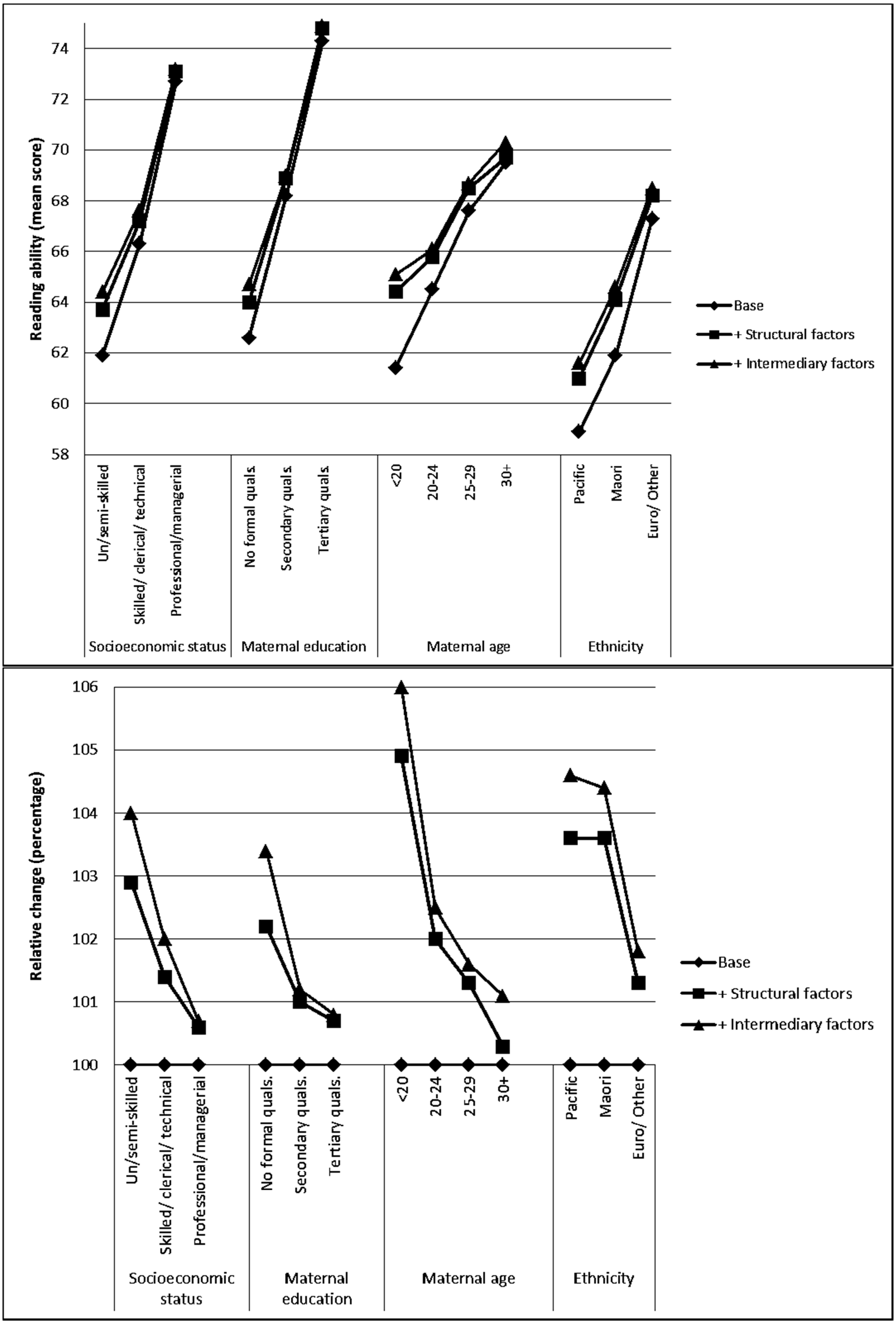


Figure A3. Conduct problems. Disparities: absolute and relative change

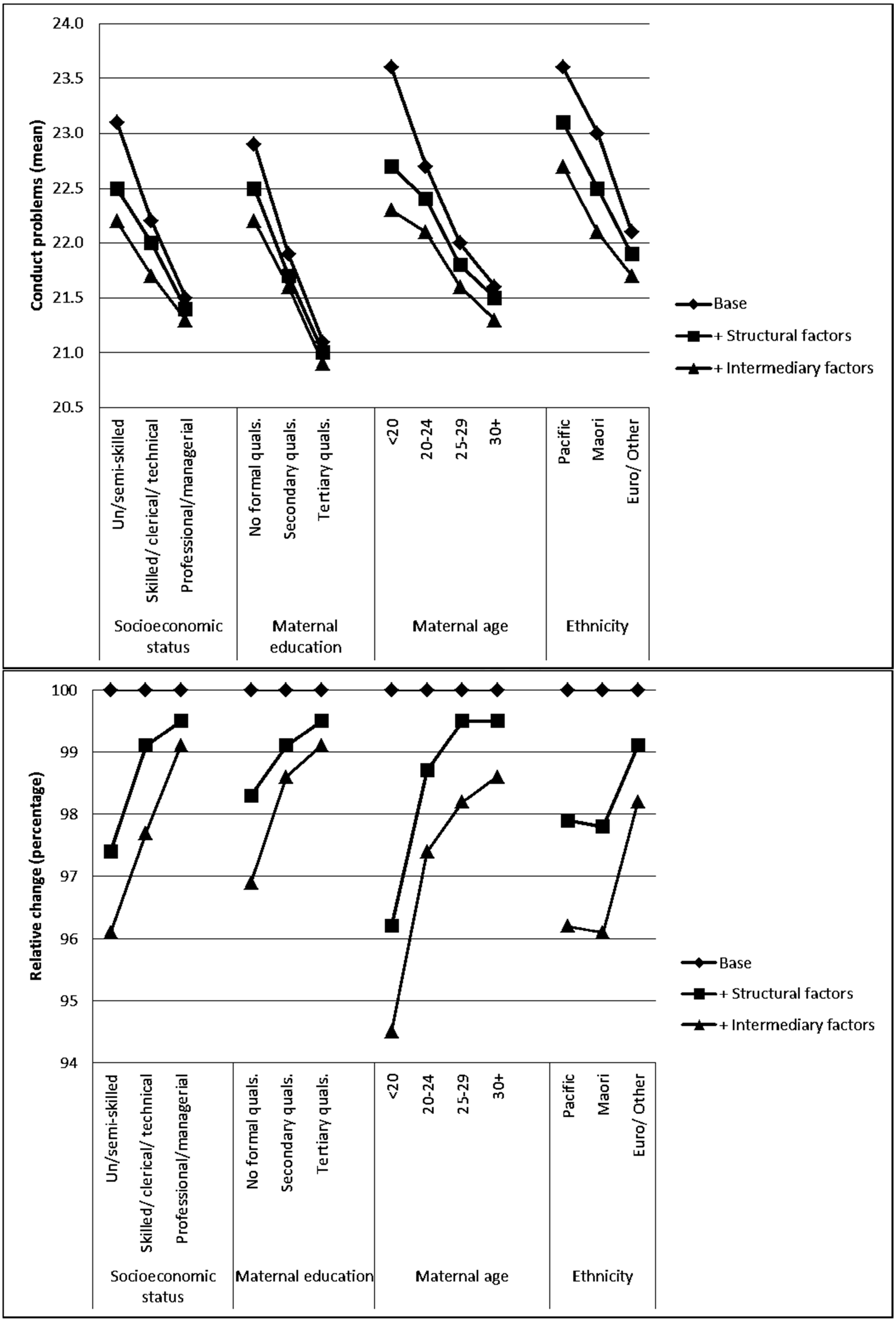


Table A1. Sub-model equations for modifiable factors and outcomes in the micro-simulation model

Modifiable factor or outcome	Type of model	Subset of data on which model was estimated	N	Predictors
Change in single-parent status	Logistic	Single in previous year	1,499	mage
		Partnered in previous year	11,479	mage meduc sesbth single single0
Change in number of children in household	Standard OLS linear		12,969	typeofchange age typeofchange:age kids_previous mage mage^2 feduc age:single0
Change in parents	Logistic	No change of parents in previous year	11,968	sptype age sptype:age gender mage single_previous age:single_previous welfare_previous mhrswrk_previous
		Change of parents in previous year	949	sptype gender mage
Change in residence	Logistic	Change in residence in previous year	2,593	age age^2 mage meduc single_previous householdsize_previous kids_previous kids_previous^2 welfare_previous
		No change of residence in previous year	10,257	age age^2 mage single_previous mhrswrk_previous fhrswrk_previous, fhrswrk_previous^2
Number of changes in residence for children	Negative binomial	Change in residence occurred	2,315	age mage mage^2 age:mage age:mage^2 meduc householdsize_previous householdsize_previous^2 mhrswrk_previous mhrswrk_previous^2 fhrswrk_previous
Change in welfare dependence	Logistic	Not on welfare in previous year	11,162	age childethn mage mage^2 age:mage meduc feduc sesbth single0
		On welfare in the previous year	1,806	fage fage^2 meduc sesbth
Mother working	Logistic	Mother not working in previous year, and is birth-mother	6,612	age sesbth single0 mage mage^2
		Mother not working in previous year, and is not birth-mother, and is not same mother as in previous year	14	Intercept only
		Mother not working in previous year, and is not birth-mother, but is same mother as in previous year	72	Intercept only
		Mother working in previous year, and is birth-mother	5,761	age z1single0 mage mage^2
		Mother working in previous year, and is not birth-mother, and is not same mother as in previous year	4	Intercept only *
		Mother working in previous year, and is not birth-mother, but is same mother as in previous year	84	Intercept only
Number of hours worked per week for working mothers	Negative binomial with dispersion parameter modelled as quadratic function of age	Mother is child's birth-mother	6,220	age mhrswrk_previous age:mhrswrk_previous mage mage^2 age:mage age:mage^2 childethn age:childethn sesbth age:sesbth single0 age:single0

Modifiable factor or outcome	Type of model	Subset of data on which model was estimated	N	Predictors
	Negative binomial	Mother is not birth-mother, and is not same mother as in previous year	12	Intercept only
		Mother is not birth-mother, but is same mother as in previous year	79	mhrswrk_previous childethn
Father working	Logistic	Father not working in previous year, and is birth-father	310	fage sesbth single0
		Father not working in previous year, and is not birth-father, and is not same father as in previous year	100	Intercept only
		Father not working in previous year, and is not birth-father, but is same father as in previous year	228	childethn
		Father working in previous year, and is birth-father	6,361	age fage childethn sesbth single0
		Father working in previous year, and is not birth-father, and is not same father as in previous year	29	single0
		Father working in previous year, and is not birth-father, but is same father as in previous year	4,115	age feduc single0 age:single
Number of hours worked per week for working fathers	Standard OLS linear	Father is child's birth-father	6,427	fhrswrk_previous fage childethn single0
		Father is not birth-father, and is not same father as in previous year	108	Intercept only
		Father is not birthfather, but is same father as in the previous year	4,094	age fhrswrk_previous
Change in accommodation type	Logistic	Living in detached house in previous year	11,947	age gender childethn mage age:mage meduc sesbth householdsize age:householdsize kids welfare mhrswrk
		Living in attached house in previous year	977	childethn single householdsize kids
Change in home-ownership status	Logistic	Did not own home in previous year	2,779	age childethn sesbth single kids age:kids welfare
		Did own home in previous year	10,090	age gender mage meduc single householdsize kids welfare mhrswrk fhrswrk age:fhrswrk
Change in over-crowding status	Logistic	Lived in overcrowded accommodation in previous year	1,603	age age^2 householdsize welfare
		Did not live in overcrowded accommodation in previous year	11,375	age gender childethn mage meduc age:meduc householdsize age:householdsize kids age:kids welfare
Mother smoking	Logistic	Mother did not smoke in previous year, and is birth-mother	8,885	age age^2 mage mage^2 methn meduc sesbth welfare age:welfare

Modifiable factor or outcome	Type of model	Subset of data on which model was estimated	N	Predictors
		Mother did not smoke in previous year, and is not birth-mother, and is not same mother as in previous year	10	Intercept only
		Mother did not smoke in previous year, and is not birth-mother, but is same mother as in previous year	85	Intercept only
		Mother did smoke in previous year, and is birth-mother	3,588	meduc sesbth welfare
		Mother did smoke in previous year, and is not birth-mother, and is not same mother as in previous year	8	Intercept only*
		Mother did smoke in previous year, and is not birth-mother, but is same mother as in previous year	71	welfare
Number of cigarettes smoked per day for smoking mothers	Standard OLS linear	Mother is child's birth-mother	3,508	msmoke_previous childethn meduc sesbth kids welfare
		Mother is not birth-mother, and is not same mother as in previous year	12	age msmoke_previous single kids
		Mother is not birth-mother, but is same mother as in previous year	66	msmoke_previous single
Father smoking	Logistic	Father did not smoke in previous year, and is birth-father	4,699	fage feduc single0 welfare
		Father did not smoke in previous year, and is not birth-father, and is not same father as in previous year	121	Intercept only
		Father did not smoke in previous year, and is not birth-father, but is same father as in previous year	3,119	sesbth fhrswrk
		Father did smoke in previous year, and is birth-father	2,077	age feduc single0
		Father did smoke in previous year, and is not birth-father, and is not same father as in previous year	10	Intercept only
		Father did smoke in previous year, and is not birth-father, but is same father as in previous year	1,245	kids
Number of cigarettes smoked per day for smoking fathers	Standard OLS linear	Father is child's birth-father	2,087	age fsmoke_previous feduc single0 age:single0 welfare
		Father is not birth-father, and is not same father as in previous year	67	fsmoke_previous

Modifiable factor or outcome	Type of model	Subset of data on which model was estimated	N	Predictors
		Father is not birth-father, but is same father as in previous year	1,192	fsmoke_previous single
Total family doctor visits	Negative binomial	Children aged 2 years	1,148	Intercept only
		Children aged 3 to 5 years	3,338	age bthorder age:bthorder childethn fage $fage^2$ householdsize_previous homeown_previous pregsmk $pregsmk^2$ pregalc $pregalc^2$
		Children aged 6 years	1,069	bthorder $bthorder^2$ kids_previous chres_previous pregalc $pregalc^2$ npresch interact $interact^2$
		Children aged 7 to 10 years	4,178	age bthorder childethn fage sesbth kids_previous homeown_previous age:homeown_previous msmoke_previous ga pregalc $pregalc^2$
Conduct score	Negative binomial	Children aged 6 years	1,084	gender meduc single overcrowd fsmoke breast pregsmk punish meanfhrswrk
	Standard OLS linear	Children aged 7 to 10 years		cond_previous age cond_previous:age gender mage meduc welfare overcrowd msmoke punish
Reading score	Standard OLS linear	Children aged 7 years	1,063	bthorder $bthorder^2$ gender mage meduc feduc meanwelfare overcrowd8 bw interact
		Children aged 9 to 13 years	5,026	read_previous $read\_previous^2$ gender feduc fhrswrk breast

Notes:

age=age of child; gender=gender of child; childethn=ethnicity of child, mage=mother's age at child's birth; fage=father's age at child's birth; methn=mother's ethnicity; meduc=mother's educational level at child's birth; feduc=father's education level at child's birth; sesbth=family's socio-economic position at child's birth; single0=single-parent status at child's birth; single=single-parent status; kids=number of children in household; mhrswrk=mother's hours worked; fhrswrk=father's hours worked; welfare=welfare dependence; householdsize=number of people in household; accom=accommodation type; homeown=home ownership; chpar=change in parents; chres=number of changes in residence; msmoke=mother's smoking; fsmoke= father's smoking; breast=breast-feeding; bw=birthweight; ga=gestational age; pregsmk=smoking in pregnancy; pregalc= drinking in pregnancy; interact=maternal receptiveness; punish=maternal punitiveness; npresch=number of years of preschool education; bthorder=birth order; read=reading ability; cond=conduct problems; meanwelfare=proportion of years that child was in family on welfare from age 1 to age 7 inclusive; overcrowd8=whether child was in overcrowded accommodation when aged 8; meanfhrswrk=mean number of hours worked by father over period when child was aged 1 to 7.

'_previous' suffix denotes that the variable is the value for the year prior to the current year.

^{2} superscript denotes that the variable has been squared.

* in these subsets, all observations for the outcome variable had the same value, so coefficients were constructed such that there was a very high predicted probability (0.999) to have the prevalent value.

Table A2. Validation: virtual versus real cohort – family doctor visits, reading ability, and conduct problems, by year of age

Year	Real cohort (CHDS) n=1017	Virtual cohort (simulated) n=1017	*Absolute error*	*Absolute error / CHDS mean*
Family doctor visits (mean (95% CI))				
1	5.82	5.82	-	-
2	5.34	5.28	0.06	-
3	3.31	3.18	0.13	-
4	3.13	3.15	0.02	-
5	3.22	3.12	0.10	-
6	3.35	3.32	0.03	-
7	2.43	2.41	0.02	-
8	2.14	2.15	0.01	-
9	1.96	1.90	0.06	-
10	1.65	1.68	0.03	-
All years	3.24	3.20 *(3.15-3.25)*	0.04	1.2%
Reading ability: BURT score (mean (95% CI))				
8	45.3	45.3	-	-
9	54.4	54.7	0.3	-
10	64.1	63.7	0.4	-
11	72.8	71.9	0.9	-
12	79.5	78.9	0.6	-
13	85.2	84.6	0.6	-
All years	66.9	66.5 *(65.7-67.4)*	0.4	0.6%
Conduct problems (mean (95% CI))				
6	10.6	10.6	-	-
7	24.6	24.8	0.2	-
8	24.4	25.0	0.6	-
9	24.7	25.3	0.6	-
10	24.9	25.6	0.7	-
All years	21.8	22.3 *(22.1-22.4)*	0.5	2.3%

Table A3. Distribution of modifiable structural and intermediary factors, and outcomes in starting sample

	Distribution (year 1) (n=1017)
Modifiable structural factors (proxy indicators)	**(%)**
Single parent family (yes)	6.8
Number of children (high: >2)	24.0
Paternal employment (no)	9.7
Welfare dependency (yes)	9.4
Modifiable intermediary factors	**(%)**
Accommodation type (Other than house)	11.6
Rented home	31.6
Overcrowding (high: >2)	13.0
Change of parents (yes)	10.0
Change of residence (yes	33.2
Mother smoking (yes)	32.7
Father smoking (yes)	33.0
Outcomes	**(mean)**
GP visits	5.82
BURT reading score	45.3 (year 8)
Anti-social behaviour	10.6 (year 6)

Table A4. Reading ability, and conduct problems: Base and improvement scenarios by fixed structural factors

Scenarios	Fixed structural factors [b]													
	Socioeconomic status			Maternal education			Maternal age				Ethnicity			All families (n=1017)
	Un/semi-skilled	Skilled/ clerical/ technical	Professional/ managerial	No formal quals.	Secondary quals.	Tertiary quals.	<20	20-24	25-29	30+	Pacific	Maori	Euro/ Other	
Years 8-13	**Reading Ability (mean BURT score)**													
Base [a] (mean)	61.9	66.3	72.7	62.6	68.2	74.3	61.4	64.5	67.6	69.5	58.9	61.9	67.3	66.5
Improve ALL modifiable structural factors (only)	63.7	67.2	73.1	64.0	68.9	74.8	64.4	65.8	68.5	69.7	61.0	64.1	68.2	67.6
Improve ALL intermediary factors (only)	62.4	67.0	73.0	63.4	68.5	74.6	62.6	64.9	68.2	69.7	60.0	62.8	67.8	67.1
Best scenario: Improve ALL structural and intermediary factors (both)	64.4	67.6	73.2	64.7	69.0	74.9	65.1	66.1	68.7	70.3	61.6	64.6	68.5	67.9
Years 6-10	**Conduct problems (mean)**													
Base [a] (mean)	23.1	22.2	21.5	22.9	21.9	21.1	23.6	22.7	22.0	21.6	23.6	23.0	22.1	22.3
Improve ALL modifiable structural factors (only)	22.5	22.0	21.4	22.5	21.7	21.0	22.7	22.4	21.8	21.5	23.1	22.5	21.9	22.0
Improve ALL intermediary factors (only)	22.6	22.0	21.4	22.5	21.7	21.0	22.9	22.4	21.8	21.5	23.0	22.6	21.9	22.0
Best scenario: Improve ALL structural and intermediary factors (both)	22.2*	21.7	21.3	22.2*	21.6	20.9	22.3*	22.1*	21.6	21.3	22.7	22.1	21.7*	21.8*

a. Base case scenario: status quo for the virtual cohort; b. At birth of child; * $p<0.05$ (difference between base and scenario)

Table A5. Reading ability, and conduct problems. Base and cumulative improvement scenarios by fixed structural factors: Relative change (percentage)

Scenarios	Fixed structural factors [b]													
	Socioeconomic status			Maternal education			Maternal age				Ethnicity			All families (n=1017)
	Un/semi -skilled	Skilled/ clerical/ technical	Professional/ managerial	No formal quals.	Secondary quals.	Tertiary quals.	<20	20-24	25-29	30+	Pacific	Maori	Euro/ Other	
(Years 8-13)	**Reading Ability**													
Base [a] *(mean score)*	61.9	66.3	72.7	62.6	68.2	74.3	61.4	64.5	67.6	69.5	58.9	61.9	67.3	66.5
Improve all modifiable structural factors														
% change	*+2.9*	*+1.4*	*+0.6*	*+2.2*	*+1.0*	*+0.7*	*+4.9*	*+2.0*	*+1.3*	*+0.3*	*+3.6*	*+3.6*	*+1.3*	*+1.7*
Best scenario: Improve all structural and intermediary factors														
% change	*+4.0*	*+2.0*	*+0.7*	*+3.4*	*+1.2*	*+0.8*	*+6.0*	*+2.5*	*+1.6*	*+1.1*	*+4.6*	*+4.4*	*+1.8*	*+2.1*
(Years 6-10)	**Conduct Problems**													
Base [a] *(mean)*	23.1	22.2	21.5	22.9	21.9	21.1	23.6	22.7	22.0	21.6	23.6	23.0	22.1	22.3
Improve all modifiable structural factors														
% change	*-2.6*	*-0.9*	*-0.5*	*-1.7*	*-0.9*	*-0.5*	*-3.8*	*-1.3*	*-0.5*	*-0.5*	*-2.1*	*-2.2*	*-0.9*	*-1.3*
Best scenario: Improve all structural and intermediary factors														
% change	*-3.9**	*-2.3*	*-0.9*	*-3.1**	*-1.4*	*-0.9*	*-5.5**	*-2.6**	*-1.8*	*-1.4*	*-3.8*	*-3.9*	*-1.8**	*-2.2**

a. Base case scenario: status quo for the virtual cohort; b. At birth of child; * p<0.05 (difference between base and scenario)