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Insights from New Zealand child poverty data

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The code used to produce the statistics used in this report can be accessed at the following GitHub address: https://github.com/Treasury-Analytics-and-Insights/analytical-note-22-04-insights-from-New-Zealand-child-poverty-data

Executive summary

One way that governments support people is by providing a safety net through main benefits like the Job Seekers Allowance, supplementary benefits like the Working for Families tax credits, and discretionary payments such as special needs grants.

A central goal of these programmes is to reduce the number of families below a minimum standard of living – in other words to reduce the number of people in poverty. But while this may be a simple idea, in practice it is no easy task.

One challenge is that there is no single, objective measure of what it means to be poor. Indeed, it has been said that "counting the poor is an exercise in the art of the possible" (Stephens & Waldegrave, 2001), where the "art" lies in choosing a poverty indicator. The best approach is to use a range of poverty indicators that illustrate different parts of the puzzle and together provide a fuller picture, enabling others to make their own judgements.

This analytical note outlines an approach that uses the available data to provide insights into three different indicators of poverty, making use of recent data and modelling improvements. It applies a statistical algorithm to identify seven different categories of children in poverty and describes the characteristics of children in each group.

This exploratory analysis confirms that the relationship between material hardship, income, and housing costs is complex. For some of the identified categories there is a direct relationship between low incomes, either before or after housing costs, and material deprivation. However, for several categories low incomes do not correspond to deprivation and vice-versa.

Key results

- There are strong links between hardship, income, and housing costs for some families, but not others. For beneficiary families, we find that families experiencing deeper income poverty are more likely to be experiencing hardship. But there is less of a link between hardship and income when we consider working families. Many appear to have adequate incomes but experience deprivation and vice versa.

- The data suggest that we also need to think about other aspects of economic wellbeing such as wealth and extra costs related to, for example, disability and childcare.

- Not all beneficiaries are in poverty, and not all children in poverty are in beneficiary families.

- Beneficiaries with high housing costs have their before housing cost incomes boosted via the Accommodation Supplement, which makes them appear to have adequate incomes even though they are in poverty on other measures.

- However, for working families with high housing costs, our model suggests that some families in poverty meet the eligibility requirements for Accommodation Supplement but are not receiving it.

- Although mostly coupled parents, working families in poverty or near poverty thresholds are more likely to be one earner families; these families are around twice as likely to have only one earner than other families with children.

Our ability to measure poverty has evolved over time

New Zealand experts have been working on poverty measurement since the 1970s, progressively building a body of work and iteratively improving our understanding of poverty[1]. As Stephens and Waldegrave (2001) noted, citing Mollie Orshansky, the developer of the US poverty threshold,

> *"Counting the poor is an exercise in the art of the possible... when it comes to defining poverty you can only be more subjective or less so".*

But what is possible continues to change. With the growing availability of data and improving computing power, we have an opportunity to better understand the incidence and causes of poverty and, in turn, help lift the living standards of New Zealand's poorest families.

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1 See for example, Easton (1976, 2018), EAG (2012), Perry (2021), Stephens, Waldegrave, & Frater (1995), Boston & Chapple (2015), and references therein.

Short history of poverty measurement in New Zealand

1970s **Easton** (1976) produced the first coherent national estimate of people in poverty based on the Benefit Datum Line, which reflected the benefit level required for beneficiaries to belong and participate in the wider community.

Household Survey started in 1973.

In the 1990s, the **New Zealand Poverty Project** (Stephens, Waldegrave, & Frater, 1995) used focus groups to identify an agreed "minimum adequate weekly expenditure". They reported on trends in a range of poverty measures, including incidence and severity.

Significant welfare and labour market reforms led to questions on how the Benefit Datum Line should increase with inflation.

In the early 2000s, MSD developed the **Economic Living Standards Index** (ELSI) (Jensen, Spittal, Crichton, S., & Krishnan, 2002) measuring material wellbeing, which was then extended in 2008 to produce the Material Wellbeing Index (MWI) and **DEP-17** (Perry B., 2009).

In 2007, MSD published the first ***Household Incomes in New Zealand*** report (Perry B., 2007), an ongoing annual report focusing on trends in inequality and hardship, with international comparisons where possible.

In 2012 the **Expert Advisory Group on Solutions to Child Poverty** (EAG, 2012) outlined their approach to defining and measuring poverty.

In 2013, the Household Economic Survey started to measure **Material Hardship.**

Child Poverty Reduction Acy 2018 set targets for child poverty reduction.

Budget 2019 contained the first **Child Poverty Report** (New Zealand Treasury, 2019).

In 2019, **HES increased significantly** to 20,000 households and incorporated linked administrative data, increasing the opportunities for poverty research.

In 2027, Stats NZ will begin reporting on persistent poverty using a new longitudinal survey.

A range of indicators can provide a fuller picture

When we think about poverty, we generally think about not having enough resources to meet a minimum standard of living. For example, the World Bank (2001) defines poverty as "pronounced deprivation in wellbeing". This is a useful definition, but we need to distinguish between absolute poverty in a global sense and what it means to be poor in New Zealand. To measure and estimate future levels of poverty, we need to define what is enough, what types of resources we are considering, and what is a minimum standard of living?

We can provide a useful picture of living standards by measuring the number of children in households experiencing material hardship using survey questions. This tells us how many households have needed to forego expenditure on essential items. Material hardship is a relatively direct measure of what we think of as poverty, but it can only be measured using a survey and is hard to forecast and model[2].

Instead, we can look at income-based measures of poverty, which vary depending on the definition of income and whether they account for key expenditures such as housing costs. The poverty threshold is also important. It can be based on a level of income that is assumed to provide a minimum standard of living or it can be a relative threshold that is defined in terms of a typical household. This can be either a typical household from a year in the past (fixed) or a current household (moving line).

These relative measures are common and provide valuable information. To paraphrase the Royal Commission of Inquiry on Social Security (1972), they can tell us about the ability of the poorest families to "participate and belong". Even if a family could afford the same material standard of living as a similar family 50 years ago, they may be less able to participate in society.

So relative measures are not only sensitive to changes in incomes among the poorest families but also to the incomes of middle-income families. When the median income rises the relative poverty threshold will increase, which means that even if absolute poverty is falling, relative poverty can increase.

Income data only give us a partial picture of the choices and opportunities faced by families. Children can appear to have reasonable levels of household income but experience material deprivation and vice versa. There are a number of reasons for this mismatch, including access to extended family resources or wealth, additional costs related to disability and childcare, and the length of time families have been on low incomes. **Income, even if perfectly measured, is an imperfect measure of economic wellbeing,** although it has the practical advantage that it can be directly influenced by policy instruments such as taxes and benefits.

2 Material Hardship measures are currently based on survey data, but it may be possible to measure access to certain essential items or services using administrative data, eg, primary healthcare. Currently, material hardship information is based on the response of one adult in the household, so it may not completely reflect the living standards of children within the household. The longitudinal survey currently being developed by Stats NZ aims to provide more comprehensive information.

Given these issues, the best approach is to use a range of poverty indicators. Indeed, this is what the government does in its reporting on child poverty. Different measures illustrate different parts of the puzzle and together provide a fuller picture.

Poverty thresholds in New Zealand

New Zealand sets targets on the following poverty indicators[3].

- **Material Hardship**
  Defined as a lack of six or more of the 17 items on the material deprivation index, Dep17 (Stats NZ, 2019).

- **Fixed-line after housing cost poverty, fixed-AHC50**
  Compares after-housing cost income[4] with that of a typical 2018 household. Defined as having an income below 50% of the median equivalised household income in 2017/18, after accounting for housing costs.

- **Moving-line before housing cost poverty, BHC50**
  Compares before-housing cost income with that of a typical household. Defined as having an income below 50% of the median equivalised household income in the year measured.

The two income poverty measures use equivalisation to allow for comparisons across households with different compositions. Two households with different compositions need different levels of income to meet the same standard of living. Equivalisation attempts to account for the additional income needed to support more people and also economies of scale due to shared housing costs, utilities, etc. This analysis uses the modified OECD equivalence scale to be consistent with the indicators specified by the Government Statistician, but other equivalisation methods could be more appropriate, particularly for after housing cost incomes (Creedy & Sleeman, 2004).

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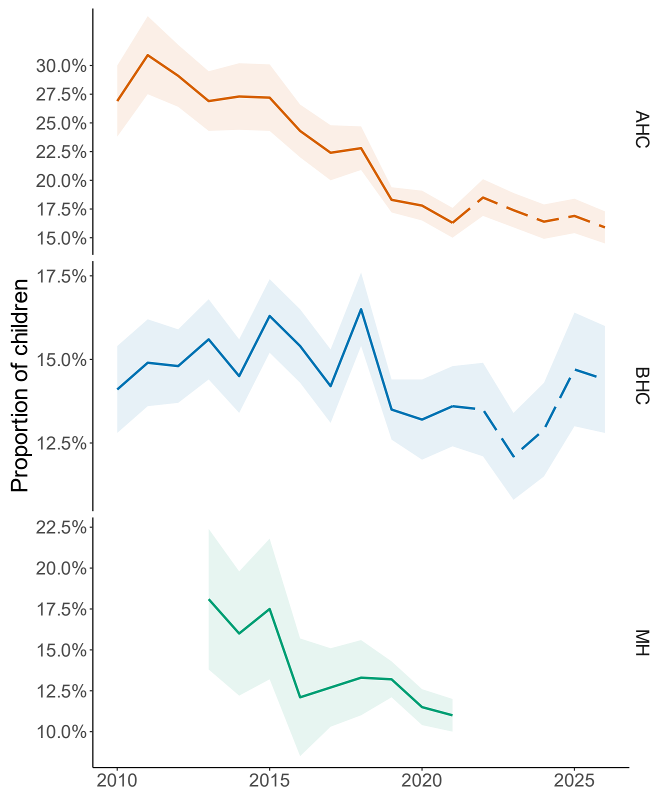
[3] There are 10 indicators, but only three have targets (Department of Prime Minister and Cabinet, 2020).

[4] Income here refers to disposable income, which includes taxes and transfers such as core benefits, Accommodation Supplement, Working for Families, etc.

Child poverty trends in New Zealand



The **fixed-line AHC50** measure compares income after paying for housing with a typical New Zealand household in 2018. It can show if inequalities are increasing over time and the impact of housing costs and inflation. Treasury's projections suggest that after an increase in 2022 driven by inflation, in the absence of policy interventions AHC poverty would remain flat in the near term, with incomes expected to increase at a similar rate to increases in housing costs and the cost of living.

The **moving-line BHC50** measure compares income before accounting for housing costs with a typical New Zealand household in the year considered. It is a very sensitive measure and can show if low incomes are increasing at the same rate as middle incomes. Treasury's projections suggest that after a drop in 2023 driven by changes to transfer payments, in the absence of policy interventions BHC poverty would increase in the near term as median incomes are expected to increase faster than low incomes.

The **Material Hardship** measure can show us if children have access to essentials such as nutritious food and medical services. It picks up the impact of income, wealth, and costs, but also other social and personal factors. We cannot forecast material hardship.

Source: Child Poverty Report (New Zealand Treasury, 2022)

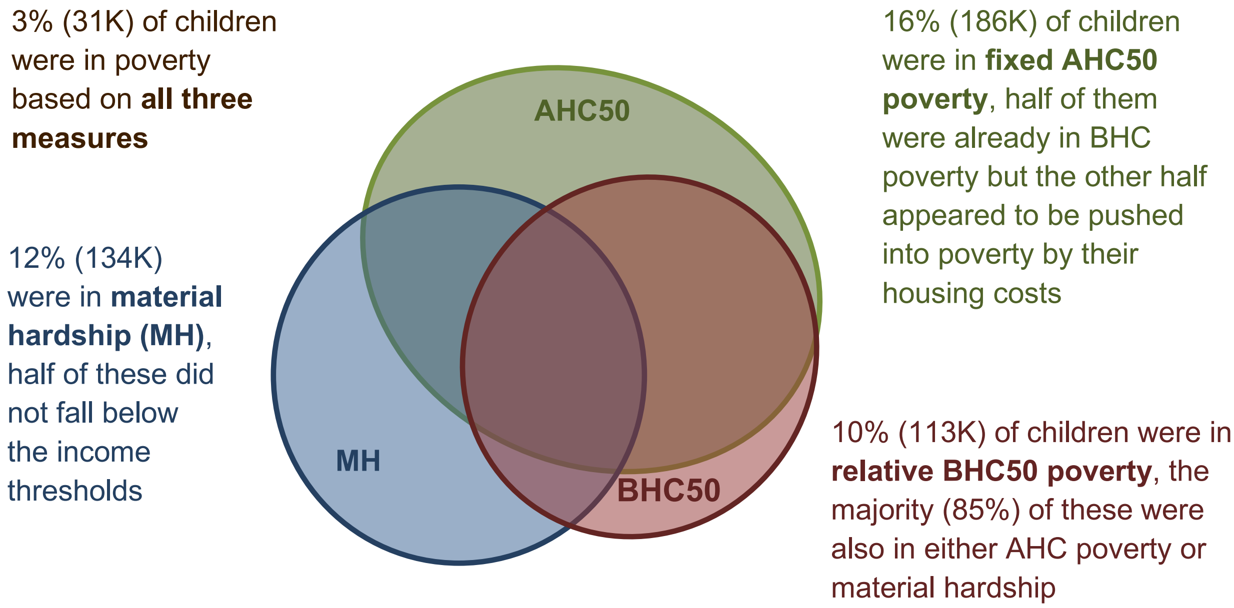
In 2019, Stats NZ increased the number of households surveyed to reduce uncertainty in measured poverty, and both Stats NZ and Treasury have improved their data and models using linked administrative data.

The mismatch between poverty measures

This note uses the Treasury's TAWA (Tax and Welfare Analysis) model [see TAWA, Annex] to estimate how three key poverty measures relate to each other. Those measures are material hardship (MH), fixed-line after housing cost poverty (AHC50), and moving-line before housing cost poverty (BHC50).

This analysis is based on modelled results for April 2019 - March 2020, which means it does not take into account recent policy announcements or line up with the poverty statistics published by Stats NZ (which combine data from multiple financial years). However, the patterns we see in the relative sizes of the overlaps between the three different measures of child poverty are consistent with Stats NZ data, so we can infer useful insights on the type of children who are experiencing poverty.

Figure 1: Coverage of different poverty measures



	Number of children
Not in poverty based on any indicator	836,000
In poverty based on at least one indicator	270,000
In poverty based on…	
MH, fixed AHC50, and moving-line BHC50	31,000
MH and fixed AHC50	27,000
MH and moving-line BHC50	6,000
MH only	70,000
Fixed AHC50 and moving-line BHC50	54,000
Moving-line BHC50 only	16,000
Fixed AHC50 only	66,000

Notes: Material Hardship is not recorded for all households, which causes some inconsistencies when comparing the totals. The numbers recorded here do not include households with missing material hardship data.

Source: Author's calculations using the TAWA model for Tax Year 2020

Some of the overlaps in the different measures of poverty are intuitive. For example, most children experiencing before housing cost poverty also experience after housing cost poverty or material hardship.

But the limited overlap between the two income poverty measures and material hardship can be surprising. This has been discussed previously, most recently in MSD's material wellbeing report (Perry B., 2021). From a data analysis or measurement perspective, the limited overlaps demonstrate the value of a multi-measure approach. If the measures overlapped exactly, we would only need to track one poverty indicator.

The complications do not stop there. All the measures discussed above are headcount measures. They tell us about the number of children in households below a threshold, but they do not tell us how far they are below or about children who are near the threshold.[5] The children in Material Hardship but not in income poverty could have incomes that only just push them over the income poverty thresholds, or they could have relatively high incomes.

A clearer picture from integrated data and modelling

Aggregate poverty indicators are important but obscure the fact that children in poverty can have very different experiences and may require different policy interventions. Not all children experiencing poverty have the same characteristics. To provide more detailed insights, we can use the TAWA model and data in Stats NZ's Integrated Data Infrastructure to look at each child's household income, housing costs, income sources (ie, are they supported by benefits), family size, etc.

But although incorporating this additional data provides a more comprehensive characterisation of children's situations, the descriptions of their circumstances become more complex and harder to interpret. This note applies a method to identify key insights for model and policy development. **The goal is to investigate the relationships between the different poverty indicators while recognising that each indicator exists on a continuum – that is, see if the data can provide information on different levels and dimensions of poverty.**

The approach taken is motivated by that of the Poverty in Perspective reports from the UK (Wood, et al., 2012; Barnes, Stares, Wood, Vibert, & Lord, 2017).[6] The authors of this work summarised their research as:

> "We are not redefining poverty or measuring it in a new way …. Instead, we are applying a new model of analysis ... to generate new insights into how to tackle it."

Clustering is one method that can be used to reduce a multi-dimensional dataset into easily interpreted groups, with the aim of accounting for characteristics that typically appear together. This analysis used clustering to identify groups of children who are near or under poverty thresholds in such a way that they are similar with respect to:[7]

- before housing costs equivalised household income
- the proportion of household income spent on housing costs
- the number of 17 basic needs that the household is going without (the Dep17 indicator)
- the proportion of family income that comes from core benefits.

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5 Other measures in the child poverty reduction act cover different depths of poverty, but do not directly measure distances from poverty thresholds.

6 Poverty in Perspective used an alternative statistical method called Latent Class Analysis, which could be used in future work.

7 The clustering method was applied to many different combinations of characteristics. The main groups were mainly consistent, although this note presents these particular results because they illustrate the complex relationship between the three main poverty indicators (that is, relative BHC50, fixed AHC50, and material hardship) in a comparatively straightforward way.

Clustering is purely driven by how similar different children are based on the characteristics we provide to the algorithm; it does not imply cause and effect. Details of the method used in this exploratory analysis are provided in the Annex.

There are seven categories of children either in poverty or near poverty thresholds

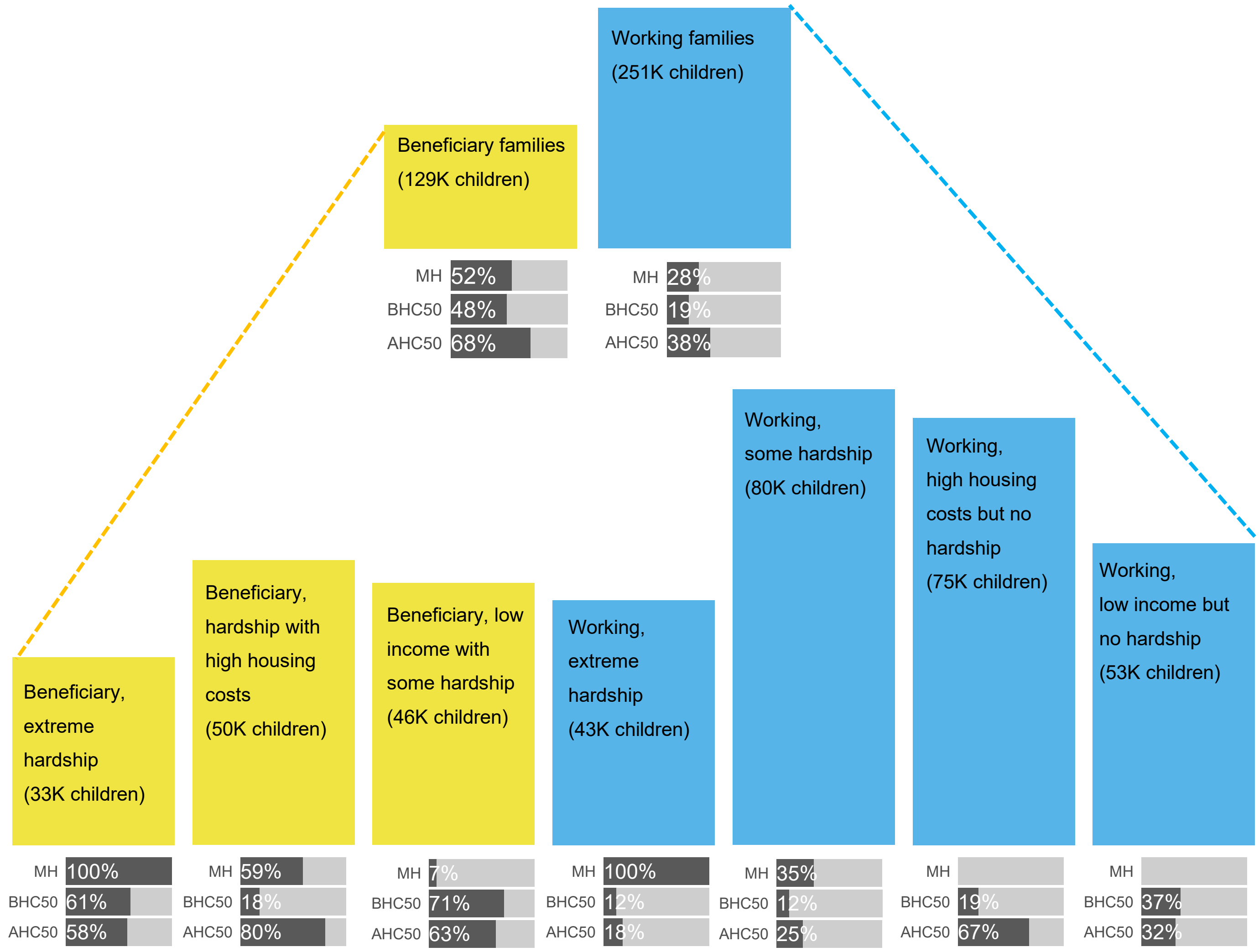
To focus on children near or under at least one poverty threshold, we defined our population of interest to be in households with either equivalised before-housing-cost incomes in the bottom 20%, after-housing-cost incomes in the bottom 20%, or Dep17 scores of 5 or more. This includes the 270,000 children who are in poverty according to at least one of the main indicators but is a larger group including a total of 360,000 children (approximately 30% of children in New Zealand).

The clustering algorithm identified seven categories within this population. Children in families who are mainly supported by core benefits represent three groups, and children in families that are mainly supported by market income represent the remaining four.[8] This distinction based on income from core benefits was an output of the clustering algorithm rather than being pre-defined. Descriptions of typical characteristics of children in each category provide useful insights into the different poverty indicators. Some children could be considered to fall between groups, so the total numbers of children in each group should be considered indicative.

Figures 2 and 3 show the different categories and how they relate to the main poverty indicators, that is moving BHC50, fixed AHC50, and material hardship. Table 1 provides more detailed characteristics and some potential insights that that could improve TAWA model outputs and inform child poverty policies. More comprehensive data is provided in the Annex, which also includes important caveats regarding sample sizes and the impact of confidentiality requirements.

8 In this analysis, we define beneficiary families as families whose main source of income over the reference year was benefits and working families as families whose main source of income was employment.

Figure 2: Seven categories of children in or at risk of poverty



Beneficiary: Benefit payments were the main income source.

Working: Market income was the main income source.

Extreme hardship: All households were in MH, many had Dep17 levels of 10 or more.

Hardship: Many in MH, others were very close to the threshold.

High housing costs: Paying more than 35% of their income on housing.

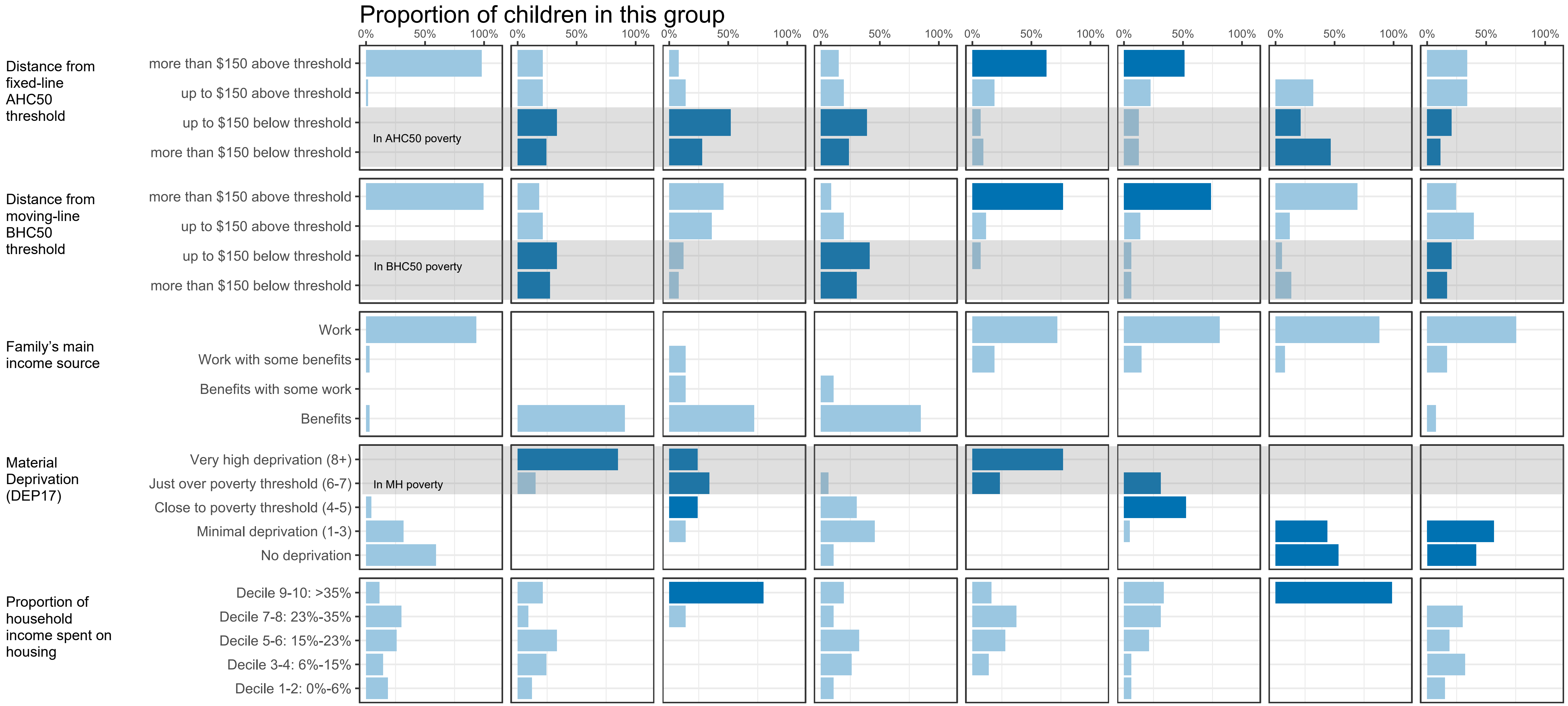
Low income: Below or close to the BHC50 threshold.

Source: Author’s calculations using the TAWA model for Tax Year 2020

Figure 3: Key characteristics of the different groups

This figure shows how the groups identified by the algorithm correspond to some key characteristics used in the clustering method. The clearest split is based on a family's main income source (benefits or market income). Within the beneficiary families, the groups are split based on deprivation level and the proportion of income spent on housing. Within the working families, the three poverty indicators appear to be less correlated. Two groups are (mostly) not in income poverty but are showing signs of hardship, one group has very high deprivation scores and the other group is mainly around the material hardship threshold. The other two working groups are not experiencing material hardship but have either very high housing costs or are below one of the income poverty thresholds. Note that although some characteristics are over-represented within groups there are still variations. The characteristics of children not near thresholds (ie, not in the population of interest) are also provided as a comparison.

	Groups derived by the algorithm						
	Benefits are the family's main source of income Different levels of deprivation, but almost all are showing some sign of material hardship			***Market income is the family's main source of income***			
Not near poverty thresholds	High deprivation levels, AHC and BHC poverty	Material hardship and AHC poverty but not BHC poverty	AHC and BHC poverty, and close to material hardship threshold	High deprivation levels, but not in income poverty	Deprivation levels around threshold, mostly not in income poverty	Very high housing costs but not experiencing material hardship	Low incomes but not experiencing material hardship



Source: Author's calculations using the TAWA model for Tax Year 2020. Totals do not add to 100% because of Stats NZ confidentiality rules.

Table 1: Seven categories of children in poverty

Beneficiary family, extreme hardship ***Very high material hardship indicators and in AHC and BHC poverty or close to thresholds.*** • All had Dep17 values of 7 or more and around 85% had Dep17 values of 10 or more. • BHC and AHC incomes were mostly below the poverty thresholds; around a quarter had household incomes more than $150 below the thresholds. • Over 90% of families did not have any wage/salary income over the year. • Housing costs were mostly low, but around 20% paid more than 35% of their household incomes on housing. Additional characteristics • **These families were the most likely to be affected by disabilities; half had a disabled person in the family and 40% had a disabled parent.** • Around half did not have a parent who finished secondary school. • **There was a high proportion of single parents in this group.** **Beneficiary, hardship with high housing costs** ***Experiencing some material hardship, in fixed AHC poverty or very close to threshold but not in BHC poverty.*** • Around 85% had Dep17 values of 4 or more, around 60% were above the Dep17 threshold of 6. • Around 80% had BHC incomes above the BHC50 poverty threshold, but some were close to it. • AHC incomes below or near the fixed AHC50 poverty threshold; around 80% were below the threshold, most of the rest were slightly above. • Around three quarters of these families did not have any wage/salary income over the year, the rest received a mix of core benefits and wages. • Most were private renters and spent a lot of their income on housing costs; around 80% spent more than 35% of their household income on housing, and 40% spent more than 45% on housing. Additional characteristics • **All these households received Accommodation Supplement (AS), which is likely why they appear to have higher BHC incomes than beneficiaries with lower housing costs. AS can make BHC incomes look better than they are in practice because they are directly linked to a family's housing costs. This suggests that beneficiaries with high housing costs are less likely to appear in the aggregate BHC poverty measure, showing the benefit of a multi-measure approach.** • **These families were also likely to be affected by disabilities; half had a disabled person in the family and 30% had a disabled parent.** **Beneficiary, low income with some hardship** ***This group had low BHC incomes but experienced less deprivation than other beneficiary households.*** • Average Dep17 score was 3, but most were showing some signs of deprivation. • Low BHC incomes; around 70% were below the BHC50 threshold, and the rest were close to it. • AHC incomes below or near the fixed AHC50 poverty threshold; similar to the previous group around 70% were below the threshold. • Around 85% of these families did not have any wage/salary income over the year; the rest received a mix of core benefits and wages. • Around 50% had relatively low housing costs, reflecting that 50% were Housing New Zealand tenants. Additional characteristics • Around a third lived in multi-family households.	The children in these three groups were all in families that received income-tested benefits over the previous year, with 85% not working at all. Around 15% had one earner at least some time over the year but most (70%) were receiving less than $3,500 year from non-benefit sources. **Not all beneficiaries were in poverty.** In this data: • around 200,000 children were in families that received income from core benefits • benefit payments were the main income source for around 140,000 of these • 140,000 children in families receiving any benefit were beneath at least one of the poverty thresholds (but not the same 140,000 children who were mainly supported by benefits[9]) • around 160,000 were in the population of interest (that is, below or near at least one of the poverty thresholds). Some characteristics highlighted in this group reflect the composition of the beneficiary population, that is, single parents, Māori, and Pacific families are overrepresented in beneficiary numbers. In the three beneficiary groups, three quarters were single parent families (compared to one quarter of the population), half were Māori children (compared to a quarter) and 20% were Pacific children (compared to 13%). **Insights for measuring poverty:** • depth of poverty is important; some policies can improve the standard of living of children in poverty or near poverty thresholds without necessarily reducing the number of children in poverty • we can consider an alternative before housing cost income definition that excludes accommodation supplement.

[9] See Detailed Results in the annex for characteristics of children grouped by the three main poverty indicators.

Working, extreme hardship

Incomes were well above BHC50 and fixed AHC50 thresholds but deprivation scores were high.

- All had Dep17 values of 7 or more and around 30% had Dep17 values of 10 or more.
- BHC and AHC incomes were mostly above the poverty thresholds. Many had AHC and BHC incomes well above the thresholds, 60% were more than $150 above the AHC threshold and nearly 90% were above the BHC threshold.
- A range of housing costs that were similar to households who weren't near poverty thresholds. Most had low housing costs, but around 15% paid more than 35% of their household incomes on housing.

Additional characteristics

- **Many of these families were affected by disabilities; around 50% had a disabled person in the family and 25% had a disabled parent.**
- **Around a quarter of these families could have been eligible to receive Accommodation Supplement but were not receiving it**.
- **There were a higher proportion of single parents in this group than the rest of the working family groups.**
- **Around a third were living in crowded houses.**

Working, hardship

Incomes were mostly above BHC50 and fixed AHC50 thresholds, but all were just above or below the material hardship threshold.

- Average Dep17 of 5.
- BHC incomes were almost all above the poverty threshold. Most AHC incomes were above the threshold, but around 25% were below.
- A range of housing costs were mostly similar to households who weren't at risk of poverty, but around a third paid more than 35% of their household incomes on housing.
- Around half (37,000 children) were "not in poverty" but were in our population of interest because they had Dep17 scores of 5 (the threshold is 6).

Additional characteristics

- **Many of these families were affected by disabilities**; around a third had a disabled person in the family.
- **Around a quarter of these families could have been eligible to receive Accommodation Supplement but did not receive it**.
- Around a quarter were living in crowded houses.
- These families were more likely to have 2 earners than any of the other groups; around a third had two earners, which is still considerably less than the two thirds of the families who weren't near the poverty threshold.

Working, high housing costs but no hardship

These households did not appear to be experiencing material hardship but had very low after housing cost incomes.

- Average Dep17 less than 1.
- BHC incomes were all well above the poverty threshold. Two thirds of AHC incomes were well below the thresholds, with the rest close to the threshold.
- **All of these households paid more than 35% of their household income on housing costs, with 70% paying more than 45% on housing.**
- Around a third (25,000 children) were "not in poverty" but are in our population of interest because their AHC50 incomes were close to the AHC50 threshold.

Additional characteristics

- Half were renting and half were home owners.
- **Around 80% were estimated to be eligible for Accommodation Supplement, but over half did not receive it.**
- Around 60% had at least one extra room in the house.
- **They could have been drawing on savings or other resources.**

Working, low incomes but no hardship

These households had low incomes but were not experiencing hardship.

- Average Dep17 of 1.
- These households had low BHC and/or AHC incomes.
- Unlike the previous group, they did not typically have high housing costs.
- Around a half (28,000 children) were "not in poverty" but are in our population of interest because they had BHC50 incomes close to the BHC50 threshold.

Additional characteristics

- **These families had the lowest earning levels of the working family categories and 60% were one earner families. 20% had no earnings, and not all of those received benefits.**
- **They could have been drawing on savings or other resources.**
- **We expect that there is some measurement error for this group, as a number have income levels well below what they would receive from benefits.**

Although some of these groups also received an income tested benefit, they received more income from private sources.

These groups have similar proportions of single to couple parents as families who were not near poverty thresholds, but there were slightly more single parents (25% were single parents compared to 15%). However, they were **more likely to be one earner families**; around 60% of the families in these groups had only one earner (as a comparison, around 30% of families with children who were not near poverty thresholds have one earner).

Insights for measuring poverty:

- **many families in material hardship wouldn't necessarily be targeted in income-based modelling outputs, so we need to add hardship information to standard modelling outputs**
- we can investigate expenditure data to estimate additional costs such as expenses related to childcare and disabilities
- we can investigate other aspects of housing status, for example, incorporating imputed rents.

Source: Author's calculations using the TAWA model for Tax Year 2020.

Key insights from the categories

This exploratory analysis has confirmed that the relationship between material hardship, income, and housing costs is complex. For some of the identified categories there is a direct relationship between low incomes, either before or after housing costs, and material deprivation. However, for several categories low incomes did not correspond to deprivation and vice-versa.

Household income over a year can be hard to estimate, so we cannot rule out that some unexpected results are due to measurement error.[10] However, we also know that income is not a perfect measure of the resources available to households. So, this work makes the case for including material hardship outputs in our standard suite of modelling to inform child poverty related policies. Although we cannot estimate how material hardship rates might change in the same way as we can for income poverty measures, we can estimate which families in material hardship would benefit from different policies.

Housing costs can also have unexpected impacts on poverty indicators. Beneficiaries with high housing costs have their before housing cost incomes boosted via the Accommodation Supplement, which makes them appear to have adequate incomes even though they are in poverty on other measures.

This analysis also highlighted insights for working families in poverty. Our model suggests that many working families with high housing costs could be eligible for Accommodation Supplement. In addition. although mostly coupled parents, working families in poverty or near poverty thresholds are more likely to be one earner families; these families are around twice as likely to have only one earner than other families with children.

What next?

Future insights could come from inquiries into:

- the effects of wealth, childcare costs, the take-up of Working for Families payments, and persistent reliance on benefits
- evidence of policies that help families escape poverty, either using administrative data or Stats NZ's new longitudinal survey (which is expected in 2027)
- alternative techniques such as Latent Class Analysis.

Acknowledgements

Many thanks to Brian Easton and Bryan Perry for their comments on a previous version of this note and for our continuing conversations. This work is made possible by the high-quality work of Treasury's Analytics and Insights team, who maintain and develop the TAWA model.

10 https://www.stats.govt.nz/methods/child-poverty-statistics-year-ended-june-2021-technical-appendix

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Annex: Method, data, and IDI disclaimer

The Treasury's TAWA model

The Treasury uses the TAWA (Tax and Welfare Analysis) model to estimate income-based measures of child poverty. TAWA is a static arithmetic[11] microsimulation model, which means it applies different tax and welfare scenarios to households in a sample of the New Zealand population to see how their disposable income would change. In the context of child poverty, TAWA is used in two ways – as part of the policy design process and to estimate future levels of child poverty. Although these are similar objectives, they require different outputs and modelling assumptions.

- As a policy development tool, we use TAWA to compare which children will be in income poverty in the future under current policy settings with alternative scenarios, for example, scenarios where there is an increase to benefits or a reduction in personal tax rates. This comparison of alternative policies is used as part of the policy design process. It provides the most useful insights for policy design, as it isolates the impact of the design choices, estimates who is eligible for payments, and in some cases, who will apply for them, and provides detailed information on who would gain or lose from a policy change.

- To estimate future levels of child poverty, we have more recently used TAWA to take the official child poverty statistics from Stats NZ and project them forward considering economic forecasts and any legislated policy changes. In this case, we are producing our best estimate of trends in the official statistic, which, in addition to tax and welfare policies, will be driven by changes to the economy and population, changes to household structures over the year, and changes to the number of families who apply for different transfers and benefits. We are continuing to investigate how to best use TAWA for the projections.

In both cases, we work closely with Stats NZ, who run the Household Economic Survey (HES) and Integrated Data Infrastructure that are used to create the TAWA input data, as well as produce the child poverty statistics for past years.

Over the last 5 years, we have been progressively improving the TAWA model to take advantage of linked administrative data. Where we previously relied solely on survey data, which can be subject to recall errors, we now link the surveyed households to administrative data on tax and welfare payments. This has improved the accuracy, but also provides extra information on, for example, the number of eligible families who receive different benefit payments.

We now have a rich dataset that provides the income and demographics of children in poverty, which could be further linked to other IDI datasets in the future.

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[11] Static arithmetic models only model first-order impacts of policy changes, in contrast to behavioural models, which attempt to estimate changes in work patterns due to a policy.

Details of the clustering method

Population of interest

The main poverty indicators used in New Zealand (BHC50, fixed AHC50, and Material Hardship) all use a threshold to determine if a child is in poverty. This is appropriate when tracking high-level trends, when we are most interested in increases or decreases in aggregate totals.

However, when considering the individual children in poverty we have no reason to think that a household with income $1 over the poverty threshold is much better off than a household $1 below the threshold. To account for this, the population of children included in the clustering data includes those in poverty according to at least one of the three indicators *and* those "near" the thresholds. Although somewhat subjective it does lead us to focus on the children we are interested in. The population of interest is thus defined as all children living in households that have:

- equivalised BHC incomes in the bottom 20% (around 208,000 children, compared to 110,000 below the moving BHC50 threshold), and/or

- equivalised AHC incomes in the bottom 20% (around 269,000 children, compared to 184,000 children who are below the fixed AHC50 threshold), and/or

- Dep17 scores of 5 or more (around 169,000 children, compared to 133,000 children who are in Material Hardship).

This includes 360,000 children, compared to 270,000 children who are in poverty based on at least one of the main indicators. Reducing the population of interest would reduce the number of children in three of the working family groups:

- **Working, hardship** – around half (37,000 children) are "not in poverty" but are in our population of interest because they have Dep17 scores of 5 (the threshold is 6).

- **Working, high housing costs but no hardship** – around a third (25,000 children) are "not in poverty" but are in our population of interest because their AHC incomes are close to the AHC50 threshold.

- **Working, low incomes but no hardship** – around a half (28,000 children) are "not in poverty" but are in our population of interest because they have BHC incomes close to the BHC50 threshold.

We could alternatively include all children and rely on the clustering algorithm to group according to the poverty indicators. This leads to an unbalanced dataset (there are many more children not in poverty) and causes the algorithm to focus on characteristics that we are less interested in, given that the objective of this work is to focus on children in poverty. Although not included in data used by the clustering algorithm, we provide summary statistics for the rest of the population for comparison.

Clustering

Clustering is an exploratory data analysis technique. It is used to define groups, such that objects in the same group are more similar to each other than to objects in other groups. There are many clustering algorithms that produce different results. These techniques are not used to look for a specific correct answer, because there is no one specific answer. The most useful grouping is generally subjective and entirely dependent on the end use – "Clustering is in the eye of the beholder" (Estivill-Castro, 2002).

Although generally considered to fall under the banner of machine learning, cluster analysis has been around for a very long time – as far back as 1932 (Driver & Kroeber, 1932). As with many statistical and data science techniques, it can and has been applied to many fields including social science, finance, climate, medicine, biology, and marketing.

Partition Around Medoids

This analysis used a clustering method called Partition Around Medoids (PAM, also referred to as *k*-medoids) (Kaufman & Rousseeuw, 2005). PAM is closely related to the more commonly known *k*-means method. These algorithms use iterative methods to determine the best *k* centre points, where these centre points define each cluster/group. The data are grouped based on their distances to the centres. The main difference between PAM and *k*-means is that the centre points in PAM are in the input dataset, whereas they are more of a derived "middle" in *k*-means. Practically, this means that PAM is less sensitive to outliers in the dataset, which can be particularly important when dealing with noisy, real-world datasets.

Gower Distance

PAM needs a definition of distance, ie, if we have two children in the dataset and a number of characteristics, we need to have some measure of how similar they are to each other. In this dataset, for example, children could have numerical characteristics such as income and categorial characteristics such as main income source (eg, Benefit or Wages).

To account for these different data types, this analysis used the Gower distance, which can summarise the dissimilarity between two records that contain combinations of numeric, binary, and ordinal variables. Using the Gower metric, the distance between each data point is the average of the distances for each characteristic, which are:

- for numeric characteristics: the difference between both values (after scaling) divided by the total range for that variable

- for categorical characteristics (including true/false characteristics): 1 the characteristics are equal, 0 if they are not

- for ordinal characteristics (that is, categories that are ordered): the difference between both values (converted to their numerical order) divided by the total range for that variable (ie, the same as numeric values).

Where a data point contains a missing value for one characteristic, that characteristic is not included in distance calculations related to that data point.

Number of clusters and sensitivity of results

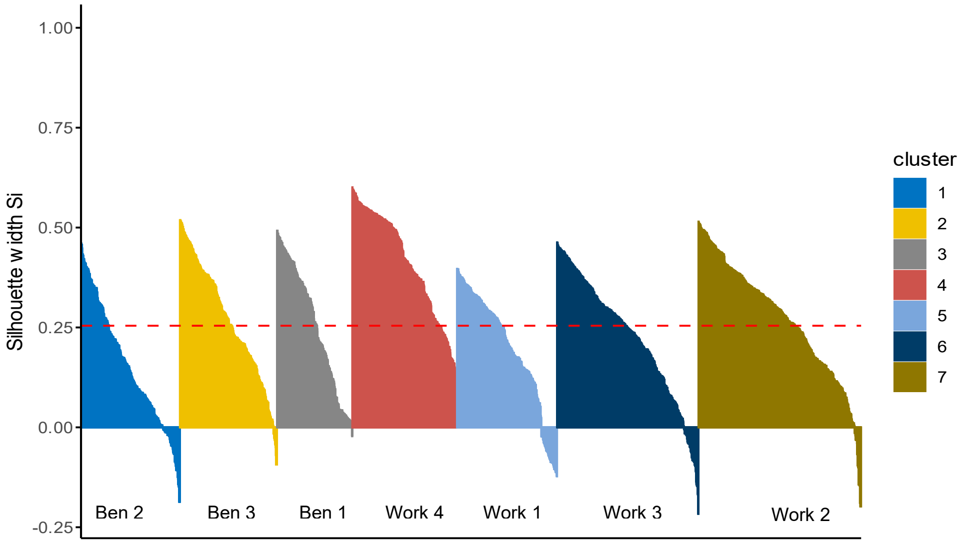
PAM also requires the user to specify the number of clusters. To do this, we chose the number of clusters that maximises the average silhouette width, where the silhouette is a measure of how similar a data point is to other points in its group compared to how similar it is to points in other groups[12]. If the silhouette width is close to 1, the data point is very similar to its cluster and very different to its neighbouring cluster. Similarly, if it is close to -1 then it would be more appropriate for it to be part of its neighbouring cluster and if it is close to zero it can be considered to lie in between clusters. Thus, the objective is to maximise the average silhouette width.

The final clustering dataset used in this analysis was iteratively chosen by removing variables one-by-one and running the algorithm for different numbers of clusters, with the aim of maximising the average silhouette widths while retaining useful policy relevant characteristics. In the final clustering, the silhouette plot (Figure 2) suggests that some children should be considered as being between clusters (because they have negative silhouette widths), but most are reasonably well separated.

In the diagnostic plots, the groups are defined as follows:

- Ben 1: Beneficiary, extreme hardship
- Ben 2: Beneficiary, hardship with high housing costs
- Ben 3: Beneficiary, low income with some hardship
- Working 1: Working, extreme hardship
- Working 2: Working, hardship
- Working 3: Working, high housing costs but no hardship
- Working 4: Working, low incomes but no hardship.

Figure 4: Silhouette plot for the final clustering



Notes: In this plot, each vertical line represents the silhouette of a child in the dataset. They show how well each child corresponds to the group it is placed in.

Source: Author's calculations using the TAWA model for Tax Year 2020.

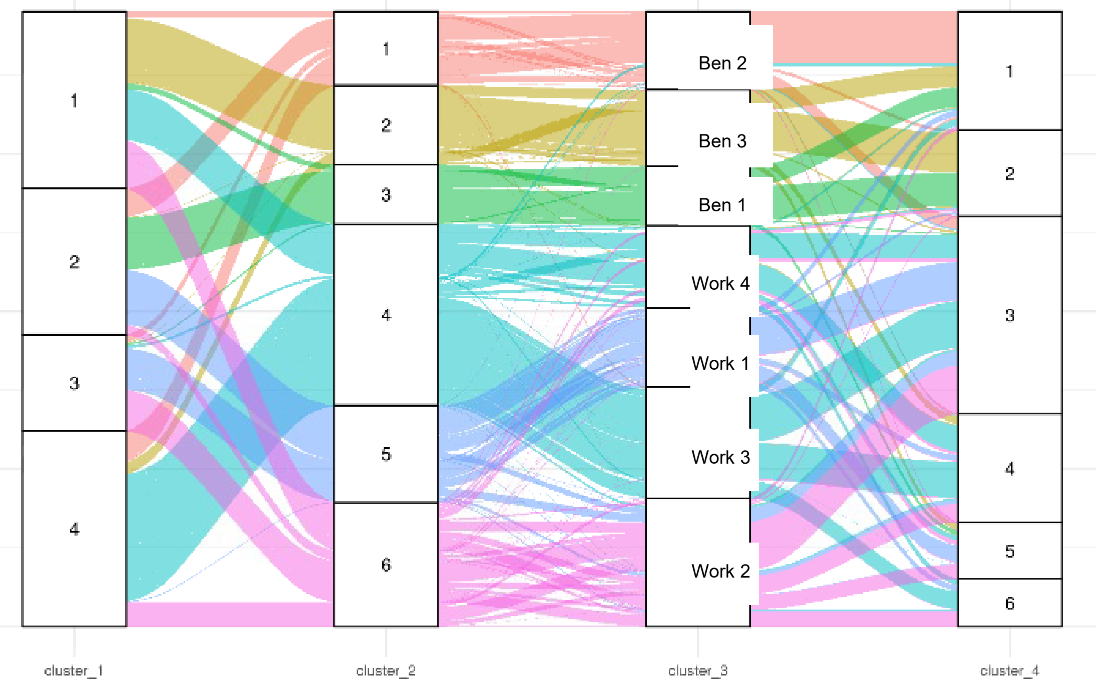
[12] See, eg, Rousseeuw (1987) and Kassambara (2017).

To be able to explain the groups as simply as possible, the final results provided in this note did not use any categorical data to derive the clusters, they were based on household equivalised income, the proportion of income spent on housing costs, Dep17, and core benefit income as a proportion of total family income.

Although the Gower metric provided a useful way of combining different data types, in this work it was biased towards clusters more focused on the categorical characteristics. Figure 5 shows how the number of clusters and assignment to clusters change with the introduction of different data. Cluster Set 1 only uses equivalised household income, the proportion of income spent on housing, and Dep17. The four clusters roughly correspond to low deprivation with low income; high deprivation with low income; high deprivation with higher income; and high housing costs. Cluster Sets 2 and 3, also included core benefit income as a proportion of total family income. This split the categories from Cluster 1 into beneficiaries/non-beneficiaries, which is useful from a modelling perspective (there are different administrative data sources) and a policy perspective (there are different policy levers). The additional category in Cluster 3 better isolated working families with very high housing costs. Cluster 4 added a categorical variable that described tenure type, which caused the algorithm to cluster only based on the type of housing and benefit status, at the expense of information on income and deprivation. Thus, it is less useful for the purposes of this analysis.

It is also important to test how robust the results are to different samples of data. One way of doing this is to look at how the results would change if we only used a subset of the data. The results were tested by randomly removing a quarter of the dataset and re-clustering to see if the same data points were grouped together. Repeating this 100 times, around 90% of children were placed in the same group every time.

Figure 5: Different clustering results



Notes: This diagram compares different cluster sets (cluster_1, cluster_2, cluster_3, cluster_4) that were based on different data. The size of each cluster in each cluster set is represented by the height of each box, and the relationships between each cluster are represented by the shaded regions.

Source: Author's calculations using the TAWA model for Tax Year 2020

IDI Disclaimer

These results are not official statistics. They have been created for research purposes from the Integrated Data Infrastructure (IDI) which is carefully managed by Stats NZ. For more information about the IDI please visit https://www.stats.govt.nz/integrated-data/. The results are based in part on tax data supplied by Inland Revenue to Stats NZ under the Tax Administration Act 1994 for statistical purposes. Any discussion of data limitations or weaknesses is in the context of using the IDI for statistical purposes, and is not related to the data's ability to support Inland Revenue's core operational requirements.

Detailed results

Detailed results can be found at the following links:

https://github.com/Treasury-Analytics-and-Insights/analytical-note-22-04-insights-from-New-Zealand-child-poverty-data

The first file presents the results using a clustering algorithm:

https://treasury-analytics-and-insights.github.io/analytical-note-22-04-insights-from-New-Zealand-child-poverty-data/analytical-note-22-04-child-poverty-data-clustered-group-characteristics.html

The second file presents similar results but for groups based on the overlaps of three poverty indicators:

https://treasury-analytics-and-insights.github.io/analytical-note-22-04-insights-from-New-Zealand-child-poverty-data/analytical-note-22-04-child-poverty-data-poverty-group-characteristics.html