Policy agility in volatile times
A new approach to modelling social policy impact
Authors

Brian Lee-Archer
Managing Director, Strategy and Consulting, Public Service, Australia and New Zealand
Accenture
brian.lee-archer@accenture.com

Gaurav Gujral
Managing Director, Strategy and Consulting, Public Service, Europe
Accenture
g.gujral@accenture.com

Sven Fuhrer
Consultant, Strategy and Consulting, Public Service, Australia and New Zealand
Accenture
sven.fuehrer@accenture.com

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Abstract

This paper describes the findings of a joint research initiative between Accenture and the Australian National University’s (ANU) Centre for Social Research and Methods (CSRM). The project set out to explore and enhance the CSRM’s methodology and modelling tool for optimising the social security system. It set out to achieve this through a powerful, ready-to-use analytics tool-set with a visualisation capability, that will assist policymakers in making evidence-based decisions. The illustrative case used to demonstrate the application of the methodology, the modelling and the visualisation tool, is minimising relative income poverty using population-based data from Australia.

The intended outcome of the research was to demonstrate the methodology and modelling tool’s flexibility, scalability, reusability and practicality beyond the illustrative case. This would prove that there is a pathway for adaptation to other countries’ social contexts. The research findings showed this is possible. The next stage is to develop a reusable, insights-driven analysis tool to support policymakers in making evidence-based social policy decisions. This tool will need to be developed through co-design with a select group of government agencies.
Introduction

Volatile times in social policy

Terms like agility and innovation are often understood to be incompatible with policymaking. Yet effective policymaking is built on the juxtaposition of certainty, stability on the one hand and agility and innovation on the other.

Social policy and related social security system design have traditionally been played out against a long-term horizon of social and economic objectives. Reform is driven through a lens of carefully calibrated checks and balances across different groups in the population to enable parallel, but mutually reinforcing, goals of social and economic development. This includes efforts to redistribute national wealth through progressive taxation, with the aim of providing a social safety-net that alleviates poverty and reduces inequality and exclusion.
Evidence shows that this long-term approach does not always deliver on its intended objectives. A report by UNSW Sydney’s Social Policy Research Centre (SPRC) and the Australian Council of Social Services (ACOSS) found that poverty rates in Australia - a modern, well-functioning and industrialised nation - have remained at much the same level for the past decade, despite continuous and strong economic growth over the past 28 years. It revealed three million people out of a population of 25 million are living in poverty in 2020 (Davidson et al. 2020). The share of people who live in relative income poverty is higher in Australia than the average in OECD countries, based on both the 50% and 60% median income poverty thresholds. (Silva, Dugain 2019).

Since the beginning of the 21st century, digitisation has been continuously disrupting the global economy. More recently, the COVID-19 pandemic, in addition to its devastating health impact, has been creating a social and economic crisis. Government, businesses and society are together seeking to adapt to a largely unknown “never normal”, while preparing for extended disruption. In this fast-moving situation, the standard timeframes for social policymaking are greatly reduced. This impacts the methods, capabilities and tools used in gathering, analysing and leveraging the evidence that is required to enable effective and agile policymaking.

Significant volatility and a once-in-a-century pandemic place significant additional pressure on social security systems, as they attempt to respond to the shocks to the labour market (Dolls et al, 2010). The International Labour Organization (ILO) estimates the global workforce could lose up to US$3.4 trillion in income in 2020 due to the pandemic, with a close to 25 million rise in global unemployment (ILO 2020).

We are witnessing a perfect storm. Increased vulnerability of at-risk groups (the poor, elderly, and disabled, and people living with mental health and substance abuse issues) will have a significant impact on social security. Rapid policy and programme changes will create confusion in determining eligibility for support.

Policymakers need a bold, new approach, enabled by the right tools, to alleviate hardship and put individuals and families on the path to recovery and restoration. To help policymakers to meet the demands of these volatile times, the Centre for Social Research and Methods at the Australian National University developed a methodology and modelling tool for optimising the Australian social security system to achieve specified outcomes such as closing the household poverty gap for a defined cohort through targeted income support.
The findings were published as a Centre for Social Research and Methods Working Paper in 2018 (Phillips, Webster, Gray 2018).

Accenture, saw that this approach had the potential to be applied broadly in other countries with different social policy contexts. Accenture and the ANU entered into a research agreement in August 2019 to investigate the broader applicability of the modelling methodology within select countries. We embarked on this agreement with the intention of developing a scalable, flexible and reusable data analysis, asset operating and open source technology platform.

The research set out to test how effectively the results of the microsimulation algorithm methodology could be translated into an accessible and usable format for consultants and policymakers. A visualisation platform and dashboards were created to display the results. This paper reports on the findings of this research and serves as a starting point for a commercial offering that delivers public value across different policy environments around the world.

The benefits of the methodology and tool that form part of the proposed offering include:

- Evidence-based / data-driven methodology, including a microsimulation modelling tool
- Powerful analytics tool to visualise calculations for different policy scenarios in real time
- Predicting and forecasting scenarios covering resource allocation, investments and social budgets
- Scalable, flexible and adaptable for other countries by leveraging the base modelling platform and algorithm.
A new approach

Optimal Policy Modelling (OPM)
Microsimulation modelling is a standard approach for understanding the impact of policy change at a detailed level. Perhaps surprisingly, microsimulation modelling has traditionally been used reactively rather than proactively in policy development. The approach has typically been used to model policy proposals that have been developed in an ad hoc manner and it sometimes allows the biases of researchers or policymakers to creep into the process.

**OPM is a new approach developed by the ANU that removes policymaker bias and develops the ‘optimal policy’ through a data-driven algorithm.**

Optimal policy is a relative term and is a function of political, social, economic and cultural vectors. It will therefore vary from country to country. Policymakers retain input into the process, because solutions can be chosen from a range of policy objectives. The machine-based algorithmic approach is not meant to replace the human expertise and experience of the policymaker. Rather, it provides an unbiased addition to the evidence-based decision-making framework, incorporating human-based expertise, internal and external data sources and other policy analysis techniques.² It is a demonstration of the emerging artificial intelligence paradigm of human + machine, where “humans and machines aren’t adversaries, fighting for each other’s jobs. Instead, they are symbiotic partners, each pushing the other to higher levels of performance (Daugherty & Wilson, 2018).

Microsimulation models perform detailed analysis of specific activities based on the data at a micro level. This supports a dynamic approach to parametric-level policy reform and can help to identify options for broader structural change. Microsimulation modelling is often used to evaluate the effect of proposed interventions before they are implemented in the real world. Microsimulation models are mainly used to simulate government programmes and demographic and economic changes for current or alternative scenarios. It allows detailed assessment of change on individuals or groups of individuals (same cohorts) or even the whole population.

Microsimulation modelling was first developed in 1957 by the well-known econometrician Guy Orcutt (Orcutt 1957). Orcutt proposed a computer-simulation-based approach for prediction in socio-economic systems. The key insight was that because the basis for modelling was at a micro level, such as a household or a person, this enabled detailed estimates and insights with far greater granularity than was previously possible.
Microsimulation modelling of social security and tax systems is now common practice throughout much of the developed world. In Australia, the federal government developed the Capita model (Stevenson et al. 2017). This evolved from the original federal government model STINMOD, which was developed by NATSEM in the 1990s. (Lambert et al. 1994). The ANU CSRM model PolicyMod was developed in 2016 and is similar to both of these models. Internationally, many countries have their own microsimulation model for their respective tax and social security systems. The most well-known of these is the EUROMOD model, which models the tax and transfer systems of each EU member country (EUROMOD 1999). Microsimulation modelling is regularly used for the analysis and development of public policy. Examples include the development of the GST in Australia in the late 1990s (Harding 2000) and the significant proposed policy changes in the federal budget 2014 (Phillips 2014).

We have not been able to identify other examples of this type of approach to modelling for the social protection system. There are some examples of the use of microsimulation techniques to optimise a system subject to constraints, although with substantial differences from the approach used in this paper. To identify a design that maximised social security, Ericson and Flood (2012) used microsimulation techniques to model the impacts of six possible broad designs for the Swedish tax system. Within each design, a number of tax system parameter values were used, resulting in the modelling of 80 different tax system designs. The authors assessed which of the 80 systems examined was optimal. Aaberge and Colombino (2013) undertook a similar style of analysis for the Norwegian system. They searched policy settings for four marginal tax rates, three income thresholds and a lump-sum transfer to find an ‘optimal’ income tax.

Our approach differs from earlier work in several ways. The main difference is that the time-intensive nature of existing approaches, means that they are limited to looking at only a relatively small number of policy options, for a tax policy that has a relatively simple structure (although the specific rules and their application in the tax system are complex). **The new approach enables us to deal with a much more complicated and multidimensional social protection system, and to consider a very large number of possible policy settings.** Simulation techniques are widely used in other areas of optimisation and operations research, for example, in areas such as traffic flows (Papageorgiou et al. 2009), public transport (Malandraki et al. 2015) and manufacturing (Salim et al. 2017).
A scalable framework
For social policy analysis
This section summarises the new methodology for optimising the social security system to achieve a particular outcome. A detailed description of the methodology and algorithm can be found in the CSRM working paper Optimal Policy Modelling: a microsimulation methodology for setting the Australian tax and transfer system (Phillips et al. 2018).

Context and conceptual framework

The social security system provides a safety net for individuals and families who otherwise would be at risk of poverty and social disadvantage. It provides this safety net through pensions, allowances, family tax benefits, childcare and other payments and supplements. Budgets are funded through general taxation. Social security payments or supplements (input variables) can be adjusted to achieve particular outcomes like reduced poverty rates, housing-stress rates or financial stress. Impacts can be simulated on household types, income levels, housing tenure or other variables (socioeconomic and demographic variables). The settings for the input variables are driven by objectives like reducing poverty within a set budget or expenditure constraint.

The conceptual framework of the methodology is shown in Figure 1 below.

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**Figure 1 - Conceptual Framework**
Methodology

The methodology involves altering social security payments (or other parameters) to achieve a policy objective such as reducing household poverty, financial stress or, in the case of this paper, housing stress. The methodology also accounts for the fact that these policy objectives need to be achieved within certain constraints, such as the overall social security budget or relationships between payment rates. The simulations are undertaken using PolicyMod.

Relative income poverty was chosen to illustrate the methodology for two reasons:

- Relative income poverty is widely used as an outcome measure for assessing how effectively social security systems are operating
- Relative poverty measures are straightforward to calculate and therefore provide a simpler starting point for testing this new methodology than some other measures.

The optimisation target, however, is the poverty gap rather than the rate. We believe that modelling the poverty ‘gap’, which is a continuous variable, rather than the ‘rate’, which is based on the binary poverty number, makes more sense conceptually and mathematically.

In theory, the problem of determining the rates of payment that result in the lowest poverty gap could be solved by running the microsimulation model repeatedly, while varying the payment rates. However, this approach is not practical, because the model would need to be run an enormous number of times, with different combinations of payment rates, and this would take an indeterminate amount of time. To overcome this problem, the CSRM developed a new methodology, which drastically reduces the number of simulations required. The methodology involves first creating a dataset, that relates different combinations of the rate of social security payments to the total poverty gap in Australia. It does this using a microsimulation model of the Australian tax and transfer system. In the version of the work reported in this paper, 2,500 combinations of the rate of social security payments are simulated. The relationship between payment rate and poverty gap is then estimated using a linear regression model. The model provides parameter values for an equation that describes how changes in payment rates affect the poverty gap.

This equation can be used to determine ‘optimal’ payment rates, subject to constraints such as a budget ceiling or changes from current payment levels.
Establishing statistical relationships between payment levels and the policy objective variable (poverty), significantly reduces the size of the problem. It does this by using standard mathematical programming techniques to optimise payment rates to achieve a particular objective. This approach means that it is not necessary to simulate a vast number of combinations of payment rates. The modelling in this paper optimises outcomes with respect to poverty. The social security system also has important impacts on work incentives (e.g. effective marginal tax rates), income inequality and horizontal equity. The results of our research should be taken with this limitation in mind. The methodology developed in this paper could be extended to optimise other criteria, such as effective marginal tax rates or measures of inequality. We intend to extend the work to a larger range of payments, payment parameters and policy objectives in the future.

Figure 2 below shows the high-level steps of the methodology, from the source data and microsimulation, to the optimisation and visualisation of results.
Modelling + Visualisation = New Insight
This section showcases the application of the methodology and tool, using the example of the Australian social security system. We draw on selected outputs of the simulation (i.e. charts) and describe possible settings and views to demonstrate the art of the possible, both in terms of analysing policy settings and potential impacts arising from varying input parameters. We describe how varying the input parameters using the data visualisation tools, can help to inform policymakers as they seek to understand how the interdependencies of the tax and social security redistribution system relate to social and economic outcomes. This leads to insight and guidance for policymakers, as they explore where resources may be reallocated to achieve better outcomes at an individual/household level, and for society at large.

A discovery-based approach, facilitated by microsimulation modelling, provides policymakers with a way of thinking beyond the detail of the administrative data within the tax and social security system. This approach shifts the modelling and insight focus to the population level. By going ‘above the clouds’, policymakers can rise above the day-to-day complexity and interdependencies within the income redistribution system. And by enabling policy-led solutions for addressing social and economic problems in volatile times, they can speed up the process of identifying possible options for innovation.

Administrative data is largely input- and output-focused (e.g. number of claims, beneficiaries and circumstances), while statistical-based population data is more representative of outcomes (e.g. where people/households are located living below the poverty line). Administrative data presents a known population, whereas population data provides insight into the known and unknown population. This is important when looking at refining eligibility and entitlement for social security programmes, as the target cohort is likely to be people at the margins of society.

Administrative data also carries an increased risk of inherent bias arising within previous and/or current policy settings. This could, for example, include long-term discrimination against women within the social security system: women’s working patterns are generally more impacted than men by raising children. The discovery approach at the population level, based on a limited set of high quality data points, is designed to rapidly guide policymakers to areas worth exploring in more detail, where they can then apply more traditional policy and evidence-gathering tools and methods.
This approach to policy targeting and impact analysis can help policymakers explore the impact, consequences and trade-offs required to achieve a given social outcome, such as an overall percentage reduction of people living in poverty across the population.

Policymakers may want to identify the location and household circumstances of potential winners/losers, for example, as they explore various scenarios based on the budget reallocation required to achieve a desired outcome.

This is achieved through analysis of the microsimulation modelling output. The output dataset contains the granular evidence derived from execution of the millions of permutations within the algorithm and the input data. The dataset, containing the results of the modelling, is brought to life through data visualisation tools, enabling the policymaker to test the impact of parameter changes through ‘what-if’ scenarios. In effect, the visualisation tool is displaying the results of the microsimulation, simulating the real-time operation of the microsimulation. In reality, the results are already within the dataset and these are dynamically accessed as parameters are varied through the visualisation tools.

Household poverty gap with optimised payment rates

The following chart (Figure 3) shows the results of optimising selected payment levels for annual budget expenditure. The range shown is from $20 billion less than current expenditure to $20 billion more than current expenditure. In this model, the base spend is $100 billion per year on a group of social programmes.

The analysis examines the poverty gap measured at a household level. The chart shows the change in the household poverty gap as the total programme spend is adjusted between 80% and 120% of current levels. For no change in the social programme budget (around $100 billion per year for a selected group of payments), the poverty gap could be reduced by around 7.7%. With an increase in the budget of $10 billion per year (+10%), the modelling shows a potential reduction in the poverty gap for households by 22.6%, if payment rates were adjusted to their poverty-minimising level.
A reduction in payments by 10% would lead to an increase in poverty of around 11.5%. A reduction in payments of around 5% could lead to an unchanged poverty gap, but only if optimal payment levels were in place. **These results suggest that poverty could be reduced significantly by adjusting existing payment rates without increasing total social programme expenditure.**

It is important to note that while the modelling shows that a significant impact can be made on the poverty gap by adjusting social programme spend, the poverty gap remains high even with large increases in the overall social programme budget.

**Figure 3 - Household poverty gap with optimised payment rates, by level of social security expenditure, 2018**

Note: The poverty gap is estimated using the equation summarising the relationship between payment rates and total poverty gap.

**Figure 3 - Household poverty gap**
Visualisation – an enriched picture of the modelling results

Data visualisation is the graphical representation of information and data. Through visual elements like bar charts and maps, data visualisation tools provide an accessible way for policymakers to identify and understand trends, and to uncover insights and discover new patterns from the modelling results.

For this illustrative modelling example, Tableau is used as the data visualisation tool. Figure 4 is a Microsimulation Summary Dashboard comprised of four charts:

01. Optimal payment level by poverty gap measure
02. Optimal payment levels compared with current payment levels by social security budget levels
03. Optimal social security payment spending share compared with current levels
04. Winner/loser analysis compared with current levels across households.

The policymaker can set different optimisation targets such as:

- **After-housing Poverty Gap**
- **Housing Stress Gap**
- **Household Poverty Gap**

In Figure 4 below, the budget is set to 0% change. It can be adjusted in 1% increments across the range of plus or minus 20% of the base or current spend.

Depending on the setting for optimisation targets and budget change, optimal values are calculated and displayed.

Several other settings are available, such as selecting and comparing specific social security payment types.
Policy Microsimulation Summary

Optimisation Target
Household Poverty Gap

Budget change % (Budget-neutral is $110 Billion)
0%

Welfare Payment Type (Click on type(s) to highlight in the chart)
- Age Pension
- Family Tax Benefit (0-13 years)
- Newstart Allowance
- Parenting Payment (Single)
- Rent Assistance

Navigate to below dashboards for detailed analysis:
- Distributional Analysis by Geographical Region
- Distributional Analysis by Household Type
- Distributional Analysis by Other Dimensions

Optimal payment level by poverty gap measure
Optimal payment levels ($): -7,022,361,091
Current payment levels ($): -5,788,896,152
Percent Change from Current: -17.6%

Towards the optimisation target is set for Household Poverty Gap and the Budget is set to 0% Budget Change (neutral). In this scenario we can see, for instance, the optimal payment level for Newstart Allowance is $821.40 which is $261.40 higher than the current rate of $560. The current Rent Assistance of $136 is $43.70 higher than the optimal Rent Assistance of $92.30.

Impact analysis (winners and losers) compared with current levels across households

Chart 2 in Figure 4 shows the optimal overall percentage share of household winners, losers and not-impacted households. In the illustrative scenario, including the optimisation target on achieving the optimal household poverty gap, 7.8% of the overall households receiving social security payments would be positioned better than before, 24.0% would be positioned worse than before and 68.2% would not be positioned differently compared to the current payments.

This analysis can give policymakers a good indication of how many households will be disadvantaged. This is an important measure for inclusion in their decisions on adjusting social security payments.
Regional-level analysis

Another important way to simulate, analyse and optimise social security payments, is to look at the distribution of social security payments by region. In Figure 5, we show this by comparing two states within Australia, looking for the distribution of winners and losers by state. The dataset also allows for region or sub-region level analysis. The optimisation target is set to Household Poverty Gap and Budget Change % is set to 0%, as in the example before.

Figure 5 - Regional level analysis dashboard

Charts 1 and 2 in the figure above show the comparison of two states within Australia: New South Wales (NSW) and Tasmania (TAS). Chart 2 shows the percentage share of households gaining, households losing and those which will experience no change to social security payments, after calculating the optimal payment levels to optimise the household poverty gap.

In this illustrative scenario, NSW has 20% losers in the capital city (28% rest of state) and Tasmania has 31% losers in the capital city (33% rest of state). This illustrative analysis, for instance, highlights that the capital city of Tasmania has 11% more disadvantaged households than the capital city of NSW. This could be used as important evidence for supporting a targeted policy intervention in Tasmania.
Distributional household type analysis

An additional lens for the modelling data is to look at households according to their type: couple only, couple with children, single parent and other – Figure 6.

Figure 6 - Household analysis dashboard

Chart 1 shows the optimal and current average poverty gap for each household type. The visualisation highlights that the household poverty gap across each household type can be improved. Chart 2 above shows the percentage share of winners, losers and households with no change, after calculating the optimal payment levels to optimise the household poverty gap.

This illustrative analysis could be used as evidence for supporting targeted policy interventions by household type.
Distributional analysis for other variables

The analysis can be expanded to address other variables such as age of head of household, income quintile, main source of income or wealth quintile. Figure 7 below is an example using income quintile (bottom 20% of income, next 20% up to top 20%).

Changing the model - COVID-19 analysis

International Social Security Association first coined the term ‘dynamic social security’ in recognition of the fact that policymakers needed to respond quicker to changing social, economic and environmental conditions (McKinnon 2007). The need for more dynamic approaches to policy analysis and policy change has never been more acute than during the COVID-19 pandemic. The social security system is one of the prime levers for governments to ameliorate the economic and social impacts of the health crisis.

The Australian Government, like most governments around the world, has responded quickly during COVID-19 with both structural- and parametric-level policy changes. As a further illustration of the OPM, the ANU research team have updated the models in line with the new JobSeeker and JobKeeper programmes. A sample set of visualisations was also developed.

The JobKeeper scheme is a temporary subsidy paid to businesses whose revenues have been significantly affected by...
government-imposed lockdowns during the pandemic. Eligible employers receive a fixed payment that must be passed through in full to each eligible employee, irrespective of the hours that employee has worked.

The JobSeeker payment replaces the traditional unemployment programme (Newstart). The traditional unemployment payment was effectively doubled through a supplement. This approach is intended both to stimulate the economy and ensure social stability.

The JobSeeker and JobKeeper programmes are under constant review as both the health and economic status of the country changes. Given the nature of the crisis and the speed at which policy changes need to be made, OPM is an ideal approach to model the potential impact on certain social variables such as poverty levels.

Using the optimisation policy modelling methodology, CSRM researchers showed the pre-COVID-19 social security system would not have been able to adequately respond to the huge negative economic shock generated by COVID-19 and associated job loss. The research found that poverty rates and housing stress are lower than they otherwise would have been in the absence of policy change such as JobKeeper. However, they concluded there were somewhat different settings that could reduce these rates even further, without increasing the budget deficit (Phillips et al. 2020). It is this ability to model these different settings through the visualisation platform and dashboard that provides new insights leading to improved policy agility capability.

Figure 8 is an example of an updated dashboard based on the updated modelling by the CSRM of the impact of the JobKeeper and JobSeeker programmes for one scenario: JobKeeper/JobSeeker with improved economic situation (JobKeeper and JobSeeker (new recipients) numbers halved).

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**Policy Microsimulation Summary**

<table>
<thead>
<tr>
<th>Optimisation Target</th>
<th>Budget change %</th>
<th>Welfare Payment Type</th>
<th>Optimal payment level by poverty gap measure</th>
<th>Optimal welfare payment spending share compared with current levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Housing Stress Gap</td>
<td>10%</td>
<td>Age Pension</td>
<td>Current: 983</td>
<td>Current: 50.6B, Optimal: 34.0B, % change: -2.9%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>CRA</td>
<td>Current: 1,583</td>
<td>Current: 38.9B, Optimal: 27%, % change: -19.4%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>FTB Part A 0-13yo</td>
<td>Current: 2,830</td>
<td>Current: 219, Optimal: 32%, % change: -0.1%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Jobkeeper</td>
<td>Current: 4,391</td>
<td>Current: 1,200, Optimal: 27%, % change: -23.8%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Parenting Paym.</td>
<td>Current: 1,250</td>
<td>Current: 250, Optimal: 5%, % change: -23.8%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Other Pens.</td>
<td>Current: 798</td>
<td>Current: 798, Optimal: 5%, % change: -23.8%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Jobkeeper</td>
<td>Current: 943</td>
<td>Current: 943, Optimal: 20%, % change: 0%</td>
</tr>
</tbody>
</table>

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**Figure 8**

Winner loser analysis compared with current levels across households

- Winner: 24.2% / Loser: 36.2% / No Change: 39.6%
Agility
In today’s time
Our ambition is that this novel approach, involving both the underlying models and related tools, should provide a vital evidence base and support for policymakers around the world. We believe that this approach is especially valuable in these difficult times. The approach is not meant to be a prescriptive or deterministic, nor is it designed to provide a single ‘right’ answer. Instead, it should provide policymakers with new insights from the set-up of ‘what if’ scenarios, with a view to compressing the time-horizons within which policy is analysed, designed and implemented. At the same time, data and insights generated from the toolset would enable the policymaker to understand the levers at their disposal and make agile course corrections as needed.

It must be noted that while we have looked at the poverty gap in this initial phase, the approach can be adapted to a range of outcomes, including effective marginal tax rates, measures of inequality, employment vulnerability and/or risk of exclusion. We are keen to extend the work to a larger range of payment parameters and policy objectives in the future. Our assumption is that **the approach is scalable to other international settings and policy contexts, including the state or provincial level**, as well as to analyse a specific area of social risk. It is important to note the modelling outcomes are a function of the structure of the social security and tax systems. The modelling outcomes in other jurisdictions will therefore vary from the illustrative Australian scenario. We intend to test the validity and efficacy of the model in these new settings, as part of the next phase of work.

Microsimulation modelling is pervasive in the analysis of social security and tax systems across the world, and several countries have established a strong scientific basis for this work. However, what is fundamentally different in our approach is the ability for the policymaker to have a wider aperture, do more complex, multidimensional analysis (across both payment and outcome variables), employ simulation and visualisation tools to discover and abstract policy intent, and use parametric evaluation techniques applied to population data (removing biases), to determine the impact of different payment rates on individual and household outcomes.

Many countries have rightly stepped in with sweeping measures to contain economic, social and labour market disruption. Policymakers in those countries, particularly those entrusted with social security payments, wage subsidies/furlough and business support schemes, find themselves navigating the unknown.
Social policy design and implementation is a daunting exercise in a stable economic and political environment, especially when conducted against the backdrop of a diverse socio-demographic population. The same exercise becomes exponentially more complex when navigating an unprecedented global pandemic.

Policymaking in social services will always entail a mix of artistry (empathy and social justice) and science (fiscal and measurable outcomes). It requires a sensitivity to public and economic sentiment, involves making trade-offs and exercising judgment. Our work doesn’t take any of that away. But it does aim to bring rigour and rationality to the choices that need to be made and its work that brings us a step closer to near-real time and agile policy design. Much more still needs to be done to achieve that goal, but we are excited by the prospects.
This research collaboration, conducted during the first half of 2020, has demonstrated the potential for the commercial application of optimal policy modelling within government and related entities’ policymaking environments. Commercialisation is made possible through Accenture’s applied intelligence capability. Transferring the modelling platform to open source technology has provided the flexibility and scalability required for reconfiguring the base algorithm to suit different social systems and data sources. By adding a data visualisation capability, policymakers have access to dashboard-based analysis methods for gaining insights from the microsimulation output.

Accenture has already started exploring how the optimal policy modelling tool will translate to other contexts. And the company is working with social services industry practitioners operating in countries/regions including France, New Zealand, the Nordics, North America, the United Kingdom and Singapore. This has generated considerable interest and has been a driving force in developing this paper and reporting on the progress of the ANU/Accenture collaboration effort. Further research and redevelopment will be guided during the second half of 2020, on the basis of commercialisation interest from countries/regions.
References


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1 The term social security has alternate meanings in different countries. For this paper it is used in a descriptive context for income support programmes which may be tax or social insurance contribution funded. In some countries, terms such as social services, social protection and/or welfare may be used.

2 For additional information on evidence based decision making, refer Centre for evidence-based management https://cebma.org/

3 While valid statistical data has been used for this illustrative modelling, it is point in time dependent. Any results or conclusions described, are subject to change. The intent is to demonstrate the outputs of the modelling process rather than seeking to derive or publish results or conclusions.

4 https://www.tableau.com/
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