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Searching for a just transition: Micro-level employment impacts of climate policies

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ABSTRACT

We develop and apply a modelling framework to estimate the micro-level employment impacts of climate policies in Aotearoa New Zealand. Our approach links an economy-wide model with a micro simulation module to calculate employment changes for different groups of the population across several dimensions (and combinations of dimensions), including sectoral, geospatial, demographic, and socio-economic categories. By simulating the linked modelling framework out to 2050 for proposed climate policies, we estimate which industries, workers, and jobs are expected to be most affected by these policies. Industries that experience the largest negative employment impacts include coal mining, oil and gas extraction, and some manufacturing activities. Reflecting the deployment of labour-intensive abatement options, some agriculture industries experience the largest employment increases. Workers that incur a disproportionate share of the transition are older, have lower levels of education, or are Māori. Employment transitions are also concentrated in certain regions. The results and modelling tools can help the New Zealand government formulate policies to ensure a 'just transition' to a low carbon future.

1. Introduction

As countries develop and implement policies to combat climate change, there has been demand for a parallel framework to protect the livelihoods of workers. The International Labour Organization (ILO) states that a 'just transition' towards environmentally sustainable economies should 'promote the creation of more decent jobs, including as appropriate: anticipating impacts on employment, adequate and sustainable social protection for job losses and displacement, skills development and social dialogue' (ILO, 2015, p. 6).

Early concerns for worker outcomes when curbing greenhouse gases (GHGs) were expressed in the Paris Agreement (UNFCCC, 2015) preamble, which urged parties 'to promote a just transition of the workforce and the creation of decent work and quality jobs'. Subsequently, at the 24th Conference of the Parties (COP24) of the United Nations Framework Convention on Climate Change (UNFCCC) in 2018, over 50 countries signed the Solidarity and Just Transition Silesia Declaration. The Declaration encouraged nations to consider 'the issue of just transition of the workforce and the creation of decent work and quality jobs' when 'developing long-term low greenhouse gas emission development strategies' (UNFCCC, 2018, p. 9). It also stressed that a 'just transition' was needed to enhance public support for achieving the goals of the Paris Agreement. In 2021, at the 26th Conference of the Parties (COP26), the Just Transition Pledge (UNFCCC, 2021) was adopted by the 27 European Union member states, Canada, New Zealand, Norway, United States (US), and United Kingdom (UK). The Pledge recognized that reducing emissions risks exacerbating gender, racial, age and other inequalities, advocated the need to support workers in the transition to new jobs, and required countries to include information on 'just transition' efforts in national Biennial Transparency Reports.

Employment is a core element for the 'just transition' movement, but individuals may also experience different outcomes from climate policies due to higher prices for carbon-intensive products, changes in relative factor returns, the allocation of revenue from carbon pricing, temporary effects during the transition (e.g., reallocation and retraining), and heterogeneous benefits from environmental improvements Fullerton (2011). Households may also differ in their ability to adjust to climate policies (Vona, 2023).

A body of research has examined the distributional impacts of climate policies using computable general equilibrium (CGE) models. Most of these studies focus on how climate policies impact factor prices and transfer payments (source-side effects), and/or the prices of goods

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and services that households buy (use-side effects). In early work, Fullerton and Heutel (2007) use a two-sector general equilibrium model to show how a pollution tax affects wages and returns to capital for alternative factor intensities and elasticities of substitution between capital and labour.

More applied studies augment CGE models using household micro-data on expenditure patterns and income sources. Static CGE modelling of the US with detailed representation of heterogenous households has shown that carbon pricing has regressive use-side effects that are more than offset by progressive source-side effects (Rausch et al., 2011; Goulder et al., 2019). These studies also find that using the tax revenue to lower income taxes improves efficiency but is regressive. US-focused studies also find that recycling carbon price revenue via household rebates has more progressive welfare impacts than recycling options that aim to improve efficiency, such as payroll taxes (Rausch et al., 2011; García-Muros et al., 2022).

For the EU, Landis et al. (2021) develop a CGE model that represents multiple households based on income deciles. They find that carbon pricing policies have progressive impacts on household utility in most countries, and that per-capita-based revenue redistribution rules generate large income gains for low-income households in all countries.

At the world level, Chepeliev et al. (2021) use a global economy-wide model linked to a micro simulation model to estimate the poverty and distributional impacts of Nationally Determined Contribution (NDC) goals under alternative carbon pricing scenarios. The authors find that, at the global level, meeting NDC emissions targets is progressive as it lowers the relative price of food and decreases skill wage premiums.

A handful of general equilibrium studies have focused on employment changes due to climate policy. Hafstead and Williams III (2019) estimate employment effects by industry using a static CGE model of the US with search-based unemployment. They find that short-run (less than 18 months) differences in unemployment rates (including size and duration) between the policy and the business-as-usual scenarios largely depend on two things: (1) the ease with which workers could change industries, and (2) the magnitude of reallocation across industries caused by environmental policies. Castellanos and Heutel (2024) use a similar framework and explore the impacts of alternative cross-industry labour mobility assumptions. When simulating a carbon tax, they find that alternative cross-industry labour mobility assumptions have small effects on aggregate unemployment, but large effects on sectoral employment.

Weitzel et al. (2023) use an economy-wide model to assess 2030 climate targets specified in the EU Green Deal. They downscale aggregate employment impacts from the CGE model to estimate outcomes by occupation and skill type (as measured by highest qualification). They find that employment changes for low-skilled workers are more favourable than those for workers with higher skills. This is because climate policies increase output of both the construction (for investment) and agriculture (for biomass) sectors, and these sectors use low-skilled workers relatively intensively.

Another strand of literature examines the impacts of environmental policies on employment outcomes using ex-post empirical studies. Marin and Vona (2019) investigate the link between climate policies, proxied by changes in energy prices, and employment by occupation for 14 European countries and 15 industrial sectors between 1995 and 2011. They find that in response to rising energy prices, firms substituted technicians for manual workers. In a related study, Marin and Vona (2021) find that French manufacturing establishments responded to rising energy prices between 1997 and 2015 by increasing capital to labour ratios. The authors also conclude that there was not a clear long-term shift in labour demand from manual workers towards technicians.

Vona et al. (2018) examine the employment impacts of more stringent standards for four criteria pollutants in the US over the period 2006 to 2014. They find that although more stringent environmental regulations do not affect overall employment, they increase the demand for technical and engineering green skills. Popp et al. (2021) estimate the employment impacts of green investments in the American Recovery and Reinvestment Act (ARRA). A key finding from their analysis is that green ARRA investments created many jobs in construction and waste management and ultimately increased the employment of manual workers.

In this paper, we link a CGE model to a micro simulation module to estimate climate policy induced employment changes for different groups of the population in Aotearoa New Zealand, a signatory to the Just Transition Pledge. The modelling framework allows us to estimate employment outcomes across several dimensions, including sectoral, geospatial, demographic, and socio-economic categories.

Our study augments the existing literature in two ways. First, it simulates proposed policies out to 2050. As such, the study provides policy-specific calculations to complement insights from studies that estimate relationships between proxies for climate policy and employment (Vona et al., 2029; Marin and Vona, 2021), or simulate hypothetical carbon prices on historical representations of the economy (Hafstead and Williams III, 2019; Castellanos and Heutel, 2024). Weitzel et al. (2023) also simulate proposed policies, but our analysis has more granularity on worker types and considers a country with a different emissions profile. Second, whereas most studies of the employment effects of climate policies consider the US or countries in the EU, we focus on New Zealand. As agriculture accounts for 51 % of New Zealand's gross greenhouse gas (GHG) emissions (MfE, 2019a), climate policies will have different employment impacts than in other developed countries.[1]

In estimating detailed employment impacts, several simplifications are made in other areas. Notably, we do not consider other distributional impacts associated with climate policies, including the welfare cost to workers from transitioning to new jobs, which may involve relocating or spells of unemployment. Nevertheless, our analysis can identify the types of workers likely to experience relatively high job turnover and inform policy responses to help those workers transition to new jobs. Potential future research to address limitations in this study is discussed in the concluding section.

This paper has three further sections. Section 2 outlines our modelling framework. Section 3 presents and discusses the results. Concluding remarks and suggestions for further research are offered in Section 4.

2. Modelling framework

Our analysis uses the Climate PoLicy Analysis (C-PLAN) model (Winchester and White, 2022) to estimate the aggregate and broad sectoral impacts of climate policy, and the Distributional Impacts Microsimulation for Employment (DIM-E) module (Riggs and Mitchell, 2021a, 2021b) to calculate employment impacts for workers with different characteristics. The two models are linked by mapping employment changes in the 38 sectors in the C-PLAN model to the 213 three-digit industries represented in the 2006 Australia and New Zealand Standard Industrial Classification (ANZSIC) (Trewin and Pink, 2006).

As the C-PLAN model assumes full employment, job losses in one sector are offset by gains in other sectors. Support for a full-employment assumption includes (1) CGE models with full-employment producing similar industry-level employment estimates to CGE models with unemployment and search functions (Hafstead et al., 2018); (2) the finding that the effect of environmental policies on overall employment is small (Vona et al., 2018; Hafstead and Williams, 2020); and (3) that pre-

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[1] The modelling tools developed in this research are open source and available from the (New Zealand) Climate Change Commission (CCC) under a creative commons licence. They can be obtained by contacting the CCC via their web site: https://www.climatecommission.govt.nz/.

announcing and phasing in policies can substantially reduce short-term labour market effects (Hafstead and Williams III, 2020). In this connection, climate policies evaluated in this study were signaled or already operating prior to 2022 (e.g., the New Zealand Emissions Trading Scheme has been operating since 2008). Consequently, employment changes may be met by replacing retiring workers with young workers with different skills.

2.1. The CLimate policy analysis (C-PLAN) model

The C-PLAN model is a global computable general equilibrium (CGE) model built for the analysis of New Zealand climate policies. In its base configuration, the model represents two regions (New Zealand and the Rest of the World), 38 production sectors (see Table 1), and three sources of final demand (household consumption, government expenditure, and investment).[2] In addition to the conventional sectors listed in Table 1, the model represents several advanced technologies: electric road transport, electric household transport, dairy farming, and beef and sheep farming with reduced methane emissions, bioheat, electric heat, and geothermal electricity with carbon capture and storage (CCS). Each advanced technology produces a perfect substitute for a conventional output or a conventional input. For example, electric road transport produces a perfect substitute for conventional road transport, and bioheat produces a perfect substitute for the coal-gas aggregate used in certain sectors. Following Morris et al. (2019), advanced technologies require inputs of technology specific factors (TSFs). Endowments of TSFs are assigned in each period to reflect deployment, resource, and/or market penetration constraints. In the absence of carbon prices, advanced technologies are (at least initially) more costly than the corresponding conventional technologies, so their deployment implies an economic cost in the model.

Table 1
Sectors represented in the C-PLAN model.

Agriculture, forestry, and fishing		Manufacturing	
rmk	Dairy farming	crp	Chemical, rubber, and plastic products
b_s	Beef and sheep farming	nmm	Non-metallic minerals (e.g., cement)
oap	Other animal products	nfm	Non-ferrous metals (e.g., aluminum)
hor	Horticulture	i_s	Iron and steel
frs	Forestry	fmp	Fabricated metal products
fsh	Fishing	mil	Dairy processing
		mtp	Meat products
Energy extraction, production & distribution		ofd	Other food products
col	Coal mining	w_p	Wood and paper products
cru	Crude oil extraction	mvh	Motor vehicles and parts
oil	Refined oil products	omf	Other manufacturing
gas	Natural gas extraction and distribution		
oxt	Other mining	**Construction and services**	
ecoa	Coal electricity	cns	Construction
egas	Gas electricity	afs	Accommodation and food services
enuc	Nuclear electricity*	ser	Other services
ehyd	Hydro electricity		
ew_s	Wind and solar electricity	**Commercial transport**	
eoth	Geothermal and other electricity	rtp	Road transport
tnd	Electricity transmission and distribution	wtp	Water transport – domestic
		wtpi	Water transport – international
		atp	Air transport – domestic
		atpi	Air transport – international
		Household transport	
		hht	Household transport

Note: * Nuclear electricity is only represented in the Rest of the World.

Production functions used for conventional and new technologies in the C-PLAN model are described in Winchester and White (2022). Values for elasticities of substitution between inputs in these functions are guided by those used in the Massachusetts Institute of Technology Economic Projection and Policy Analysis (MIT-EPPA) model (Chen et al., 2016, 2022), which are informed by a literature review of econometric estimates. The elasticity of substitution between energy and a capital-labour aggregate is 0.6 in all sectors. As the scope for abating emissions via energy efficiency improvements depends on this elasticity value and sectoral cost shares, opportunities for this abatement option vary across sectors. Values for other elasticity parameters in the model are set out in Winchester and White, (2022, Table 4, p. 12).

For each production and expenditure activity, the model tracks four GHGs (carbon dioxide, CO_2; methane, CH_4; nitrous oxide, N_2O; and aggregated fluorinated gases, F-gases) measured in tonnes of CO_2-equivalent (CO_2e) units. The C-PLAN model also represents land-use change, and emissions sequestration from afforestation. The model is recursive dynamic and is solved annually from 2014 to 2050. For each year and scenario, the equilibrium solution in the model projects, among other variables, production, employment, GHG emissions, imports and exports for each sector. The C-PLAN model is described in detail by Winchester and White (2022).

Calibration of the model in the benchmark year (2014) uses economic data from Version 10 of the Global Trade Analysis Project (GTAP) Power Database (Peters, 2016; Chepeliev, 2020), and GHG emissions data from New Zealand's GHG Inventory 1990–2017 (MfE, 2019a).[3] The C-PLAN model is coded using the Mathematical Programming Subsystem for General Equilibrium (MPSGE) (Rutherford, 1999), a subsystem of the Generalized Algebraic Modelling System (GAMS, 2021), and utilizes data aggregation tools provided by Lanz and Rutherford (2016).

2.2. Linking C-PLAN and DIM-E

The C-PLAN model estimates employment indexes for 38 sectors and the DIM-E module categorizes production according to 213 ANZSIC three-digit industries. C-PLAN sectors are built on sectors in the GTAP Database and there is not a concordance between GTAP and ANZSIC sectors. Consequently, sectoral results from the C-PLAN model are first downscaled using a concordance from GTAP to International Standard Industrial Classification (ISIC) sectors (Center for Global Trade Analysis, 2019), and then a concordance from ISIC sectors to ANZSIC 3-digit groups (Australian Bureau of Statistics, 2008).

Table 2 provides examples of the three types of mappings from C-PLAN sectors to ANZSIC 3-digit industries in the downscaling procedure.[4] One-to-one and one-to-many mappings are used for 207 of the 213 ANSIC industries. In these mappings, the proportional employment change in a C-PLAN sector is assigned to all ANZSIC groups that correspond to that sector. For example, the proportional employment change in the C-PLAN horticulture sector is assigned to three ANZSIC industries: nursery and floriculture production (011), mushroom and vegetable growing (012), and fruit and tree nut growing (013). A potential issue with one-to-many mapping is that proportional employment changes

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[2] To represent resource constraints and regulations not specifically considered in the model, output is capped in some sectors. Sectors for which output is constrained include fishing, water transport, and non-ferrous metals.

[3] The air transport and water transport sectors in the GTAP Database include both domestic and international activities. In calibrating the C-PLAN model, each transport sector is split into domestic and international components using data on emissions shares MfE (2019a, 2019b).

[4] See Riggs and Mitchell (2021a, Appendix A) for the mapping from C-PLAN sectors to ANZSIC06 3-digit codes.

Table 2
Selected mappings from C-PLAN sectors to ANZSIC groups.

Mapping type	C-PLAN sector(s)	ANZSIC 3-digit group(s)
One-to-one	mil Dairy processing	013 Dairy Product Manufacturing
One-to-many	hor Horticulture	011 Nursery and floriculture production 012 Mushroom and vegetable growing 013 Fruit and tree nut growing
Many-to-one	cru Crude oil extraction gas Natural gas extraction and distribution	070 Oil and gas extraction

are the same in the constituent ANZSIC industries. One-to-many mapping is most prolific for the services sectors, which maps to 106 ANZSIC 3-digit industries. Other manufacturing, which maps to the second most groups, maps to 14 ANZSIC industries. On average, other C-PLAN sectors each map to fewer than three ANZSIC industries.

Six ANZSIC 3-digit groups map to more than one C-PLAN sector. In these cases, the proportional employment change in each ANZSIC group is calculated as an employment-weighted average of employment changes in the corresponding C-PLAN sectors. For example, employment changes for the ANZIC group oil and gas extraction (070) are employment-weighted averages of changes in the crude oil and natural gas extraction and distribution in the C-PLAN model.

As the C-PLAN model only represents one labour type, our framework allows us to examine outcomes for workers from changes in employment between sectors, but it does not capture changes in within-sector employment (e.g., a sector increasing its demand for skilled labour and decreasing its demand for unskilled workers). Empirical studies suggest that increases in energy prices in Europe (Marin and Vona, 2019, 2021) and environmental regulations in the US (Vona et al., 2018) resulted in shifts in labour demand that differed across occupations/skill groups. There is some evidence that these changes favoured technicians at the expense of manual workers (Maron and Vona, 2019; Vona et al., 2018), but Marin and Vona (2021, p. 3) conclude that 'the bias in favour of technicians and against manual workers does not clearly emerge' in the long run. In a forward-looking study, Tamba et al. (2022) estimate that the production of more electric vehicles (and fewer internal combustion engine vehicles) in the EU will increase demand for skilled workers in the automobile manufacturing industry. Establishing the impact of climate policies on within-sector employment in New Zealand – a nation with a different emissions profile and economic structure compared to other developed countries and without an automobile manufacturing industry – warrants further investigation but is not considered in this paper.

2.3. The distributional impacts microsimulation for employment (DIM-E) module

The DIM-E module consists of two components: the first component estimates industry-level employment effects, and the second simulates the characteristics of impacted workers and jobs. The module is described in detail in Riggs and Mitchell (2021b).

The DIM-E module uses data sourced from Statistics New Zealand's Integrated Data Infrastructure (IDI) and Longitudinal Business Database (LBD). These data include population-wide, administrative, census, and survey data for people and businesses. Each individual person or entity is given a unique identification number which allows them to be linked across different data sets. This allows us to observe enterprise-level (the tax-reporting legal entity) and establishment-level (geographic units such as retail shops or warehouses) information related to the business(es) for which an individual works as well as information about the employees themselves (e.g., age, gender, ethnicity). This employer-employee matched dataset, therefore, includes detailed information on workers in all industries, which would not be possible using information from the New Zealand Household Labour Force Survey.

The unit of observation in the dataset is a worker-job, which is the employment relationship between a worker and a single enterprise. Each worker-job is assigned to an establishment, and the industry and region for each worker-job is based on the establishment's industry and region.

Using linked employer-employee data, we calculate the number of worker-jobs in each ANZSIC three-digit industry in 2014 (the benchmark year for our analysis). For each worker-job, we also observe the following worker-job characteristics: gender, ethnicity, age, highest qualification attained (no qualification, secondary, post-secondary, bachelor's, post-graduate), earnings from wages and salaries, region of employment (for 15 geographical areas), and level of effort (measured in full-time equivalent, FTE, units). As worker characteristics typically differ for short spell worker-jobs (a worker-job relationship of fewer than three months) compared to other worker-jobs in the same industry, we also identify whether each worker-job was a short spell or a non-short spell worker-job. The DIM-E module estimates employment in terms of worker-jobs in each industry by multiplying the employment indexes (downscaled from C-PLAN sectors to ANZSIC three-digit industries) by base-year worker-jobs in each industry. As the mix of full-time and part-time workers varies across industries in the DIM-E module, the number of jobs in the economy can change even though the number of FTE workers remains constant.

The DIM-E module also estimates changes in employment by worker characteristics (gender, age, highest qualification, ethnicity, average earnings, and region of employment). In the baseline scenario, worker characteristics in each industry are assumed to move in fixed proportions with industry employment.[5] In the policy scenario, the types of worker-jobs that leave contracting industries (or are added to expanding industries) are estimated, using a two-level simulation procedure. First, the DIM-E module simulates if each worker-job lost (or added) was a short-spell or non-short-spell worker-job. Second, for each type of worker-job, the characteristics of each lost (or added) worker-job are determined using a series of simulations (one for each characteristic) using the Mersenne-Twister random number generator (Matsumoto and Nishimura, 1998) and an appropriate distribution for each characteristic. As an example, suppose that 100 worker-jobs are lost in coal mining in the policy scenario relative to the baseline in 2025. The DIM-E module first determines whether each worker-job lost was a short-spell or non-short-spell employee based on a random draw from a Bernoulli distribution with a mean equal to the proportion of short-spell jobs in coal mining. The age group (15–24, 25–34, 35–44, 45–54, 55–64, 65+) of each displaced worker is then determined using a similar process, with the random assignment based on the proportion of workers in each age group. The simulation is run separately for short-spell and non-short-spell workers to account for different age distributions for the two types of workers. The simulations are repeated 1000 times, and the means of those simulations are used to calculate the number of displaced workers by age group. The same process is used for each worker characteristic and for all affected worker-jobs in each industry. See Riggs and Mitchell (2021b) for further details.

2.4. Scenarios

To evaluate the impact of climate policies, we simulate the modelling framework for the 'baseline' and 'policy' scenarios considered by Winchester and White (2022). The baseline scenario simulates current policies, business as usual changes in technology and socioeconomic

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[5] In this approach, the share of workers with each characteristic is constant over time. A more sophisticated approach would adjust employee characteristics in each industry using forecasts of changes in population characteristics.

drivers, and resource and regulatory constraints that limit the expansion of certain sectors. In the policy scenario, we simulate two Emissions Trading Schemes (ETSs) that begin in 2022 and impose caps on GHG emissions consistent with the Climate Change Response (Zero Carbon) Amendment Act 2019 (New Zealand Government, 2019). One ETS in the model only includes biogenic methane emissions. The cap on these emissions is gradually lowered over time so that they are 24 % below their 2017 level in 2050. All other GHG emissions, except emissions from international transportation, are included in the other ETS. The cap on these emissions is reduced over time so that net emissions (gross emissions minus emissions sequestered by forests) are zero in 2050. The impacts of the climate policy are evaluated by comparing results from the policy scenario to those from the baseline scenario.

3. Results and discussion

Winchester and White (2022) discuss the economy-wide impacts of the ETS policies in detail. In this section, we briefly summarize the results from the C-PLAN model (Section 3.1) and focus on the impacts of the policies on workers simulated by the DIM-E module (Section 3.2).

3.1. Economy-wide impacts

Economy-wide results are presented in Table 3. Reflecting advances in technologies for reducing biogenic methane emissions, the ETS price for these emissions, in 2017 New Zealand dollars, falls from \$115 per tCO_2e in 2035 to \$53 in 2050. In contrast, driven by the tightening of the emissions cap, the ETS price on other GHGs rises consistently over time and reaches \$338/tCO_2e in 2050. In 2050, GDP in the Policy scenario is 0.34 % lower than in the baseline, and welfare, measured using the Hicksian equivalent variation in income, is 0.26 % lower. The macroeconomic costs of the emissions targets are relatively modest. This is driven by projected technology developments and other policies reducing GHG emissions over time in the baseline. Ultimately, this means that 2050 emissions reductions in the policy scenario relative to the baseline are moderate (13 % for biogenic methane and 30 % for other GHGs). The carbon price on other GHGs is ten times higher in the policy scenario than in the baseline, but this price applies to less than half of total GHG emissions and a relatively small proportion of the economy.[6]

Table 3
Summary results for 2035 and 2050.

	2015	2035		2050	
		Baseline	Policy	Baseline	Policy
CO2 prices, 2017\$/tCO_2e					
Biogenic methane ETS	–	35.00	114.68	35.00	53.44
Other GHGs ETS	3.37	35.00	120.81	35.00	337.79
GDP and welfare					
GDP, billion 2017\$	252.0	396.0	395.4	512.1	510.4
Consumer welfare, billion 2017\$	120.7	190.4	190.2	247.0	246.3

Source: Winchester and White (2022).

Table 4
Percentage changes in employment by C-PLAN sector between 2022 and 2050 in the policy scenario relative to the baseline.

Sector	% change	Sector	% change
Dairy farming	2.29	Chemical, rubber, and plastics	0.30
Beef and sheep farming	4.16	Non-metallic minerals	2.24
Other animal products	2.42	Non-ferrous metals	0.85
Horticulture	0.52	Iron and steel	2.64
Forestry	2.84	Fabricated metal products	−2.33
Fishing	9.24	Dairy processing	0.74
Coal mining	−15.36	Meat products	0.41
Crude oil extraction	−27.06	Other food products	0.76
Natural gas extraction and dist.	−26.10	Wood and paper products	−3.00
Other mining	6.67	Motor vehicles and parts	2.51
Refined oil products	−7.77	Other manufacturing	−4.66
Coal electricity	–	Road transport	−2.03
Gas electricity	0.04	Water transport	11.78
Hydro electricity	0.50	Air transport	10.38
Wind and solar electricity	21.71	Construction	0.17
Geothermal and other electricity	−0.01	Accommodation and food	0.53
Electricity transmission and dist.	0.17	Other services	0.15

Proportional changes in employment by C-PLAN sector between 2022 and 2050 in the policy scenario relative to the baseline are displayed in Table 4.[7] In the policy scenario, employment is impacted through at least four channels. First, it increases the relative cost/price of emissions-intensive supply chains and ultimately reduces output and employment in these sectors. Consequently, sectors that experience the largest proportional decreases in employment in the policy scenario relative to the baseline are crude oil extraction (27.1 %), and natural gas extraction and distribution (27.1 %).

Second, the policy scenario increases employment by encouraging producers to substitute away from energy inputs and towards capital and labour inputs. This impact channel is most prominent in sectors that are output constrained (to represent resource constraints and regulations). As a result, the largest proportional employment increases are in water transport (11.8 %) and fishing (9.2 %).

Third, sectoral employment is influenced by the deployment of new technologies with different sectoral labour intensities than the conventional techniques that they replace. This impact drives employment increases in sheep and beef farming (4.2 %), and dairy farming (2.3 %) as additional workers are required to reduce methane from these activities (e.g., to administer methane vaccines to livestock).

Fourth, it increases employment in wind and solar electricity generation as the output of this sector expands. As noted in Section 2.2, employment changes in C-PLAN sectors drive employment changes in the DIM-E module, which are discussed in the next section.

3.2. Distributional impacts

As noted above, we map employment changes for C-PLAN sectors to ANZSIC three-digit industries and use the DIM-E module to assess the

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[6] The estimated macroeconomic costs are comparable to those estimated by Weitzel et al. (2023) to meet ambitious climate targets in the EU. These authors also project declining baseline emissions and estimate that the cost of reducing EU emissions by 55 % below 1990 levels in 2030 using carbon pricing reduces GDP by about 0.25 %.

[7] Employment changes in Table 4 are calculated using the following equation for each sector: *100 × [(employment change between 2050 and 2022 in the policy scenario) – (employment change between 2050 and 2022 in the baseline scenario)]/(employment in 2022 in the baseline scenario).*

impact of the climate policies on employment. Employment is measured in worker-jobs (where, as noted above, a worker-job is an employment relationship between a worker and a single enterprise in the base year). To focus on long-term impacts, we evaluate employment changes between 2022 and 2050.

To compute employment changes due to climate policies, we first calculate year-on-year changes in employment by characteristic (e.g., industry, or level of education) in each scenario. For each year, the change in employment due to climate policies is then calculated as the year-on-year employment change in the policy scenario minus the year-on-year change in the baseline scenario. For example, if employment of iron and steel workers increases by 200 workers between 2030 and 2031 in the baseline scenario, and by 150 workers in the policy scenario, climate policies will decrease employment in the iron and steel industry by 50 workers.

As employment for a particular characteristic can increase in some years and decrease in other years relative to the baseline, we consider (1) total employment gains; (2) total employment losses, (3) total net changes in employment, and (4) total affected workers during the period 2022 to 2050. Total employment gains are calculated by adding only positive annual employment changes, while total employment losses are the sum of only negative annual employment changes. Net employment changes between 2022 and 2050 equal total employment gains minus total employment losses.

Total affected worker-jobs are computed by adding total employment gains and total employment losses. This allows us to identify worker characteristics that are expected to experience substantial transitions due to the policies. Evaluating total affected workers is pertinent for ensuring a 'just transition': while certain groups of workers may not be negatively affected by climate policies in terms of total available jobs, they may still face substantial transitional changes from one job to another (what we call "churn"). That is, there may be continued economy-wide demand for workers with a particular characteristic but due to changes in sectoral output, workers will have to switch jobs.

The distributional analysis by the DIM-E module examines employment changes in at least two dimensions: (1) it assesses how climate policies affect workers relative to the baseline; and (2) it scrutinizes how interactions between climate policies and underlying trends affect transition pathways. Regarding the second dimension, a decline in employment for a particular worker type in the policy scenario relative to the baseline may cause heightened concerns if employment for that worker type is already declining in the baseline. Conversely, a decrease in employment relative to the baseline may not be an issue (and may even be beneficial) if employment for that worker type is expanding rapidly in the baseline. Accordingly, for selected worker characteristics, we identify whether, relative to the baseline, climate policies (1) accelerate a decline in employment, (2) moderate a decline in employment, (3) moderate an increase in employment, or (4) accelerate an increase in employment relative to the baseline. In addition to evaluating results over the period 2022–2050 (29 years) we also examine employment effects between 2022 and three other years: 2025 (four years), 2030 (nine years), and 2035 (14 years).

3.2.1. *Employment by industry*

To assess the magnitude of employment changes across the economy, Table 5 reports net gains in employment due to climate policies for the ten industries with the largest absolute net employment gains (measured in worker-jobs). The table also displays selected average worker characteristics in those industries: annual FTE (estimated full-time equivalency based on monthly earnings relative to the minimum wage), annual earnings (in New Zealand dollars before tax), jobs per worker (the average number of jobs held by each worker in one month), and age (in years).

As emissions from international transportation are excluded from climate policies, some of the largest employment increases are in sectors related to this activity (e.g., Air and space transport, and Water transport support services). There are also relatively large employment increases in sheep, beef cattle and grain farming; and dairy cattle farming. This is because, as noted above, the methane-reducing technology used in the policy scenario results in more labor-intensive farming (e.g., additional workers to administer methane vaccines) than in the baseline scenario. There are also relatively large absolute employment increases in tourist-related industries (cafes, restaurants and takeaway food services; and accommodation).

The ten industries that experience the largest net-employment decreases in the policy scenario relative to the baseline are displayed in Table 6. The list includes oil and gas extraction and nine manufacturing industries. The professional and scientific equipment manufacturing sector includes several potential green activities (Bontadini and Vona, 2023). There are two reasons why this sector experiences a decrease in employment. First, around 70 % of New Zealand investment goods in the base data are imported (Aguiar et al., 2019). Consequently, climate policy-induced substitutions towards capital have a muted impact on demand for domestically produced manufactured goods. Second, employment changes for this sector are driven by the proportional change in the other manufacturing sector in the C-PLAN model, which includes production of many goods in addition to green products. The latter reason highlights a potential aggregation issue, but given the structure of the New Zealand economy, employment effects from the expansion of green sectors is likely to be small. There is also a large proportional decrease in coal mining worker-jobs (not listed in Table 6) but, due to the size of this sector, a modest absolute decrease.

Comparing the average characteristics of workers in Table 5 to those of workers in Table 6 shows that, in general, workers in positively impacted industries have relatively low FTE appointments, low annual earnings, and a high number of jobs (in any industry) in a month. Other notable features are that workers in 'cafes, restaurants and takeaway food services' are relatively young, and workers in 'oil and gas extraction' are older and are paid significantly more than workers in other industries.

3.2.2. *Employment by worker characteristics*

As net changes in employment by worker characteristics relative to the baseline are small (see Riggs and Mitchell, 2021a, 2021b) and small net changes may hide significant employment transitions (i.e., churn), we focus on affected workers. As noted above, for each characteristic, the total number of affected workers is calculated by summing annual employment losses and employment gains for the years 2022 to 2050. We focus on four worker-job categories: highest qualification, ethnicity, gender and employment duration.

Table 7 displays the proportion of affected worker-jobs for each characteristic over the period 2022–2050, and the proportion of worker-jobs with each characteristic in the base data. Comparing the two proportions allows us to determine if employment impacts are concentrated in worker-jobs with particular characteristics. To assist this comparison, the final column of Table 7 reports the proportion of affected worker-jobs divided by the proportion of worker-jobs in the base data. For each worker-job characteristic, a value greater than one for this ratio indicates that that worker-jobs with that characteristic experience a disproportionate share of employment churn due to climate policy. To further evaluate employment changes, Figs. 1–3 display affected worker-job ratios by the employment change categories defined in section 3.2 (accelerated decline, moderated decline, moderated gain, and accelerated gain) and time period (2022–2025, 2022–2030, 2022–2035 and 2022–2050).

The results indicate that workers with lower education levels are expected to experience more churn than workers with higher qualifications. For example, 12 % of worker-jobs in 2018 are held by those with no qualifications (Table 7) yet, over the period 2022–2050, they account for 20 % of affected worker-jobs, an affected worker-job ratio of 1.7. Of potential concern, as illustrated in panel (a) of Fig. 1, worker-jobs with no qualification are overrepresented in worker-jobs for which climate

Table 5
Industries with the largest net employment increases in the policy scenario relative to the baseline between 2022 and 2050 and average worker characteristics.

ANZSIC three-digit sector		Employments changes		Average worker characteristics			
Code	Description	Number	Percent	Annual FTE	Annual earnings	Jobs per worker	Age
I490	Air and Space Transport	967	10.38 %	0.80	70,476	1.14	37.8
A014	Sheep, Beef Cattle and Grain Farming	751	4.16 %	0.40	23,427	2.69	35.2
I521	Water Transport Support Services	607	11.78 %	0.78	66,253	1.15	43.7
H451	Cafes, Restaurants and Takeaway Food	569	0.53 %	0.48	21,466	1.30	28.3
A016	Dairy Cattle Farming	562	2.29 %	0.65	38,663	1.25	32.9
A052	Agriculture and Fishing Services	470	2.24 %	0.46	25,868	1.52	31.9
I552	Air Transport Support Services	255	10.38 %	0.80	70,476	1.14	37.8
C239	Other Transport Equip. Manufacturing	229	2.34 %	0.88	75,646	1.08	41.6
H440	Accommodation	183	0.53 %	0.54	26,145	1.29	34.1
A041	Fishing	148	9.24 %	0.67	51,087	1.21	38.0

Table 6
Industries with the largest net employment losses in the policy scenario relative to the baseline between 2022 and 2050 and average worker characteristics.

ANZSIC06 three-digit sector		Employment changes		Worker characteristics			
Code	Description	Number	Percent	Annual FTE	Annual earnings	Jobs per worker	Age
C249	Other Machinery and Equipment Manufacturing	−606	−4.66 %	0.81	59,127	1.13	36.7
C149	Other Wood Product Manufacturing	−341	−3.00 %	0.83	52,401	1.11	32.4
C161	Printing	−305	−3.00 %	0.77	49,716	1.14	30.1
C251	Furniture Manufacturing	−304	−4.66 %	0.80	47,712	1.11	31.0
C222	Structural Metal Product Manufacturing	−271	−2.23 %	0.85	57,686	1.10	34.0
C246	Specialised Machinery and Equipment Manufacturing	−270	−4.66 %	0.85	63,686	1.11	31.6
C141	Log Sawmilling and Timber Dressing	−257	−3.00 %	0.84	53,158	1.11	33.7
B070	Oil and Gas Extraction	−247	−26.85 %	0.94	211,722	1.04	45.9
C241	Professional and Scientific Equipment Manufacturing	−220	−4.66 %	0.90	72,723	1.08	33.4
C133	Textile Product Manufacturing	−207	−4.66 %	0.80	47,913	1.12	32.4

Table 7
Proportion of worker-jobs with each characteristic and proportion of total affected worker-jobs between 2022 and 2050.

Category/ characteristic	Proportion of worker-jobs	Proportion of affected worker-jobs	Proportion of affected workers/Proportion of workers
Highest qualification			
No qualification	12 %	20 %	1.7
Secondary	41 %	44 %	1.1
Post secondary	19 %	21 %	1.1
Bachelor's	17 %	10 %	0.6
Post-graduate	11 %	6 %	0.5
Age			
15–24	24 %	18 %	0.8
25–34	26 %	23 %	0.9
35–44	17 %	17 %	1.0
45–54	17 %	20 %	1.1
55–64	12 %	16 %	1.3
65+	4 %	6 %	1.5
Ethnicity			
Asian	17 %	14 %	0.8
European	56 %	56 %	1.0
Māori	16 %	19 %	1.2
Pacific	7 %	7 %	1.0
Other	4 %	4 %	1.0
Gender			
Female	50 %	30 %	0.6
Male	50 %	70 %	1.4
Employment duration			
Short spell	16 %	14 %	0.9
Non-short spell	84 %	86 %	1.0

policies accelerate employment decreases both in the short-run (2022–2025) and the long-run (2022–2050). These employment changes are compensated for by climate policies accelerating employment gains in other no qualification jobs, but a relative high proportion of these individuals will have to transition to new jobs. Conversely, workers with bachelor's and postgraduate degrees are underrepresented in the churn in nearly all time periods and employment change types (Fig. 1).

Older workers (those in the age groups 55–64, and 65+) are also overrepresented in the churn. For example, in the long-run, workers aged 55–64 account for 12 % of the workforce but experience 16 % of the churn (Table 7). In the long-run, the overrepresentation of older workers is most acute in worker-jobs that experience accelerated declines (Fig. 2). This is driven by a sharp decline in road transport, which has an average worker age of 54, between 2040 and 2050, both in absolute terms and relative to baseline. The overrepresentation of older workers in worker-jobs that experience accelerated declines in the short-run is relatively modest.

One component of a 'just transition' would be to help workers traditionally employed in declining industries to find employment in growing industries. As both workers with low levels of education and older workers are disproportionately affected by climate policies and these workers are generally less mobile than other workers (Autor and Dorn, 2009; Bayer et al., 2005; Edwards, 2022; Hellerstein et al., 2008, 2013; Machin et al., 2008; Mincer, 1991; Poot, 1987), efforts to help these workers transition to new jobs may be particularly beneficial. For older workers, the appropriate assistance will depend on the extent to which employment changes are expected and the speed of employment changes. As the results indicate employment changes for older workers will be largest in the long-run (Fig. 2), retirements may absorb most of the changes and little (or no) assistance to transition to new industries will be required for these workers. In this connection, European Commission (2018, Table 18) estimate that for EU low-carbon transition

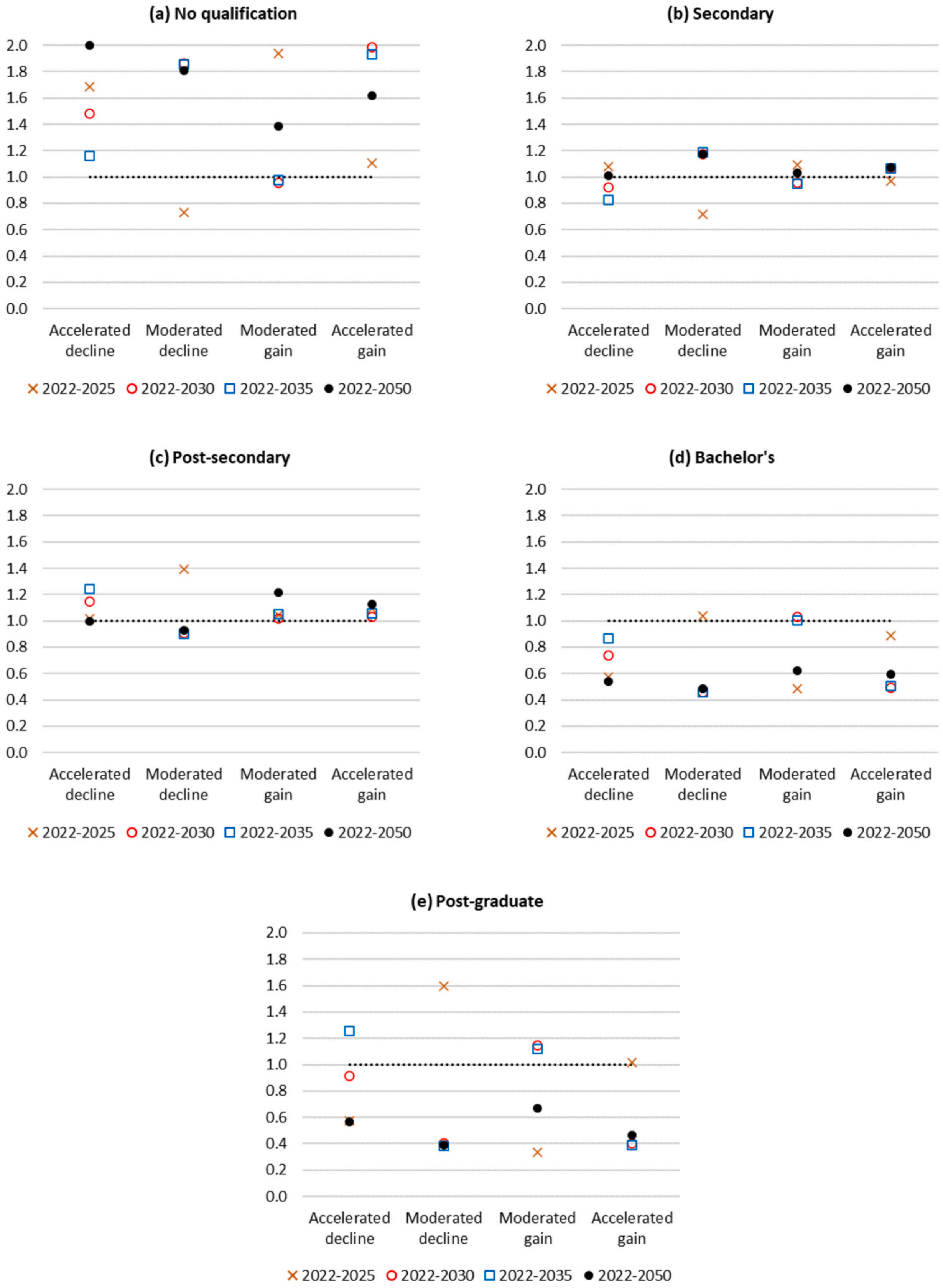

Fig. 1. Affected worker-job ratios (y-axis) by highest qualification, employment change type, and time period.

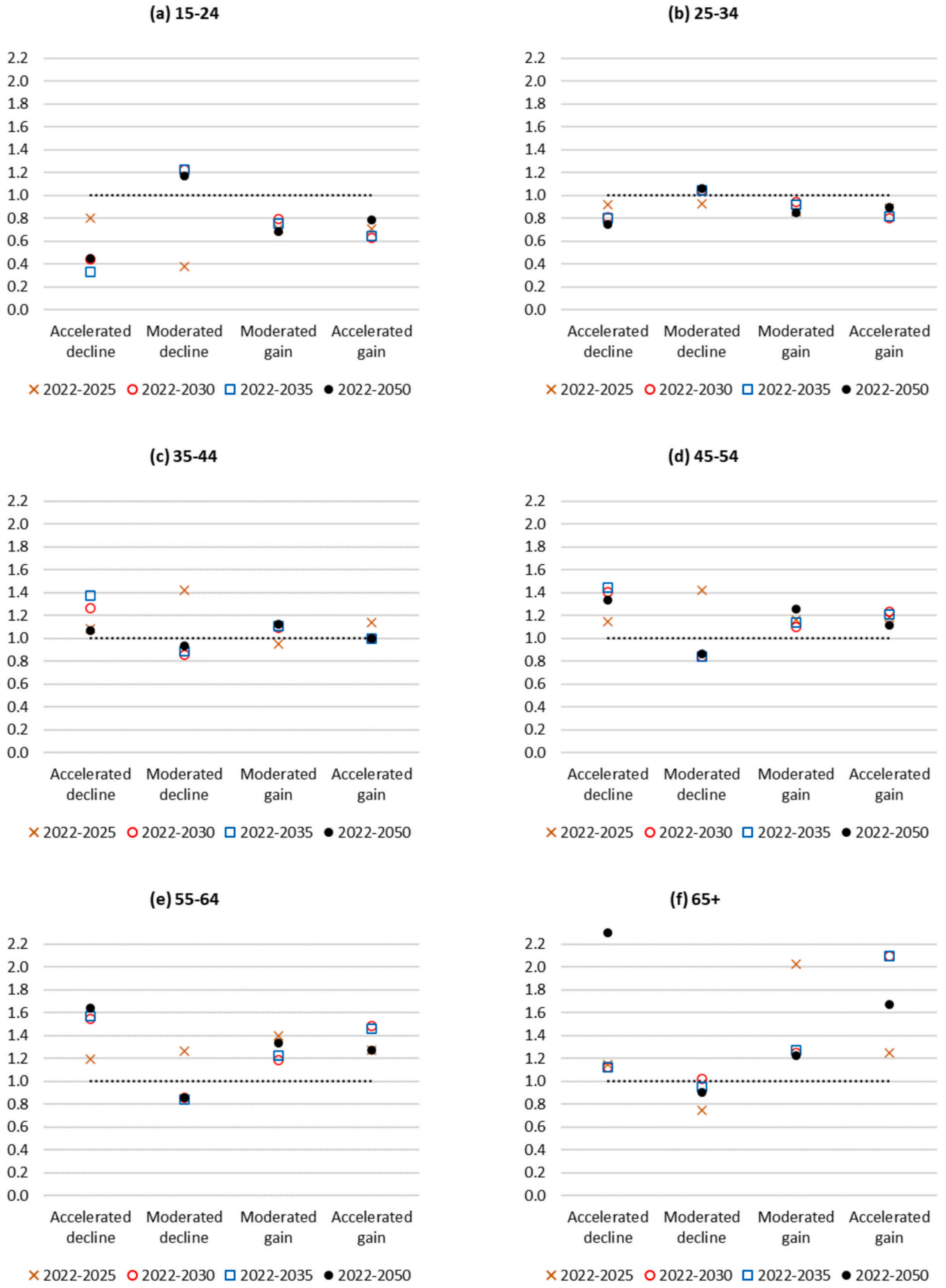

Fig. 2. Affected worker-job ratios (y-axis) by age group, employment change type, and time period.

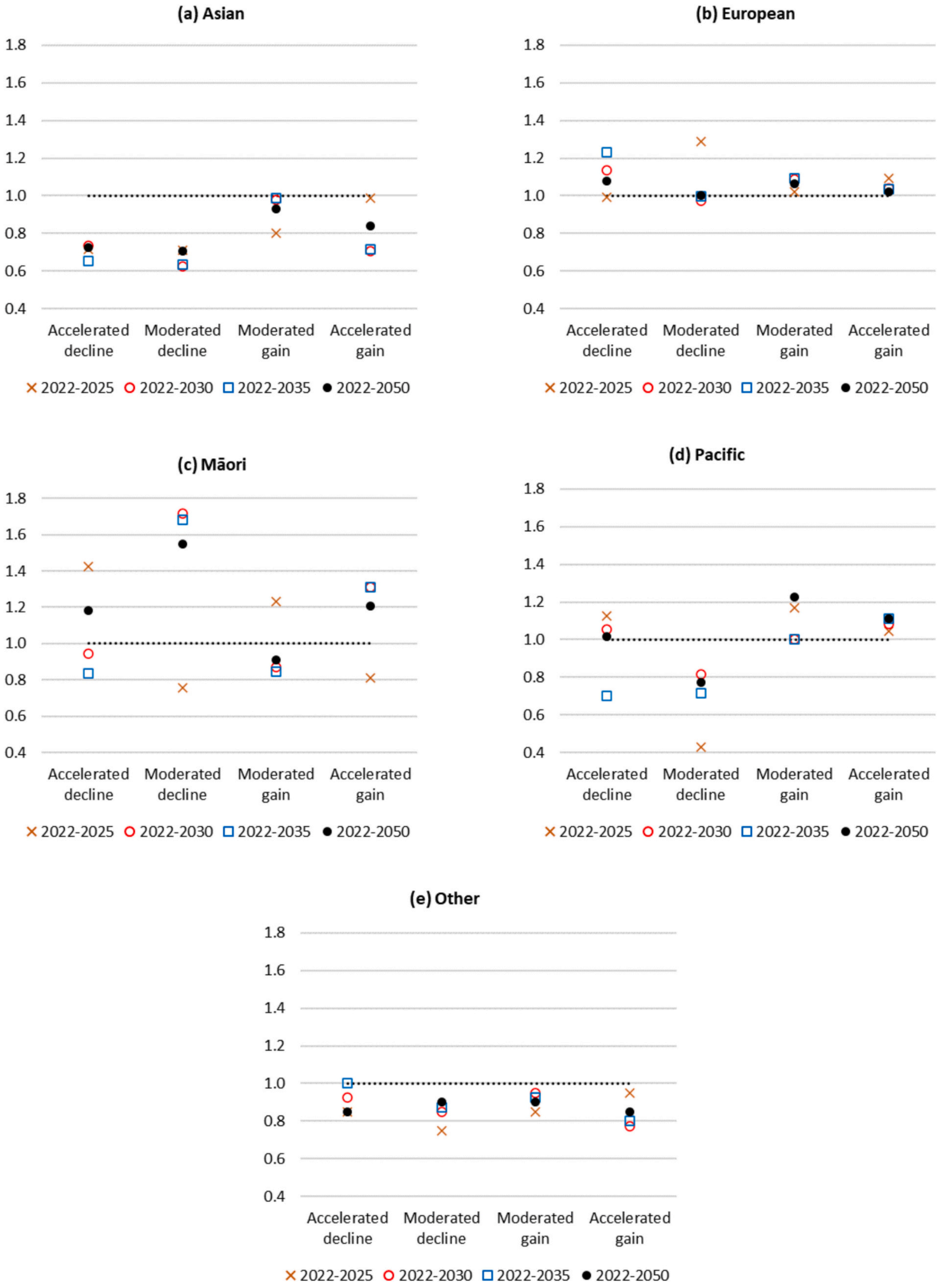

Fig. 3. Affected worker-job ratios (y-axis) by ethnicity, employment change type, and time period.

scenarios, retirements can absorb employment losses in all sectors that experience declining employment, except the mining and extraction sector.

The results by ethnicity indicate that Māori represent 16 % of total worker-jobs but account for 19 % of affected worker-jobs. Significantly, the overrepresentation of Māori is relatively high for worker-jobs for which climate policies accelerate employment decreases in the period 2022–2025 (Fig. 3). The overrepresentation of Māori in the employment churn due to climate policies is pertinent for policymakers for at least two reasons. First, it is more likely to be difficult to adjust to short-run changes than long-run changes. Second, the Zero Carbon Act states that the New Zealand government 'must include in an emissions reduction plan a strategy to recognise and mitigate the impacts on iwi and Māori of reducing emissions' (New Zealand Government, 2019, Section 3A(ad)).

Turning to impacts by gender, 50 % of worker-jobs are held by males but male worker-jobs account for 70 % of affected worker jobs during the period 2022–2050 (Table 7). This is because males account for a disproportionate share of worker-jobs in several industries with the largest employment gains and losses. For example, male worker-jobs account for 68 % of total worker-jobs in sheep, beef cattle and grain farming, and 76 % in oil and gas extraction. The overrepresentation of male workers in employment churn is present in all employment change categories and time periods and is largest for worker-jobs in which climate policies accelerate employment declines (Fig. 4).

3.2.3. Employment by region

The largest regional employment losses are in Taranaki and West Coast (Riggs and Mitchell, 2021a). This is because oil and gas extraction accounts for around 40 % of GDP in Taranaki and coal mining accounts for approximately 10 % of GDP in West Coast, and there are significant proportional employment declines in these industries due to climate policies.[8]

Fig. 5 presents affected worker-job ratios for each region. Taranaki experiences a disproportionately large amount of employment churn - its share of affected worker-jobs almost twice that of its share of all worker-jobs (a ratio of 1.81). Southland, at the bottom of the South Island, is similarly disproportionately affected by the policies, with a ratio of affected to total worker-jobs of 1.75. Gisborne, one of the most disadvantaged regions in New Zealand, also has a high rate of affected worker-jobs (1.51) compared to its total share. These results may be important in formulating targeted support packages to help regions adjust to a low carbon future.

4. Conclusions

We developed a modelling framework to estimate detailed employment effects due to climate policies. The tool suite used a CGE model to estimate the economy-wide and employment impacts of climate policy for 38 aggregated sectors in New Zealand. These employment changes were mapped to 213 industries in an employment module. A micro dataset and a simulation model were then used to estimate employment changes for workers across several dimensions. Industries that experience the largest negative employment impacts include coal mining, oil and gas extraction, and some manufacturing activities. Reflecting the deployment of labour-intensive abatement options, some agricultural industries experienced the largest employment increases. The expansion of sectors that use manual labour relatively intensively mean that, similar to Weitzel et al. (2023), climate policies do not favour skilled workers at the expense of unskilled workers.

We found that climate policies have the largest impact on workers that are older, or less well educated. Moreover, these workers generally have lower mobility compared to other worker groups. This indicates that to support a 'just transition' to a low carbon future, policies should focus on improving the mobility of the most affected workers, and particularly those expected to have lower mobility. Māori workers are also expected to be overrepresented in these transitions, and hence, is another group that could benefit from programs to improve worker mobility.

At the regional level, climate policies are expected to exacerbate employment declines in Taranaki and West Coast, which both have high concentrations of negatively affected industries. This suggests that these regions will need additional support as New Zealand increases the stringency of its climate policies.

The overall net employment effects are expected to be modest in terms of the number of worker-jobs, yet these results depend on workers' ability to transition out of negatively impacted jobs to positively impacted jobs. A large proportion of job losses will be due to attrition rather than layoffs, especially for older workers. Consequently, the focus should not necessarily be on re-employment of displaced workers but on transitioning new workers who would have been employed in negatively impacted jobs to finding employment in positively impacted jobs.

The modelling framework outlined in the paper is currently used by the CCC to provide climate policy advice to the New Zealand government. It is hoped that the models can be used to inform the development of complementary policies to assist a 'just transition' to a low carbon future in New Zealand and, by making them open source, in other countries as well.

We close by observing three limitations to our study that could be addressed in further research. First, although our analysis can help formulate policy responses to assist workers transition to new jobs, it does not estimate welfare costs borne by workers who must change jobs and/or locations. Temporary effects during the transition include unemployment, relocation, retraining, and decreased returns from investment in industry-specific capital Fullerton (2011). Temporary costs will be largest if climate policies are not foreseen. If policies are signaled in advance and anticipated by current and future workers, transitional costs will be lower (Hafstead and Williams III, 2020). In this connection, as New Zealand's long-term emissions targets rely on the gradual tightening of the emissions cap in an existing ETS, temporary effects may be lower than in countries without such policies in place. Our modelling framework could be extended to consider one dimension of temporary effects by including involuntary unemployment in the C-PLAN model following the approach of Hafstead and Williams III (2020) and Castellanos and Heutel (2024).

Second, our modelling framework only considers between-sector changes in employment and ignores within-sector employment effects. Including within-sector employment effects in the C-PLAN model would require representing different labour types and specifying production nesting structures and elasticities of substitution to capture desired tradeoff possibilities.

Third, additional work could explore the validity of our modelling framework and the sensitivity of the results to key modelling choices. Dixon and Rimmer (2010) provide guidance on how this could be done.

CRediT authorship contribution statement

Niven Winchester: Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Lynn Riggs:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Livvy Mitchell:** Data curation. **Dominic White:** Writing – review & editing, Data curation.

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[8] Although workers displaced from fossil fuel industries are re-employed in other sectors in our modelling framework, imperfect regional labour mobility may limit these job shifts in reality (Lim et al., 2023).

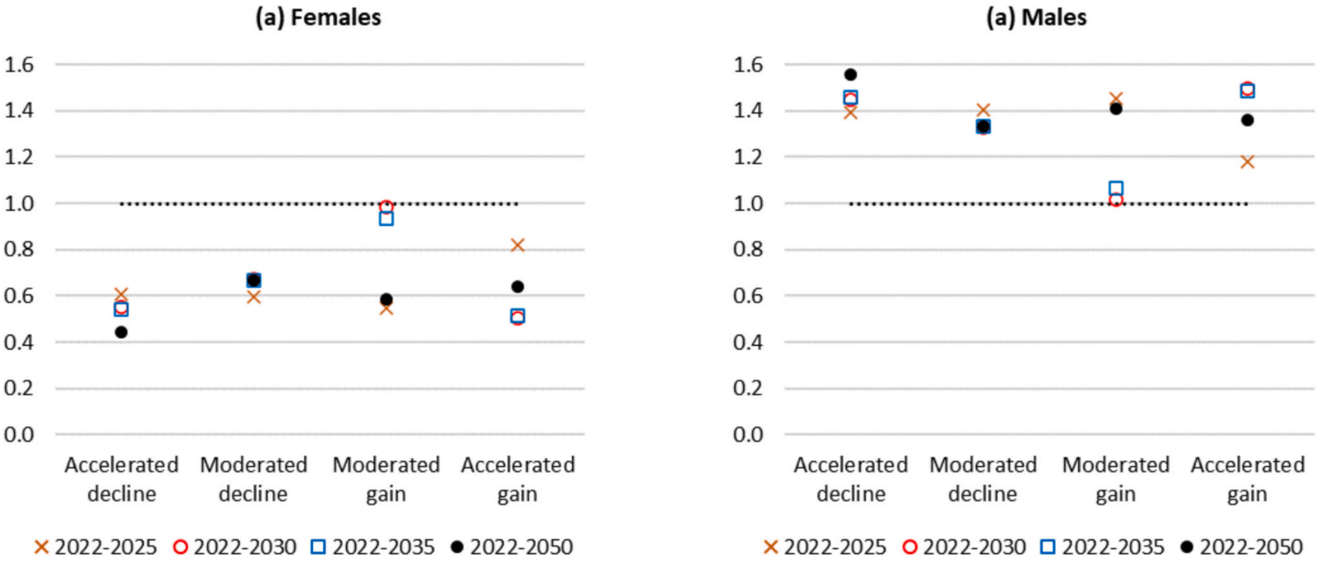

Fig. 4. Affected worker-job ratios (y-axis) by gender, employment change type, and time period.

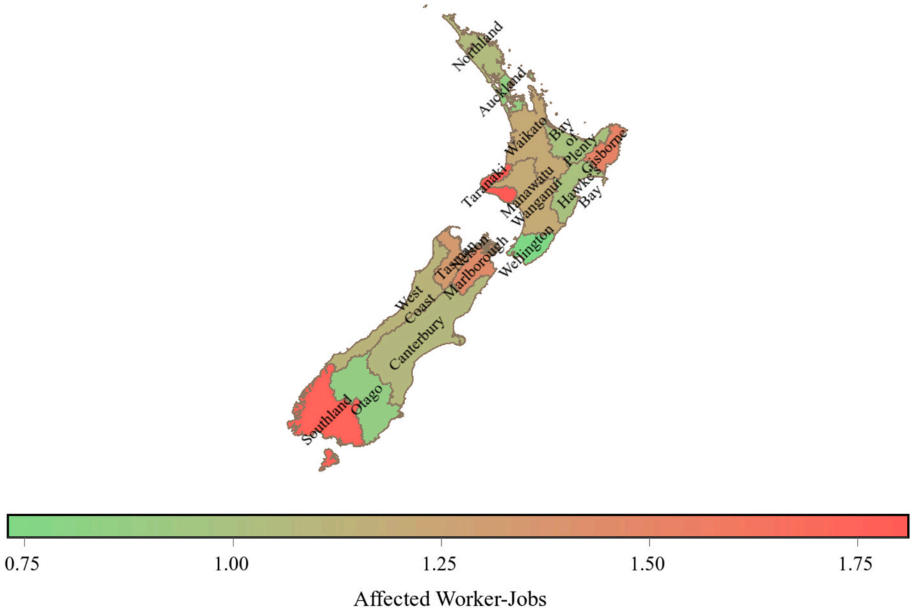

Fig. 5. Affected worker-job ratios by region for the period 2022–2050.

Declaration of competing interest

None.

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The results presented in this paper are not official statistics. They have been created for research purposes from the Integrated Data Infrastructure (IDI) and Longitudinal Business Database (LBD) which are carefully managed by Stats NZ. For more information about the [IDI and/or LBD] 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.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2024.108086.

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