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Methodology for Modelling Distributional Impacts of Emissions Budgets on Employment in New Zealand

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Disclaimer

Access to the data used in this study was provided by Stats NZ under conditions designed to give effect to the security and confidentiality provisions of the Statistics Act 1975. The results presented in this study are the work of the authors, not Stats NZ or individual data suppliers.

These results 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 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.

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Abstract

Efforts to reduce emissions to counter climate change are expected to have both costs and benefits, and these effects are likely to be unevenly distributed across the population. Hence, we developed the Distributional Impacts Microsimulation for Employment (DIM-E) to examine the potential distributional employment impacts for different mitigation options to reduce greenhouse gas emissions. DIM-E is comprised of two main components: the first component estimates industry-level employment effects, and the second simulates the characteristics of impacted workers and jobs. We based DIM-E on results from a computable general equilibrium (CGE) model, C-PLAN, and applied them to more detailed employment information in order to better understand the extent to which industries, jobs and workers are likely to be impacted by the different pathways. It is possible, however, for DIM-E to be used to analyse any policy scenario and its baseline using employment indices and similar employment information. In this paper, we describe DIM-E in the context of the initial case for which it was developed – to analyse emissions budgets for greenhouse gasses to be set by the New Zealand government for three time periods (2022-2025, 2026-2030, and 2031-2035). We also provide a sampling of results from this initial case in order to put the methodology into context. Hence, we show that DIM-E can be used to examine changes in employment trends due to policy changes as well as the different types of workers that are most likely to be affected by the reallocation of employment across industries. We found that the DIM-E results produced for the initial case were in line with previous research in this area – the overall net industry employment effects were predicted to be relatively small, though some industries will be more affected than others especially in the short- and medium-term. Moreover, very few worker groups would be negatively affected (in terms of the number of jobs) by any of the proposed mitigation options especially over the long term.

JEL codes

J01, Q52, R11

Keywords

Environmental Economics, Climate Change Mitigation, Distributional Impacts of Employment

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1. Introduction

Efforts to reduce emissions to counter climate change are expected to have both costs and benefits, and these effects are likely to be unevenly distributed across the population. Hence, we developed the Distributional Impacts Microsimulation for Employment (DIM-E) to examine the potential distributional employment impacts for different mitigation options to reduce emissions[1]. DIM-E is comprised of two main components: the first estimates industry-level employment effects, and the second simulates the characteristics of impacted workers and jobs. We based DIM-E on results from a computable general equilibrium (CGE) model, C-PLAN[2]. However, employment indices from any policy scenario and its baseline could be used.

In this paper, we describe DIM-E in the context of the initial case for which it was developed – to analyse emissions budgets for greenhouse gasses to be set by the New Zealand government for three time periods (2022-2025, 2026-2030, and 2031-2035). Since there are many different policy-mix options that could be used to meet these budgets, the New Zealand Climate Change Commission developed different pathways which were simulated over these time periods to ensure that their proposed budgets were achievable. These pathways were modelled using C-PLAN to assess the potential economic effects of these different options. We used projected employment indices from C-PLAN under these different pathways and applied them to more detailed employment information in order to better understand the extent to which industries, jobs and workers are likely to be impacted by the different pathways.

Most of the systematic, quantitative research in the international literature relating to within-country distributional impacts of climate change policies primarily assesses the impact of carbon pricing on household energy bills, household incomes, or overall employment levels. (Büchs et al., 2011; Gough, 2013; Goulder et al., 2019; Longhi, 2015; Nikodinoska & Schröder, 2016; Preston et al., 2010; Rausch et al., 2011; Schaffrin & Reibling, 2015; Wang et al., 2016; White & Thumim, 2009). There is little quantitative research on the effects of these policies, or even the effects of climate change itself, on employment in terms of the types of jobs and workers most likely to be affected. Hsiang et al. (2017) estimate economic damage at the US county level from climate change using low- and high-risk labour[3] as one of many outcome

[1] The initial case was to examine the effects of mitigation efforts to achieve net zero emissions of long-lived gases and to reduce biogenic methane emissions by 24-47% by 2050 in New Zealand.
[2] The C-PLAN model is a global, recursive, dynamic CGE model tailored to the economic and emissions characteristics of New Zealand. (Winchester & White, 2021)
[3] This article categorises jobs into two groups: low-risk and high-risk. Low-risk jobs are defined as those where workers are minimally exposed to outdoor temperatures, and high-risk jobs are defined as those who are heavily exposed (construction, mining, agriculture, and manufacturing).

measures (e.g., agricultural yields, mortality, crime); however, this paper provides little detail about those groups most likely to be affected.

Relatively few papers have examined the distributional effects of environmental policies on employment. Roland-Holst et al. (2020) is one example of a study that downscaled results from a CGE model to examine net job creation (using Full-Time Equivalent (FTE) jobs) by county in an assessment of the US state of Oregon's Cap-and-Trade Program.[4] They found most counties in the state experienced small FTE changes (between 0 and 1000) by 2050; however, the report did not include an analysis of job changes by industry, job, or worker characteristics.

Hafstead & Williams (2020) provide a general review of the literature and a thorough discussion about the policy questions related to employment in this area. In this article, the authors concluded that existing research provides clear answers to some questions. For example, existing research indicates that changes in jobs due to policies are primarily reallocations across industries as opposed to substantial aggregate effects such as large net job gains or net job losses. Moreover, most of this reallocation occurs via less hiring rather than through separations.[5] They find that both results hold even for large, economy-wide policies. The latter result, however, may depend on the policy design (scale, scope, and implementation speed), but even so, policy design has a greater impact on short-term outcomes[6] and has little effect on the long term. Pre-announcements (as found in Hafstead & Williams (2019)) and phasing-in policies have also been found as measures to counter some of the short-term effects caused by these policies. In summary, research in this area has generally shown that environmental policy has little effect on overall employment – particularly in the long run.

Hafstead & Williams (2019) is one of the few papers that focused on employment effects for workers in different industries. They used an extension of the search-CGE model (based on US labour markets) from Hafstead et al. (2018) which included industry switching frictions and staggered wage bargaining using three different types of environmental policies. In this model, the authors followed simulated workers based on their industry when the policy was implemented. These industries were categorised as follows: mining industries, utility industries, manufacturing industries, and other industries. Hafstead & Williams (2019) concluded that the short-run differences (less than 18 months) in unemployment rates (including size and duration) between the policies and the business-as-usual scenario largely depended on two things: the

[4] This analysis assumed that future jobs would be created in the locations where the current jobs exist because there was not enough information available to predict the locations of these new jobs.

[5] However, the authors note that this may be less true for already declining industries – these industries may have already reduced hiring substantially and hence increased job separations may be the only viable option remaining.

[6] This is particularly true for distributional effects the policy design is such that layoffs are required given that layoffs tend to increase the duration of unemployment and are more likely to lead to persistent negative effects for these workers.

ease with which workers could change industries and the magnitude of reallocation across industries caused by the policy.[7] This was particularly true for workers in mining and utilities[8]. Moreover, in their model, some high-turnover sectors like coal mining, which had high unemployment rates even without the policy, had lower unemployment rates in the medium term under the policy as it accelerated workers movement into lower-turnover sectors. The switching friction was also found to be relatively unimportant in determining the unemployment rate across all workers.

In this paper, we describe the DIM-E methodology and provide a sampling of results in order to put the methodology into context[9]. DIM-E can be used to examine changes in employment trends due to policy changes as well as the different types of workers that are most likely to be affected by the reallocation of employment across industries, which is one area highlighted in Hafstead & Williams (2020) as needing more research. In so doing, we hope that DIM-E can be used to target policy to help reduce search frictions and improve worker mobility which should ultimately reduce the short-term negative effects of the reallocation.

In line with previous research in this area, our initial analysis using DIM-E indicates that the overall net employment effects estimated in this analysis are predicted to be relatively small, though some industries will be more affected than others especially in the short- and medium-term. In fact, the industry rankings of the top net negative and top net positive industries using cumulative changes were fairly consistent across the four time periods and across the four pathways that we analysed.[10] On the net positive side, transport Industries tended to dominate the industry rankings, and in later periods, some agricultural industries also tended to rank highly (e.g., Dairy Cattle Farming and Sheep/Beef Farming). On the net negative side, various manufacturing industries tended to dominate the top ranks; however, the Oil and Gas Extraction industry was also consistently in the top ranks.

Our DIM-E results also indicated that very few groups would be negatively affected (in terms of the number of worker-jobs) by any of the proposed pathways especially over the long term. Workers holding jobs in Mining, Manufacturing, and Electricity, Gas, Water and Waste

[7] More reallocation was better for workers as it provided more opportunities to move.
[8] Castellanos & Heutel (2019) found similar results using a static model to compare results when assuming perfect mobility between jobs to those assuming perfect immobility. They found little overall effect on the aggregate unemployment rate but more substantial differences for unemployment of workers in the oil and gas extraction sector and in the coal mining sector (more negativity affected under perfect immobility). They also found that policy design could be used to mitigate these effects.
[9] For demonstration purposes, we will use publicly available data to generate some results included in the paper as representative of the types of analyses that can be done using DIM-E. Primarily, these will be results that would have more difficulty passing the confidentiality protections of Statistics New Zealand.
[10] The net effects are in terms of the pathway results compared to the current policy scenario. Hence, industries that are net positive have more employment under the pathway than under the current policy scenario, and net negative industries have less employment under the pathway than under the current policy scenario.

Services will be negatively affected, but Manufacturing more so than the other two industries. Workers holding jobs in Taranaki and the West Coast are also expected to be negatively affected under all four pathways by the end of the period; however, this is largely due to the concentration of negatively affected industries located in these regions. Given that the negative employment effects will likely outweigh the positive employment effects in these regions, these workers may have more difficulty transitioning into new sectors.

It is important to remember that DIM-E is a model and that the simulated results derived from the model need to be taken in context. Models such as DIM-E and C-PLAN are generally designed to better understand the implications of different actions and assumptions and to provide insights into the effects that could potentially occur under certain scenarios – they are not designed to exactly predict the future. Hence, any of the DIM-E results must be interpreted carefully, drawing on the scenario details and the outputs from the model used to generate the employment indices (in this case C-PLAN).

The remainder of the paper is organised as follows. Section 2 describes the transition pathways that were used as the basis for the initial analysis. Section 3 describes the DIM-E methodology, including information about the data, the CGE model, and the simulation model. Section 4 presents results to demonstrate DIM-E's functionality, Section 5 provides further discussion, and Section 6 concludes.

2. The Pathways and Current Policy Reference

There are a number of different ways that New Zealand could use to reduce greenhouse gas emissions to its targeted levels by 2050, and different mitigation options to achieve these results were considered. The Climate Change Commission (CCC) considered four different scenarios to achieve the proposed emissions budgets, called transition pathways, in developing its draft advice.

All pathways considered two baskets of emission prices that factor in the split gas target[11], one for biogenic methane and one for all other gases. Transition Pathway 1 (TP1) was designed to set out the central assumptions across the energy and land system while the other three transition pathways were designed to test different mitigation options and technology uncertainties by deviating from these central assumptions in different ways. For example, Transition Pathway 2 (TP2) focused on methane technology and combined quicker uptake of methane reduction technologies with tighter methane targets. Transition Pathway 3 (TP3)

[11] The split gas target is to achieve net zero emissions of long-lived gases and to reduce biogenic methane emissions by 24-47% by 2050.

constrained forestry removals in order to identify the costs of relying more heavily on emissions reductions. Transition Pathway 4 (TP4) focused on faster reductions and was designed to test the impacts of adopting more ambitious near-term emissions reduction targets for non-biogenic methane. As a baseline, a scenario was also developed to simulate the New Zealand economy under "business as usual" assumptions. This is called the Current Policy Reference scenario (CPR). The main differences between the CPR and the transition pathways are shown in Table 1.

For the CCC's final advice, they considered a fifth transition pathway using an updated CPR. The updated CPR aligns more closely with baseline assumptions used in other modelling commissioned by the CCC including but not limited to assumptions on removals, land use, agricultural productivity, agricultural and waste emissions intensity, electricity generation, electric vehicle uptake, and oil prices. The fifth transition pathway used for the final advice was designed to reduce emissions faster than the original four pathways to achieve net zero by 2040 rather than by 2050.

3. Methodology

1.1 Data

We used data sourced from Statistics New Zealand's Integrated Data Infrastructure (IDI) and Longitudinal Business Database (LBD).[12] These data include population-wide, linked 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 allowed us to observe establishment- and enterprise-level information related to the business or businesses for which an individual works as well as information about individuals themselves.

Within the LBD, data are provided at different levels of the business including the enterprise level and the geographic unit level. The enterprise level pertains to a tax-reporting legal entity (e.g., sole proprietor, partnership, company). In the data, each enterprise is given a unique, permanent enterprise number ("PENT") to allow the enterprise to be tracked over time, even if there is a change in the type of legal entity.[13] Geographic units are establishments of the enterprise (e.g., a grocery store chain would be represented in the data as the enterprise and each store would be considered a geographic unit). These establishments could be storefronts,

[12] For more information about these data, see the Statistics New Zealand website.
[13] For example, if a partnership decides to change to a limited liability company but is otherwise essentially the same entity, its PENT should remain the same.

headquarters, warehouses, or plants. Each establishment has been given a permanent unique identifier ("PBN"), which allowed us to track continuing activity at the same location.

Our analysis primarily relied on the monthly, linked employee-employer data to connect individual-level worker data in the IDI with business-level data in the LBD.[14] This allowed us to observe both establishment- and enterprise-level information for each employee as well as information about the workers themselves (e.g., age, gender, ethnicity). The unit of observation in the monthly data set is a worker-job, which we defined as the employment relationship between a worker and a single enterprise.[15] 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.[16] For these analyses, we used the group level of the ANZSIC06 codes to define industries.[17] We use the group level since it provides sufficiently distinct production activities while still providing sufficient aggregation of workers and businesses across most categories to protect confidentiality.

We used these data for the 2014 calendar year – the base year for the employment indices from C-PLAN – to estimate the number of worker-jobs in each ANZSIC06 industry code.[18] This was done by counting the number of unique worker-jobs in each month and averaging over the course of the year.

We also used worker-jobs data for the 2018 calendar year[19] to describe characteristics of the workers in these jobs using unique worker-jobs over the course of the year. In addition to estimating characteristics for all worker-jobs, we estimated the characteristics for two mutually-exclusive sub-samples – worker-jobs with at least one short spell of work during the year ("short-

[14] More detailed information about the LBD can be found on the Statistics NZ website and in Fabling and Sanderson (2016).
[15] Individuals appear in these data more than once if they have multiple jobs with different enterprises. However, if a worker was reassigned to a different location within the same enterprise, this is not counted as a new worker-job because the enterprise remains the same and only the enterprise changes.
[16] Note also that establishments and enterprises can be assigned separate industry codes, and these can even differ across the broadest industry classification level – the 1-digit ANZSIC06 industry classifications, called the division level, is the broadest level.
[17] More information about the ANZSIC2006 system can be found in Trewin & Pink (2006).
[18] We cleaned the data such that a worker-job can only be assigned to one ANZSIC06 industry code. It is possible for establishments to switch industry codes during a year, so to avoid double-counting worker-jobs in this instance, we replaced a worker-job's industry code to equal the most frequent ANZSIC06 code over the months for which the worker-job is observed during the year. When multiple industry codes were observed for the same number of months, we selected the lowest industry code (e.g., if the worker-job is observed in A011 for 6 months and in A012 for 6 months, the worker-job will be assigned to A011). However, these instances were infrequent. Workers could also be assigned to multiple establishments within the enterprise over the course of a year, and we used a similar methodology to assign workers to a single establishment within the enterprise during the year.
[19] We used 2018 for two reasons. Firstly, it was the most complete year of data available when we began the analysis. Secondly, it allowed us to link with 2018 Census data in order to obtain more detailed information about workers.

spell worker-job") and worker-jobs with no short spells during the year ("not-short-spell worker-job").[20]

For demonstration purposes, we will also use publicly available data[21] from Statistics New Zealand to simulate some results that might otherwise be problematic to have released. These data are from the official quarterly statistics produced from the Linked Employer-Employee Data (LEED) made available by Statistics New via *NZ.Stat*. Since these data are quarterly, we use the annual average for the year. For example, we use data on filled jobs in 2014 from the LEED measures by industry (based on ANZSIC06) to show the industry-level distribution of affected jobs.

This component of the analysis used data from a variety of sources. For example, we merged 2018 Census data with the worker-jobs data to obtain workers' highest educational attainment. We used data for all worker-job months in 2018 and aggregated these to the annual level for each ANZSIC06 code listed in the Appendix.

Across multiple datasets in the IDI, we observed the following characteristics of workers: gender, ethnicity, age, highest qualification, migrant status[22], and number of jobs held per month. For worker-job characteristics, we used earnings from wages and salaries[23], Full-Time Equivalent (FTE)[24], and region. We also distinguished worker-jobs that had at least one starting month during the year ("starts"), at least one ending month during the year ("ends"), and no start or end months during the year ("continuers"). These data provided the basis for the annual counts and averages per worker-job in each industry.

1.2 Downscaling CGE Model Results

We used the employment indices generated by C-PLAN[25] which used 2014 as the base year and included projections through 2050.[26] For these calculations, C-PLAN assumed full employment using a natural unemployment rate of 4.5% in the modelling for the CCC's draft advice, which was based on the long-term unemployment rate used in the Treasury's Long-Term Fiscal Model.

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[20] A short spell is defined as a period of employment without an interior month, and thus consists only of a start and end month. Hence, short spells, by definition, are less than 3 months in duration. See Fabling and Maré (2015) for more details about the derivation of the data.

[21] These data are more aggregated than the data that is available in the data labs. Hence, these data are just used to demonstrate the types of analyses that can be conducted using LEED, but the results using these data are not necessarily the same as those found using the confidential data sets.

[22] This was a binary variable depending on whether the worker had a visa accepted in the MBIE immigration data.

[23] These are administrative data submitted to Inland Revenue by employers who deduct and pay PAYE (pay as you earn) income tax on employees' behalf.

[24] This measure is based on worker's earnings in the month relative to the minimum wage as described in Fabling and Maré (2015).

[25] More details about C-PLAN are provided in Winchester & White (2021)

[26] From the CGE model, the relevant parameter for employment is Employment (f,i,r,t) where *f* represents production factors, *i* represents industries, *r* represents regions (New Zealand or the rest of the world), and *t* represents time (annual). This parameter reports an employment index (EI) for each sector equal to one in the base year (2014) for each sector.

(Piscetik & Bell, 2016) For the final advice, the unemployment rate used in the modelling was 4.25% to align with the Treasury's Fiscal Strategy Model Projections.

The full-employment assumption requires employment losses to be offset by employment gains in other sectors of the economy, and hence, employment growth is based on expected population changes. One critique of using full-employment CGE models for estimating employment effects is that these models do not account for frictional, structural, or cyclical unemployment. (Hafstead et al., 2018) However, CGE models like C-PLAN are generally meant to be used for mid- and long-term projections (a decade or longer) – they are not designed to look at short-term outcomes (e.g., annual or shorter) because most of these models do not fully account for short-term fluctuations due to economic shocks or the business cycle. (Chen et al., 2016) While the full-employment assumption may be unrealistic to examine employment changes in the short run, over longer time periods, economies generally fluctuate around full employment.

To better understand the potential effects of the full employment assumption, Hafstead et al. (2018) compared a full-employment CGE model (which assumed that labour markets fully clear) to a search-CGE model (which introduced a search friction) in order to compare changes in aggregate and industry-level employment from different environmental policies.[27] Their results showed that both models produced similar changes in the aggregate quantities of labour (in terms of number of hours) but that using an FTE calculation in the full employment model overestimated changes in the number of employed workers compared to the search model. They attributed this to the search model's ability to allow the hours per worker to vary as workers searching for work negotiated their hours with employers, whereas the number of hours per worker in the FTE calculation remained static. Their findings were similar across the different policies assessed.

In addition, Hafstead et al. (2018) found that the two models produced similar industry-level estimates of the number of employed workers because changes at this level were primarily driven by changes in demand across sectors, and these were generally much larger than the changes in hours per worker. Moreover, they concluded that both models produced roughly the same ranking of industries in terms of net effects because these changes were driven by substitution away from carbon-intensive goods.

Hafstead et al. (2018) also noted that their research did not evaluate which model – the search-friction or full-employment model – would generate more accurate predictions. Their

[27] Their search CGE-model matched firms and unemployed workers while imposing search costs on firms to find these workers and allowed for negotiation over wages and hours.

research primarily illustrated the robustness of results given these different assumptions. It is plausible that changes in hours will not translate directly to changes in the number of jobs. For example, during the pandemic, there were anecdotal reports that some employers in New Zealand reduced workers' hours or earnings rather than laying off or terminating employees. While that may be a feasible strategy in the short run, it seems unlikely that workers would be able to sustain this over longer timeframes. In fact, Hafstead & Williams III (2019) and Hafstead & Williams III (2020) used a search-CGE model to examine transitional employment dynamics which they analysed in terms of months (up to 18 months in the former and 42 months in the latter). So, for shorter-term analyses, the search-CGE model may be a more accurate representation. Our analysis, however, focuses on longer time periods ranging from 4 years to 29 years. Still, we recognize that the full employment assumption has limitations and present results in line with the areas where Hafstead et al. (2018) felt their results were robust.

Moreovoer, Hafstead et al. (2018) focused on differences in the numbers of employed workers; however, our results are based on 'worker-job equivalents' which is one worker employed by one firm. While it is possible that in the future one 40-hour-per-week worker-job in 2014 is filled by two workers working 20 hours per week (i.e., two worker-jobs), modelling this systematically would require a number of assumptions. For this reason, we use the term 'worker-job equivalent' or WJE as these two workers-jobs are equivalent in production terms to one worker-job in 2014.

The employment index from C-PLAN is based on changes in the total hours of work demanded by each sector. Generally, to estimate employment in terms of the number of jobs, the estimated hours are converted into full-time equivalents (FTE) using a constant hours-per-FTE conversion factor as described in Hafstead et al. (2018). We considered a similar estimation strategy using industry-level hours data and industry-level jobs data (to estimate the hours per job). However, hours data are not collected systematically for all industries in New Zealand and are particularly problematic for agricultural industries. Moreover, using a constant hours-per-job measure that is calculated from the worker-jobs data provides the same results as simply applying the employment index directly to the worker-jobs data. Hence, we used the simpler approach of applying the employment indices directly to the worker-jobs data rather than using the more complicated hours-conversion approach which would not have added anything more to the analysis.

Employment indices were generated for the Current Policy Reference Scenario (CPR) and for each transition pathway for each industry. To define our industries, we used the 38 sectors represented in C-PLAN which were converted to the *2006 Australian and New Zealand Standard*

Industrial Classification (ANZSIC06) codes to match Statistics New Zealand business and employment data. The ANZSIC06 codes and the corresponding C-PLAN sectors are shown in the Appendix.

Since the employment indices from C-PLAN include changes in labour productivity and since we wanted to isolate the employment changes related to workers, we adjusted the employment indices by removing the labour productivity (LP) component using the same growth rate originally used in C-PLAN. For the draft advice, the growth rate used in the modelling was 1.2% annually for all sectors. For the final advice, this was adjusted to 1% to align with general government climate projections and with the Fiscal Strategy Model Projections. In DIM-E, this is a macro variable to allow for easy adjustment of the rate.

As an example, Figure 1 shows the employment indices used in the draft advice for industries in Agriculture, Forestry, and Fishing (A)[28] from C-PLAN which include changes from LP (top panel) and with LP removed (bottom panel). Under the CPR and each TP, we can see that Forestry and Logging (A030) and Forestry Support Services (A051) are expected to grow (both before and after adjusting for LP) between 2022 and 2050. Sheep, Beef Cattle and Grain Farming (A014), on the other hand, is expected to decline between 2022 and 2050 under the CPR as well as under all four transition pathways both before and after adjusting for LP; however, the decline is more pronounced after adjusting for LP.

DIME-E then estimates annual employment (in terms of worker-job equivalents) over the time period starting with the base year to the end of the projection (2014-2050 for our analysis) under each scenario (i.e., the CPR and each TP) by multiplying the LP-adjusted employment indices by the number of worker-jobs in each ANZSIC06 industry[29] in the base year (2014). Our base year estimates are from the LEED from Statistics NZ[30]. DIM-E then uses these annual employment numbers to assess the year-over-year changes in worker-job equivalents (“WJEs”) under each scenario for each ANZSIC06 industry. From year-to-year, an industry might grow, contract, or stay the same size in terms of WJEs, and this may be different across the different scenarios. If the year-over-year change was positive (i.e., an industry in 2016 has more jobs than in 2015), DIM-E counts this change as WJEs gained. Conversely, If the year-over-year change was negative (i.e., an industry in 2016 has fewer jobs than in 2015), DIM-E counts the change as WJEs lost.

[28] When we discuss a specific ANZSIC06 industry, we will include the corresponding ANZSIC06 code in parentheses.
[29] A description of each industry, as well as the corresponding ANZSIC06 code, is provided in the Appendix.
[30] See Section 3 for more detail about the data used.

Next, DIM-E compares the number of WJEs gained ("gains") and WJEs lost ("losses") under each transition pathway to those gained or lost under the CPR to calculate the net gains, net losses, and overall net change ("net") in each year for each transition pathway:

$$net\ gains_{TPi} = gains_{TPi} - gains_{CPR}$$
$$net\ losses_{TPi} = losses_{TPi} - losses_{CPR}$$
$$net_{TPi} = net\ gains_{TPi} - net\ losses_{TPi}$$

where i indicates the transition pathway.

The net changes are then summed over the specified time periods, and these time periods can be flexibly specified as macro variables in DIM-E.[31] In the initial case, these time periods aligned with the CCC's budget cycles: 4 years, 9 years, 14 years, and 29 years after implementation (with 2022 being the first year where effects are observed). This allowed us to evaluate the cumulative effects of each transition pathway at multiple points in time over the forecast period (2022-2050). As an example, we show the cumulative employment changes in Sheep, Beef Cattle and Grain Farming – which we hereafter call Sheep/Beef (A014) – in Figure 2. Each panel in the figure shows the cumulative gains (green lines) and losses (orange lines) for each policy scenario (i.e., each pathway) relative to its reference scenario (e.g., CPR). The solid lines represent the predicted employment changes under the pathway scenarios, and the dashed lines represent the predicted employment changes under the reference scenarios.[32]

In Figure 2, one can quickly see that substantial losses are predicted for the industry in all scenarios, that these losses are expected to be less under each pathway relative to its CPR by the end of the forecast period, and that the net differences vary across the pathways. From Figure 2, we also see some gains are predicted under the transition pathways used for the draft advice over the last period (but not under the CPRs) and that the overall net effects (dark blue lines) of the transition pathways combines these gains with fewer losses to achieve an overall net positive effect for this industry by the end of the forecast period. It is also important to highlight that the cumulative net positive effect indicates that the industry is expected to have more WJEs at the end of the period under the pathways than would be the case under the CPRs. However, this does not mean that the industry is expected to end the forecast period with more jobs. Clearly, this industry is expected to decline between 2014 and 2050 – by almost 50% as shown in Figure 1 under the CPR and slightly less so under the four pathways.

[31] DIM-E was constructed using SAS software. Copyright ©2019-2020, Institute Inc. SAS and all other SAS Institute Inc. product or service names are registered trademarks or trademarks of SAS Institute Inc., Cary, NC, USA. SAS and all other SAS Institute Inc. product or service names are registered trademarks or trademarks of SAS Institute Inc. in the USA and other countries. ® indicates USA registration.

[32] For the draft advice, the same reference scenario was used for each transition pathway; however, the reference scenario was updated for developing the final advice. This can be seen by the differences in the dashed lines between the draft advice panels and the final advice panels.

While it is possible to evaluate the year-to-year effects given that we have annual data, the annual predictions from the model are likely to be lumpier (i.e., large changes from year-to-year) than the changes would actually be in reality and subject to more error caused by short-term fluctuations. As can be seen in the bottom panel Figure 1, there are some sharp changes in the LP-adjusted employment indices under the transition pathways which indicate sharp changes in annual employment levels. Therefore, examining the cumulative effects is more meaningful than examining the annual changes. (Chen et al., 2016)

Moreover, we can still examine the predicted annual effects by estimating the average annual effects during each time period. These results are shown in Figure 3 where we once again use Sheep/Beef (A014) as our example industry. In the figure, losses are again shown in orange, gains are shown in green, and the net effects are shown in blue. This figure is complementary to Figure 2 but provides a better view of the timing of gains and losses and an easier comparison of the average annual difference between the pathway and its CPR. In the case of Sheep/Beef (A014), it shows that the largest losses are predicted to occur between 2022 and 2025 and that there are very small differences between the losses expected under the pathways and the CPRs.

Aggregating results over longer time periods smooths shorter-term fluctuations in the predicted effects, which should provide more robust results. Even so, the timing of the results may not happen exactly as predicted. However, sensitivity analyses could be used to examine the effect the time period selection has on the average cumulative effects, which can be easily done by using the flexible time period specification that DIM-E provides.

Using DIM-E, we can also assess the distribution of industries over net employment effects for each cumulative time period as shown in Figure 4 and Figure 5. These figures can also be used to examine how the distributions of these effects change as time passes. In Figure 4 and Figure 5, we used publicly available LEED data for the kernel density estimates, and hence, these results are very likely to differ from the results using the non-public LEED data that was used in Riggs & Mitchell (2021). We provide these results as representative of the types of results that can be obtained using data from DIM-E, but these results are for demonstration purposes only.

In Figure 4, we can see that the industry-level net effects under TP4 spread out over time. We can also see that after 4 years a large number of industries have zero net gains (green line) under TP4 compared to the CPR and that there are far fewer industries with zero net losses (red line). Moreover, we can see that after nine years the density of industries with net gains around zero under TP4 reduces substantially, and after 29 years, the density of industries with net gains is actually surpassed by the density of industries with net losses. Hence, we can conclude from this that after the first period, most affected industries that are affected by losses but over time about the same number of industries are affected by gains and by losses.

To see the implications for the total net effects, we separately show these for TP4 in Figure 5. Given the similarity in the distributions between the net gains shown in Figure 4 and those shown for the total net effects shown in Figure 5, especially in the first three periods, it appears that the distribution of net effects is largely reflective of the distribution in net gains in this example. The exception may be the long, left tail seen in the total net effects distribution over the whole time period (over 29 years) which reflects the long right tail seen in the distribution of net losses in Figure 4. Using distributions in this manner provides insights into the extent to which the effects of the policy will be felt across the economy and how this may change over time.

The next step in DIM-E is to use these net changes to rank each industry under each transition pathway in terms of those with net positive changes ($net_{TPi} > 0$) and in terms of those with net negative changes ($net_{TPi} < 0$) during a given time period. As mentioned previously, a net positive change indicates that the industry will have more jobs under the transition pathway than under the CPR; however, this does not mean that the industry will grow during the time period. It is possible for an industry to lose jobs over the time period under both the transition pathway and under the CPR – a net positive change for the industry in this case indicates that the industry is expected to lose fewer jobs under the transition pathway than under the CPR. Similarly, a growing industry can have a net negative change which indicates that the industry is growing less under the transition pathway than under the CPR. Moreover, in a given time period, an industry can both grow and contract – the net effect depends on whether the industry ends up with more or less jobs under the transition pathway than under the CPR.

In Table 2 and Table 3, we show these rankings for the cumulative net effects over the full forecast period (2022-2050). Table 2 shows the industries with the largest net positive effects under each pathway. From this table, we can see that the results are fairly consistent across all of the pathways, with Air and Space Transport (I490) ranked first in 4 out of 5. From this table, we can also compare the relative net effects across the pathways. For example, the net effects for Air and Space Transport (I490) under TP1 and TP2 are fairly similar (967 WJE under TP1 and 956 under TP2) and that the net effects under TP3 (1,995) and TP4 (2,076) would be almost double.

Table 3 shows the industries with the largest net positive effects under each pathway. On the net negative side, the industries are not as consistently ranked across the pathways as they are on the net positive side. For example, Other Machinery and Equipment Manufacturing

(C249) is ranked first under TP1 (-606 WJE) and TP2 (-645), but Road Freight Transport (I461) is ranked first under TP3 (-1,835 WJE) and TP4 (-2,181 WJE). Still, the relative magnitudes across the pathways are still similar when looking across ranks.

To better understand these changes, we categorise the net effects into four types:

- **Gain-Less Loss:** these are net positive changes due to fewer jobs lost under the transition pathway than under the CPR;
- **Gain-More Gain**: these are net positive changes due to more jobs gained under the transition pathway than under the CPR;
- **Loss-Less Gain**: these are net negative changes due to fewer jobs gained under the transition pathway than under the CPR; or
- **Loss-More Loss**: these are net negative changes due to more jobs lost under the transition pathway than under the CPR.

In Sheep/Beef (A014), we can see these different net effects in Figure 3. For example, under TP1 and TP2 in the first time period (2022-2025), we can see that the industry has more losses under the pathway than under the CPR, and hence, these net negative effects would be counted as “Loss-More Loss”. On the other hand, under TP3, we can see that the industry has fewer losses during the same time period compared to the CPR, resulting in a net positive effect for the pathway (or a “gain” for the pathway over the CPR). However, this gain is not resulting from growth in the industry but from less decline. For this reason, we would label this net effect as “Gain-Less Loss”. In the final period, we see some growth in the industry and some decline in the industry under all pathways, and there is more growth and less decline under the pathways compared to the CPR. Hence, there are gains to the economy from the pathway (relative to the CPR) from both more jobs gained and from fewer jobs lost, and DIM-E distinguishes these effects as “Gain-More Gain” and “Gain-Less Loss” because while these effects may be mathematically equivalent, they may not be functionally equivalent in actual application.

It is important to understand that these simulation models are designed to examine how various aspects of the economy are likely to change due to different economic or policy conditions (Chen et al., 2016), and any of the DIM-E results must be interpreted carefully, drawing on the scenario details and the outputs from the C-PLAN model. Moreover, a key strength of this type of analysis is in the ability to assess the net effects of different policy decisions relative to the baseline scenario.

1.3 Simulation of Worker-Job Characteristics

To better understand the types of workers that are expected to be affected under each transition pathway, DIM-E uses the net change in worker-jobs for each of the four time periods (4-, 9-, 14-, and 29-years post-implementation) in each ANZSIC06 industry. DIM-E uses these numbers as the basis for the counts of the simulated worker-jobs, with each simulated worker-job flagged as one of the four net effect types (based on industry) as specified at the end of the last section: Gain-Less Loss (GLL); Gain-More Gain (GMG); Loss-Less Gain (LLG); or Loss-More Loss (LML). The counts of WJE used in the simulation in each of these four categories for the first time period (2022-2025) are shown in the left panel of Figure 6 and for the full time period (2022-2050) are shown in the right panel. These results show us how much reallocation or "churn" should be expected under the different pathways and over time. For example, TP4 is predicted to have the most churn in the first time period relative to the other pathways considered in the draft advice, but by the end of the forecast period TP3 has almost as much churn as TP4. In addition, TP4 has more LML than TP3 over the full time period (10,652 and 7,134 respectively), but TP4 also has more GMG than TP3 (22,408 and 17,785 respectively).

Next, DIM-E uses the 2018 percentage of short-spell worker-jobs in each ANZSIC06 industry to simulate whether the worker-job was a short-spell worker-job and then separates the simulated data set into short-spell and non-short-spell worker-jobs. This is done to simulate the characteristics for each worker-job using separate profiles for short-spell and non-short-spell worker-jobs in each ANZSIC06 industry from the 2018 worker-jobs data.[33]

The simulation was done using SAS software[34] -- specifically, DIM-E uses the RAND function to simulate characteristics of the worker and the job for each worker-job. The RAND function uses the Mersenne-Twister random number generator developed by Matsumoto & Nishimura (1998) and can generate random numbers from a variety of different distributions. (Wicklin, 2013, 2015) DIM-E primarily uses the Table and Bernoulli distributions, though the Normal distribution is also used for simulating annual earnings for the worker-jobs using the mean and standard deviation for the ANZSIC06 industry and restricting the values to be between the industry's minimum and maximum values because this provided a more reasonable approximation of earnings in the simulation. The simulation is run 1000 times (though this is

[33] A number of industries, especially agricultural industries, use a number of short-spell workers, and the characteristics of worker-jobs are often very different for short-spell and non-short-spell worker-jobs.
[34] Copyright © 2019-2020, SAS Institute Inc.

flexibly specified using a macro variable) and the sample mean for each characteristic is calculated.[35]

For characteristics of workers holding these jobs, DIM-E simulates workers' gender, age, highest qualification, and ethnicity. For characteristics of the jobs themselves, DIM-E simulates average annual earnings (in 2018 NZD), region, and whether the worker-job was a continuer[36]. For workers' ages, the simulation was based on the percentage of workers in each age group in each ANZSIC06 industry rather than on the continuous distribution of worker age because using age groups provided a more accurate approximation of the different profiles of worker-jobs for our industries. For average annual earnings, we used a minimum and maximum value based on the distribution of earnings in each ANZSIC06 industry.

While we have actual values for the characteristics of workers in the affected industries, the simulation allows us to go beyond industry classifications to examine the cumulative net effects of the policy scenarios on different groups of workers across New Zealand and in different regions.

4. Sample of Results from DIM-E Worker-Job Simulation

The following section provides a sampling of results from the DIM-E simulation of worker-jobs to illustrate the different ways in which DIM-E can be used. There are far more results that could be produced from DIM-E, with many of our main results presented in Riggs & Mitchell (2021). Many of these results are shown as percentages of the affected jobs. To calculate these percentages, we estimated the total number of worker-jobs affected either in a positive or negative way under the pathway and then estimate the percentage of worker-jobs in each group from the total number affected. For example, if 100 women are in worker-jobs expected to be negatively affected under a given transition pathway and 100 men are in worker-jobs expected to be positively affected, then the total number of affected worker-jobs is 200 and the percentage of worker-jobs affected for women would be -50% (negative to represent the negative direction) and 50% for men (positive to represent the positive direction). We can then compare the percentage of affected worker-jobs for the group to the percentage of all worker-jobs held by the group in 2018. Hence, we can see if some groups are disproportionately affected by the changes.

[35] We compared the sample means from the simulation (based on the profiles for short-spell and non-short-spell worker-jobs) to the overall profile of all worker-jobs in a sample of industries, and the simulated sample means were close approximations of the overall worker-job profile for the industries.

[36] Continuers apply only to non-short-spell jobs only since short-spell jobs, by definition, are not continuers.

We begin with the results for earnings by net effect type as shown in Figure 7. The left panel of Figure 7 shows average annual earnings for the first period (2022-2025), and we can see that the average annual earnings for worker-jobs in all categories under all four pathways (between $40-$50,000) are fairly similar with the exception of jobs in the LML category under TP4. The average for this category exceeds $80,000. Hence, under TP4, the jobs where more losses are expected under the pathway are relatively well paid. By 2050, however, average annual earnings in the LML category are similar to those seen in the other categories (results in right panel of Figure 7). It is of note that worker-jobs in the GLL category appear to average less than worker-jobs in the other categories under all four pathways. Hence, WJE gained from industries that decline less than they would have otherwise under the CPR are less well-paid than WJE in the other categories.

It is important to note that earnings will vary over the forecast period due to inflation and changes in supply and demand; however, these estimates do not account for those changes. This analysis still provides an indication of the relative earnings across different net effect types as those are less likely to change especially in the short and medium term.

DIM-E can also be used to examine the proportional changes across broader industries categories which include all industries and not just the industries with the largest changes (as we had with the industry rankings). Figure 8 shows share of net effects for one-digit ANZSIC06 categories over the full forecast period (2022-2050). From this, we can see that the net effects for most of these broad industry groupings will be small. Manufacturing (C) is predicted to have the largest share of affected worker-jobs under almost every pathway, and the direction is always negative (ranging from -30% to -35% depending on the pathway). Only two other broad industries consistently have net negative effects over the full forecast period under all four pathways: 1) Mining (B) and 2) Electricity, Gas, Water and Waste Services (D). However, the shares for these industries are small (between -1% and -3% in all cases). On the positive side, Agriculture, Forestry, and Fishing (A) is expected to have a large share of affected worker-jobs under all four pathways (ranging from 14% to 36%).

Using the DIM-E simulation of worker-jobs, we can also examine the aggregate effects of these changes for different groups of workers. As an example, we present the results for workers based on their highest qualification with net effects aggregated over the full forecast period (2022-2050) as shown in Figure 9. These results indicate that each group of workers is expected to have a net positive share of the effects at the end of the forecast period under all four transition pathways. The one exception is post-graduate workers under TP2 who are expected to have a net share of approximately -2%. This indicates that for each category of worker under most scenarios, we would expect them to have more WJE under the pathways than they would have otherwise had under the CPR at the end of 2050. This is even true for workers with no qualifications. However, given that 12% of WJE in 2018 were held by workers with no qualifications, this group's share is disproportionately small under TP3 and TP4. Workers whose highest qualification is from secondary school have the largest share of the net effects under each transition pathway (44% to 55%); however, they also hold the largest share of worker jobs in 2018 (41%).

Figure 10 shows the share of each net effect type held by each group of workers (based on highest qualification) under each of the four pathways considered for the draft advice. The first column in Figure 10 shows the percentage of all worker-jobs held by workers in each category. From this, we can see that workers with no qualifications hold a disproportionately large share of jobs in all of the net effect types under all four pathways, but this is particularly large in the LML category (26%) relative to their share of all 2018 worker-jobs (12%). Hence, we expect that these workers will experience the most churn in the reallocation.

Generally speaking, we found net positive effects for most groups of workers when aggregating over the full forecast period. This indicates that most of the negative effects of the pathways are expected to be offset by positive effects within each group, which means that jobs traditionally held by workers in these groups will be fairly balanced across the negative and positive effects. However, as we have seen in Sheep/Beef (A014), the timing of the gains and losses can be very different. For this reason, we used the DIM-E results to examine the net effects over different time periods.

5. Discussion

DIM-E provides a framework for assessing and comparing the distributional impacts of mitigation efforts on employment, and in particular, on specific industries and specific groups of workers. In general, our results are similar to those found in previous research. The net effect of the pathways is predicted to be relatively small (compared to more than 2 million filled jobs in the economy), especially annualised over the full forecast period. However, some industries are predicted to be disproportionately affected, some positively and some negatively under the four pathways. Moreover, the industries predicted to have the most negative net effects are similar to those found in other research: coal mining, oil and gas extraction, and manufacturing. Our results also indicate early negative effects in some agricultural sectors under TP1 and TP2. Even in the most affected industries, however, the net effects were predicted to be relatively small in scale compared to the larger economy.

The results from DIM-E are largely based on modelling that predicts employment into the future using a variety of different assumptions, and while there are some events that cannot be foreseen or assumed (e.g., new technologies, recessions), these events will generally only change the net effects to the extent that they differentially affect the CPR relative to the transition pathways. Hence, these events may have less of an effect on the industry-level net effects and more of an effect at the worker-job level. For example, if a new technology arises in Air and Space Transport that eliminates 50% of worker-jobs and this industry is a main area of growth for workers with advanced degrees, we might find that workers with advanced degrees have a harder time balancing their net losses under the transition pathways without the expected gains in this industry.

One assumption used in the modelling behind DIM-E is the full employment assumption used in C-PLAN when deriving the employment indices. This assumption causes the C-PLAN model to rebalance employment losses in declining industries with employment gains in growing industries to achieve full employment within the economy (assuming some fixed rate of growth). Other CGE models used internationally also use this assumption for their analyses, and generally given the length of time analysed using these models, this is a reasonable assumption as the labour market adjusts. Hence, this is one reason that we do not focus on annual changes but look at the cumulative effects over longer time periods. It is also important to note that in DIM-E we use a different source of data for our employment numbers, and we do not rebalance the employment estimates in DIM-E because we found that the overall differences between losses and gains under each scenario is fairly small especially relative to the size of the total number of worker-jobs in the economy.

Moreover, other research comparing the results from a full employment CGE model to a CGE model with more labour market dynamics (a search-CGE model) found that the full employment model overestimated the net effects in terms of the aggregate number of employed workers (using full-time equivalents) and that the industry-level results, including the rankings of industries based on net effects, were fairly similar. (Hafstead et al., 2018) Hence, based on these findings, our estimates of the overall net effects may be an overestimate.

Another implicit assumption in DIM-E is that the characteristics of workers from 2018 will hold over the forecast period. While we expect the composition of the workforce to change, however, estimating these changes would require more assumptions about the ways in which we expect the workforce to change. Moreover, because we focus on differential changes, these changes to the composition of the workforce would have to change the relative differences between industries that are negatively impacted and those that are positively impacted. The most likely scenario for this to occur is in the aging of the workforce which could bring workers with higher qualifications into the workforce given higher qualification levels of the younger generation. However, it is less likely that these effects will affect our short- and medium-term results given the time it takes for these changes to manifest.

The DIM-E also used the characteristics for the average short-spell and not-short-spell worker-job in the simulation of worker-job characteristics, but some types of workers may be more likely to enter and exit these industries especially in industries where large changes are expected. However, this would again require more assumptions about how these changes might occur across different industries. Without more research, modelling these transitions would be difficult.

In DIM-E, the focus is on employees, and it does not include working proprietors. However, because the net effects analysis focuses on the differences between the CPR and the transition pathways and on the differences across the different transition pathways, the results are expected to be similar. Again, the area that might be most impacted by the inclusion of working proprietors is in the examination of the effects on different groups of workers, yet this is only true if their characteristics differ dramatically across industries that are positively affected compared to those in industries that are negatively affected. Plus, the dynamics for working proprietors may be more affected by firm entry and exit which would require additional assumptions to the model.

It is also important to note that the numbers presented in these results are to provide scale to the predicted effects and to allow for relative comparisons across different scenarios, time periods, and groups. The best use of these results is to understand which industries, regions and workers are likely to be most affected by the changes and the expected direction these effects are likely to take in different time periods in order to prepare for the future. For example, Road Freight Transport and Road Passenger Transport are expected to grow between now and 2035 under the CPR, and substantially more under each of the four transition pathways, but then much of that growth is predicted to be lost by 2050. Knowing this, policymakers can find policy solutions to ease this transition for workers when the time comes. Alternatively, policymakers could assess what is limiting growth and see if there are feasible policy solutions to overcome these limitations.

Still, without workers with the right skills, predicted growth could be limited, so it is important to ensure that workers will have the rights skills to fill these jobs and that the jobs meet the needs of workers. If growth is in jobs that are low pay and low FTE with intermittent work, firms may also have trouble filling these jobs if workers want higher pay and more consistent schedules. As shown by other research, frictions that limit workers ability to transition plays a significant role in the short-term effects on workers, so reducing these frictions is important to reducing the negative effects of these policies. (Castellanos & Heutel, 2019; Hafstead et al., 2018) These results have flagged some potential issues with worker-jobs in some of the industries expected to grow, but further work needs to be done to better understand the skills required in areas of growth.

Moreover, while this work can be used to identify areas of potential growth and decline across industries, changes to the jobs within industries driven by these policies may be more difficult to identify. For example, changes in the industry Electricity Generation (D261) away from fossil fuels to renewable energy may require different types in workers and in different quantities. However, the results in this paper combine all types of electricity generation into one industry, and while we might assume that losses are related to electricity generation using fossil fuels and gains are in renewable energy areas, the current model is unable to separate these. Similarly, if reduced emissions in these scenarios are driven by a move to electric vehicles, mechanics for electric vehicles may require different skills than mechanics for other types of vehicles. Fewer mechanics may also be required if electric vehicles require less maintenance. Currently, DIM-E is silent on these types of effects because the main objective of the analysis was to better understand the shifts in employment across industries. Assessing these types of within-industry changes in skill requirements or in labour productivity may be better addressed using sector-specific analyses.

6. Conclusion

Using DIM-E, we assessed the potential distributional impacts on employment using pathways designed to deliver on New Zealand’s targets to reduce biogenic methane emissions by at least 10% by 2030 and by 24-47% by 2050 relative to 2017, and to reduce emissions of all other greenhouse gases to net zero by 2050. These pathways allowed us to examine which industries and workers are most likely to be affected by different mitigation actions that could be taken to meet New Zealand’s emissions budgets under varying assumptions.

Overall, we find that the net employment effects estimated in this analysis are predicted to be relatively small, though in percentage terms, some industries will be more affected than others especially in the short- and medium-term. Previous research in this area has found similar results. (Hafstead & Williams III, 2020) Moreover, we found the industry rankings were fairly consistent across the four time periods and across the different pathways that we analysed. On the net positive side, transport industries tended to dominate the industry rankings, and in later periods, some agriculture industries also tended to rank highly (e.g., Dairy Cattle Farming and Sheep/Beef Farming). On the net negative side, various manufacturing industries tended to dominate the top ranks, though oil and gas extraction was also consistently ranked.

Using our simulation model, we also found that very few groups were negatively affected (in terms of the number of worker-jobs) by any of the pathways especially over the long term. Of course, there were exceptions. For example, workers in three sectors – Mining; Manufacturing; and Electricity, Gas, Water and Waste Services – were predicted to be negatively affected over the forecast period but Manufacturing more so than the other two industries which reflected our results from the top-ranked industries. Workers in Taranaki and the West Coast were also predicted to be negatively affected by the end of the period; however, this is largely due to the concentration of negatively affected industries located in these regions. Given that the negative employment effects will likely outweigh the positive employment effects in these regions, workers in these regions may have reduced mobility and more difficulty during the transition.

It is important to note that the DIM-E results are derived from modelling and that this modelling is designed to provide insights into the effects of changing actions and changing assumptions on our outcomes, but they are not designed to exactly predict the future. Hence, these results should be interpreted carefully, drawing on the scenario details and the outputs from the C-PLAN model.

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7. Tables

Table 1. Key Assumptions used for Draft Advice and Final Advice Scenarios

	Scenario	Forestry	Methane technology	Long-lived gases	Biogenic methane
DRAFT ADVICE	**Current Policy Reference (CPR)**	Projections from Ministry of Primary Industries	None	Business as usual	Business as usual (from 2026)
	Transition Pathway 1 (TP1): More removals	CPR exotic forestry (with additional native forests)	Low effectiveness and uptake only	Straight line path for gross emissions to net-zero in 2050	24% reduction in 2050
	Transition Pathway 2 (TP2): Methane technology	CPR exotic forestry (with additional native forests)	Higher effectiveness and uptake (vaccine)	Straight line path for gross emissions to net-zero in 2050	47% reduction in 2050
	Transition Pathway 3: (TP3) Less removals	About 2/3 of CPR exotic forestry (with additional native forests as in TP1)	Low effectiveness and uptake only	Straight line path for gross emissions to net-zero in 2050, accounting for forestry removals	24% reduction in 2050
	Transition Pathway 4 (TP4): Faster reductions	About 2/3 of CPR exotic forestry (with additional native forests as in TP1)	Low effectiveness and uptake only	36% reduction in gross emissions in 2030, net-zero in 2050	24% reduction in 2050
FINAL ADVICE	**Demonstration Path**	Annual average of 25,000 ha of exotic forestry in BP1 and BP2 and ramp down in BP3 (with additional native forests in BP1 and BP2; establish 25,000 ha annually in BP3)*	No methane technology, but improved agricultural emissions efficiency	Net zero in 2040*	24-47% reduction in 2050*

* As in ENZ demonstration path.

Table 2: Industries with Largest Net Positive Employment Changes, 2022-2050

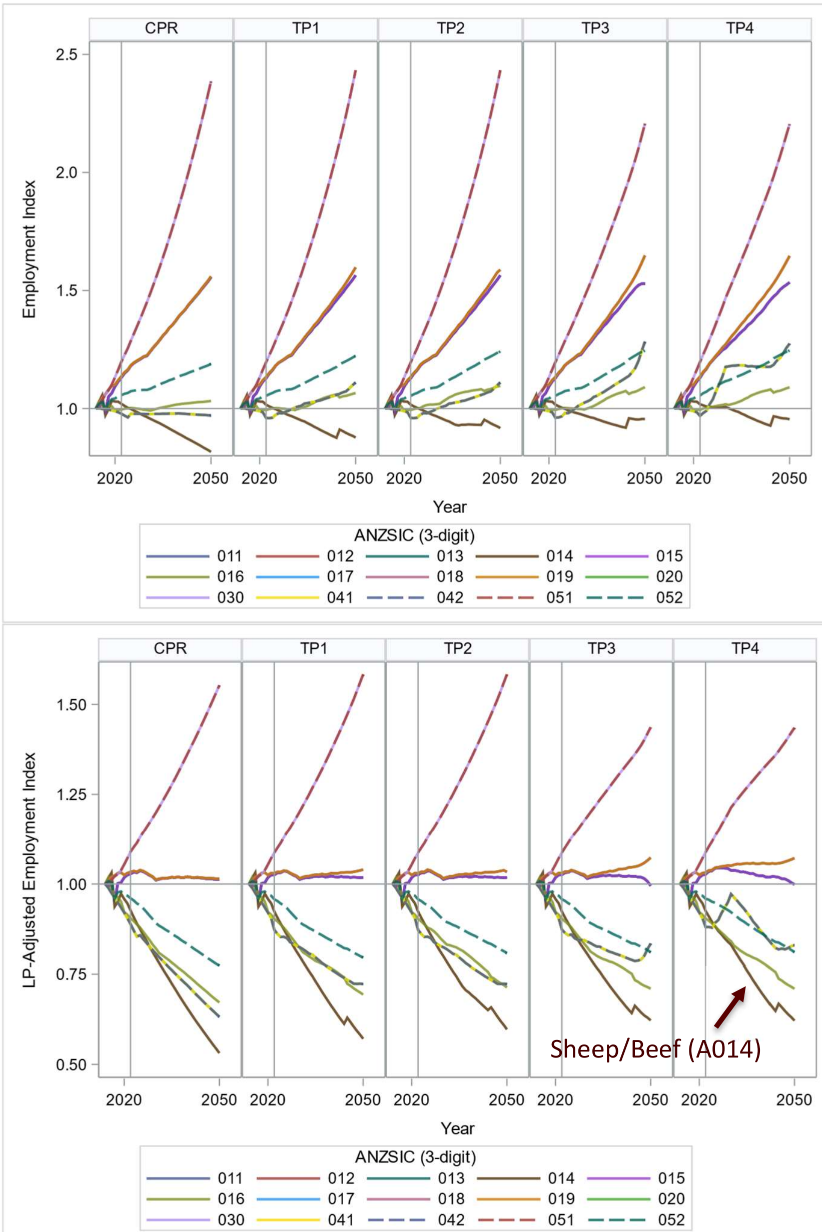
	Industry	Draft Advice												Final Advice		
		TP1 Net Positive			TP2 Net Positive			TP3 Net Positive			TP4 Net Positive			Demo Path Net Positive		
			Worker-Job Equivalents			Worker-Job Equivalents			Rank			Worker-Job Equivalents			Worker-job Equivalents	
		Rank	N	%	Rank	N	%	Rank	N	%	Rank	N	%	Rank	N	%
I490	Air and Space Transport	**1**	**967**	**10.38%**	3	956	10.26%	**1**	**1995**	**21.42%**	**1**	**2076**	**22.28%**	**1**	**3225**	**35.14%**
A014	Sheep, Beef Cattle and Grain Farming	2	751	4.16%	**1**	**1255**	**6.96%**	2	1643	9.11%	2	1669	9.25%	4	1571	8.67%
I521	Water Transport Support Services	3	607	11.78%	5	605	11.75%	4	1256	24.36%	4	1315	25.52%	3	2216	41.50%
H451	Cafes, Restaurants and Takeaway Food Services	4	569	0.53%	6	482	0.45%	3	1271	1.18%	3	1339	1.24%	2	2474	2.39%
A016	Dairy Cattle Farming	5	562	2.29%	2	1111	4.53%	5	958	3.90%	5	982	4.00%	8	995	4.02%
A052	Agriculture and Fishing Support Services	6	470	2.24%	4	757	3.61%	7	830	3.95%	7	828	3.94%	25	417	1.99%
I522	Air Transport Support Services	7	255	10.38%	7	252	10.26%	10	526	21.42%	10	547	22.28%	10	850	35.14%
C239	Other Transport Equipment Manufacturing	8	229	2.34%	8	207	2.11%	8	558	5.71%	8	592	6.06%	6	1125	12.51%
H440	Accommodation	9	183	0.53%	9	155	0.45%	11	410	1.18%	11	432	1.24%	11	798	2.39%
A041	Fishing	10	148	9.24%	10	148	9.21%	13	319	19.85%	13	333	20.75%	17	583	35.94%
C111	Meat and Meat Product Manufacturing	16	100	0.38%	14	102	0.38%	6	945	3.54%	6	969	3.63%	9	967	3.68%
P802	School Education	17	100	0.09%				9	534	0.47%	9	592	0.52%	5	1424	1.29%
Q840	Hospitals													7	1027	1.29%

Table 3: Industries with Largest Net Negative Employment Changes, 2022-2050

		Draft Advice												**Final Advice**		
		TP1 Net Negative			**TP2 Net Negative**			**TP3 Net Negative**			**TP4 Net Negative**			**Demo Path Net Negative**		
			Worker-Job Equivalents			**Worker-Job Equivalents**			**Worker-Job Equivalents**			**Worker-Job Equivalents**			**Worker-Job Equivalents**	
	Industry	**Rank**	**N**	**%**	**Rank**	**N**	**%**	**Rank**	**N**	**%**	**Rank**	**N**	**%**	**Rank**	**N**	**%**
C249	Other Machinery and Equipment Manufacturing	**1**	**-606**	**4.66%**	**1**	**-645**	**4.96%**	2	-1265	9.73%	2	-1329	10.21%	2	-2723	24.07%
C149	Other Wood Product Manufacturing	2	-341	3.00%	2	-365	3.21%	3	-886	7.80%	3	-887	7.81%	10	-864	8.27%
C161	Printing	3	-305	3.00%	3	-327	3.21%	4	-793	7.80%	5	-794	7.81%	14	-773	8.27%
C251	Furniture Manufacturing	4	-304	4.66%	4	-323	4.96%	7	-634	9.73%	7	-666	10.21%	4	-1364	24.07%
C222	Structural Metal Product Manufacturing	5	-271	2.23%	6	-285	2.34%	8	-629	5.17%	8	-661	5.43%			
C246	Specialised Machinery and Equipment Manufacturing	6	-270	4.66%	5	-287	4.96%	9	-563	9.73%	9	-591	10.21%	5	-1211	24.07%
C141	Log Sawmilling and Timber Dressing	7	-257	3.00%	7	-275	3.21%	6	-667	7.80%	6	-667	7.81%	16	-650	8.27%
B070	Oil and Gas Extraction	8	-247	26.85%	8	-247	26.86%	11	-492	53.53%	10	-533	58.01%	17	-629	70.26%
C241	Professional and Scientific Equipment Manufacturing	9	-220	4.66%	9	-234	4.96%	12	-459	9.73%	12	-482	10.21%	7	-988	24.07%
C133	Textile Product Manufacturing	10	-207	4.66%	10	-221	4.96%	14	-433	9.73%	14	-454	10.21%	8	-931	24.07%
I461	Road Freight Transport	25	-59	0.21%	20	-87	0.31%	**1**	**-1835**	**6.43%**	**1**	**-2181**	**7.65%**	**1**	**-4981**	**17.92%**
I462	Road Passenger Transport	31	-22	0.21%	30	-33	0.31%	5	-692	6.43%	4	-823	7.65%	3	-1880	17.92%
A030	Forestry and Logging							10	-506	10.61%	11	-494	10.37%			
C242	Computer and Electronic Equipment Manufacturing													9	-923	24.07%
A013	Fruit and Tree Nut Growing													6	-1026	6.84%

8. Figures

Figure 1. Employment Indices from C-PLAN for Agriculture before (top panel) and after (bottom panel) Productivity Adjustment for Draft Advice, 2014-2050



ANZSIC06 Industry	
A011	Nursery and Floriculture Production
A012	Mushroom and Vegetable Growing
A013	Fruit and Tree Nut Growing
A014	Sheep, Beef Cattle and Grain Farming
A015	Other Crop Growing
A016	Dairy Cattle Farming
A017	Poultry Farming
A018	Deer Farming
A019	Other Livestock Farming
A020	Aquaculture
A030	Forestry and Logging
A041	Fishing
A042	Hunting and Trapping
A051	Forestry Support Services
A052	Agriculture and Fishing Support Services

Figure 2. Cumulative Employment Changes (WJE) in Sheep, Beef Cattle and Grain Farming (A014)

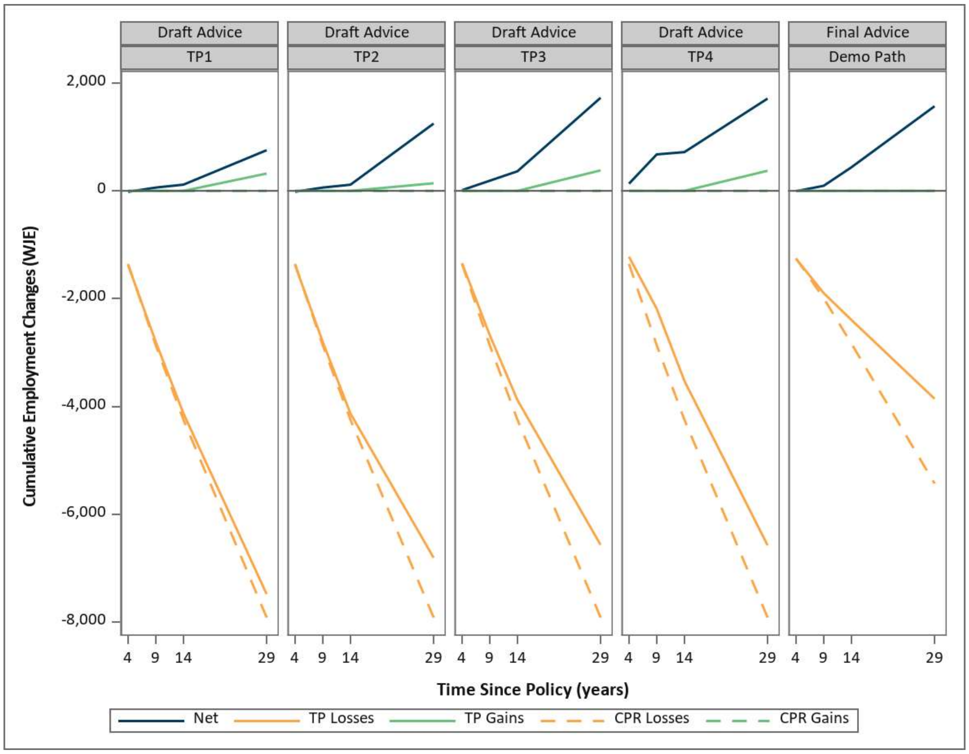


Figure 3. Average Annual Employment Changes (WJE) Predicted in each Time Period

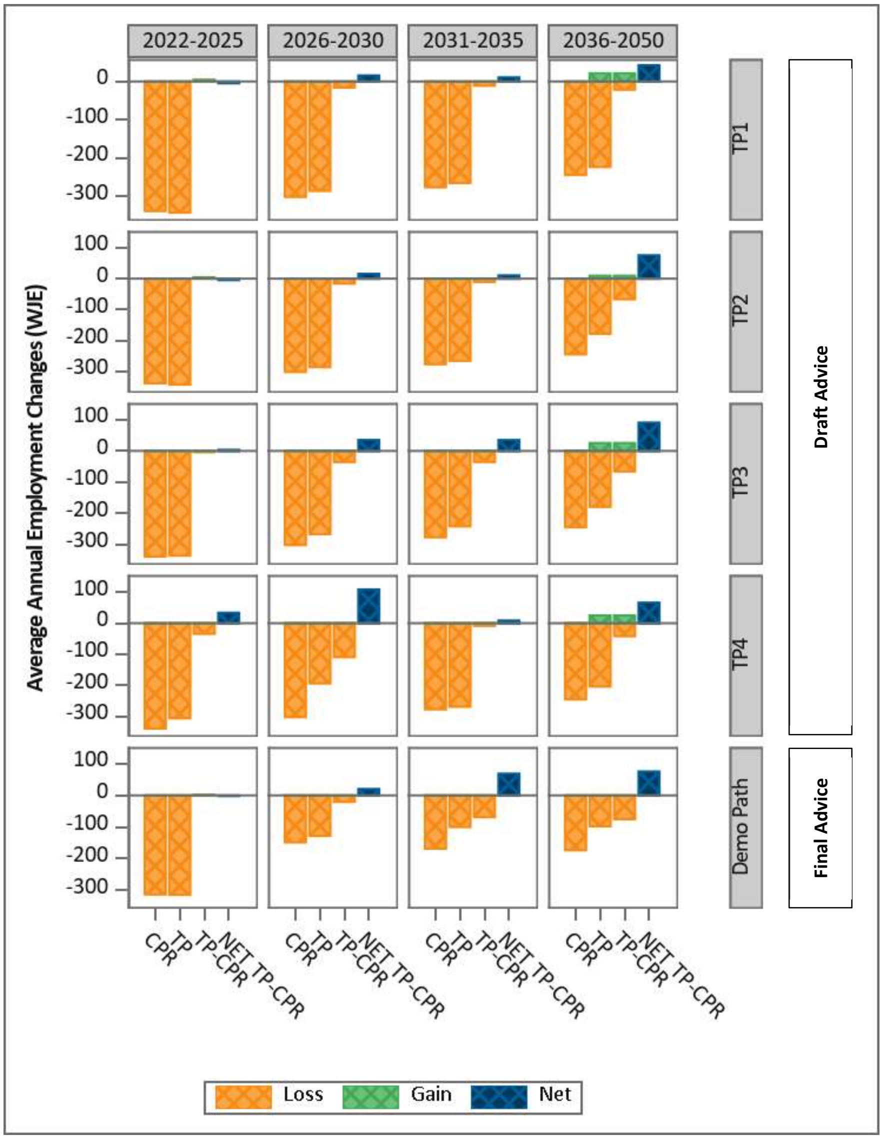


Figure 4. Industry Distribution of Cumulative Net Employment Effects (Gains, Losses, and Total Net) under TP4 from Publicly Available Employment Data

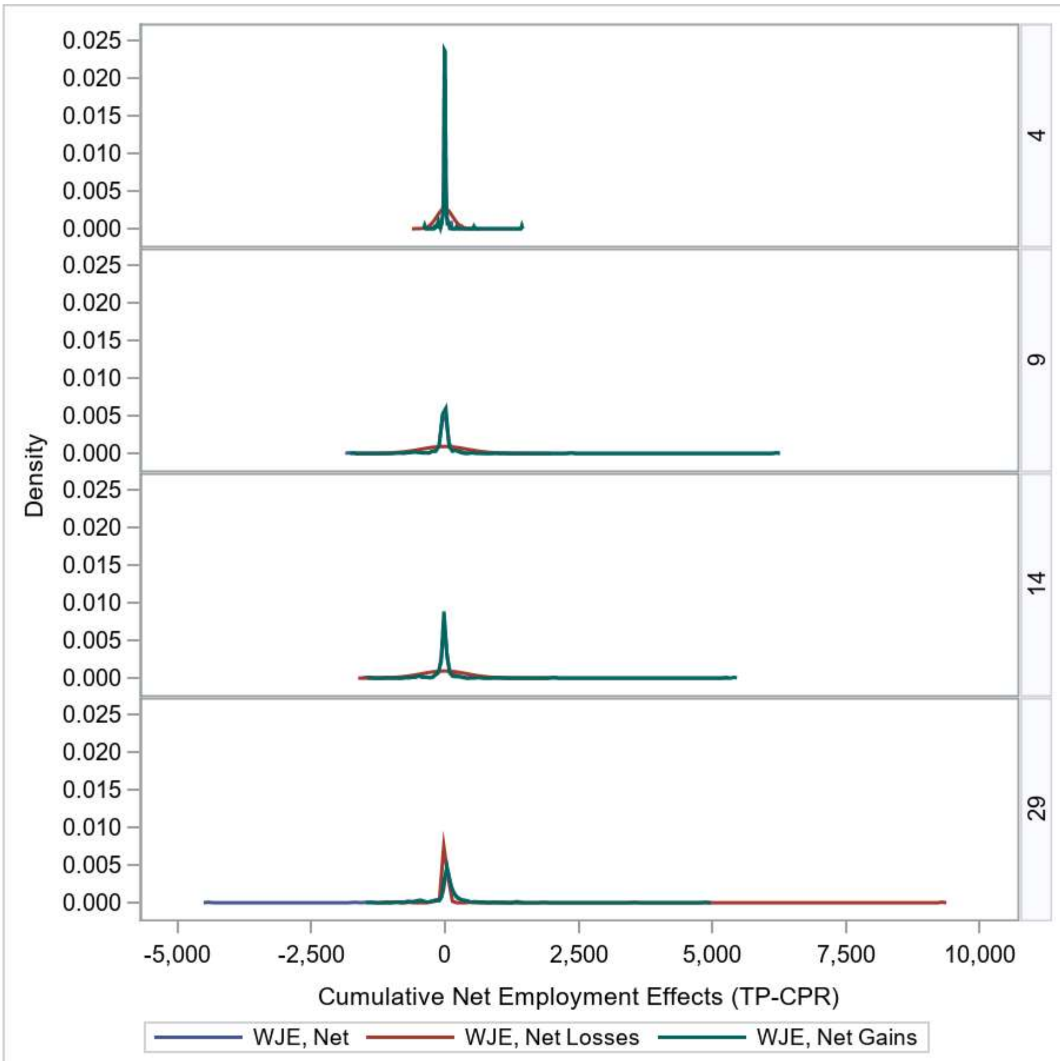


Figure 5. Industry Distribution of Cumulative Total Net Employment Effects under TP4 from Publicly Available Employment Data

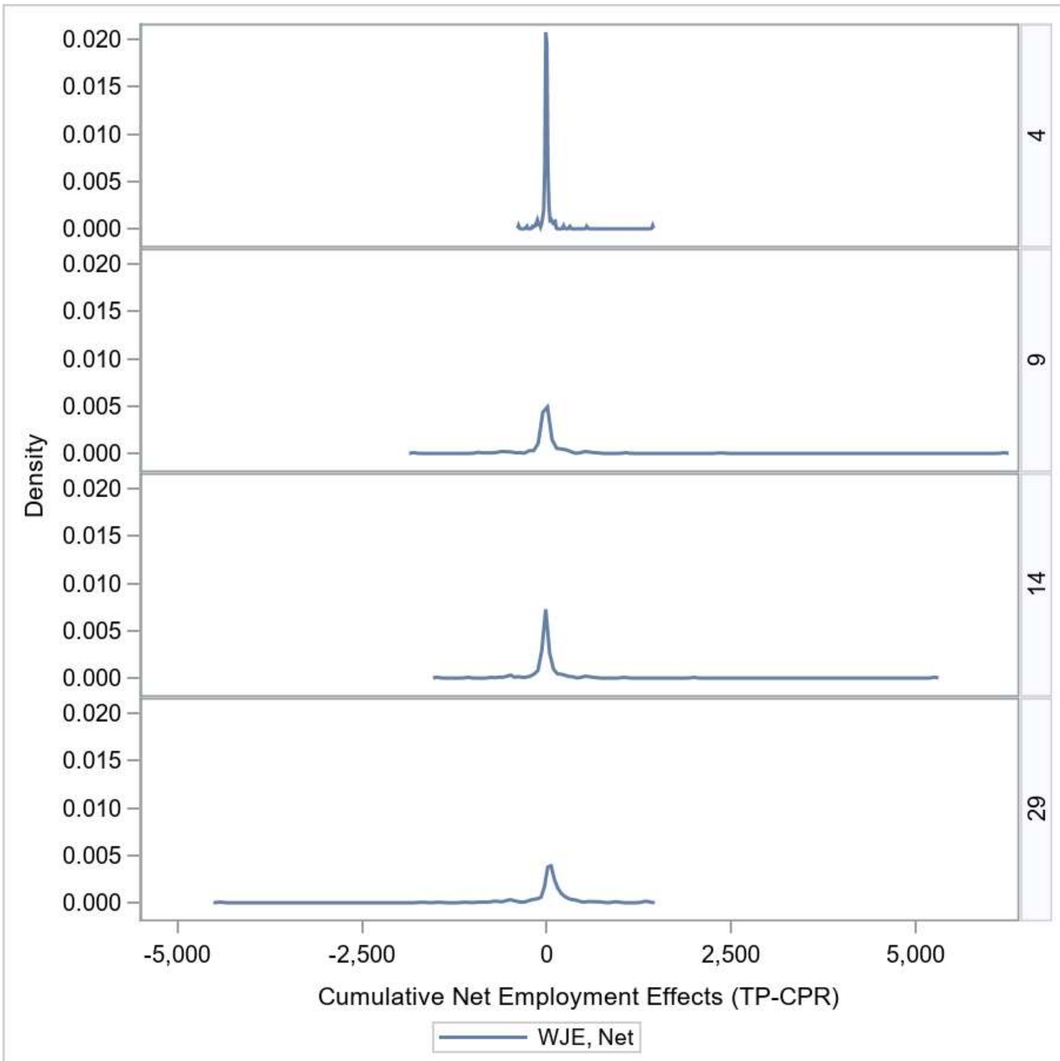


Figure 6. Counts of Simulated Worker-Jobs by Net Effect Type for 2022-2025 (Left Panel) and for 2022-2050 (Right Panel)

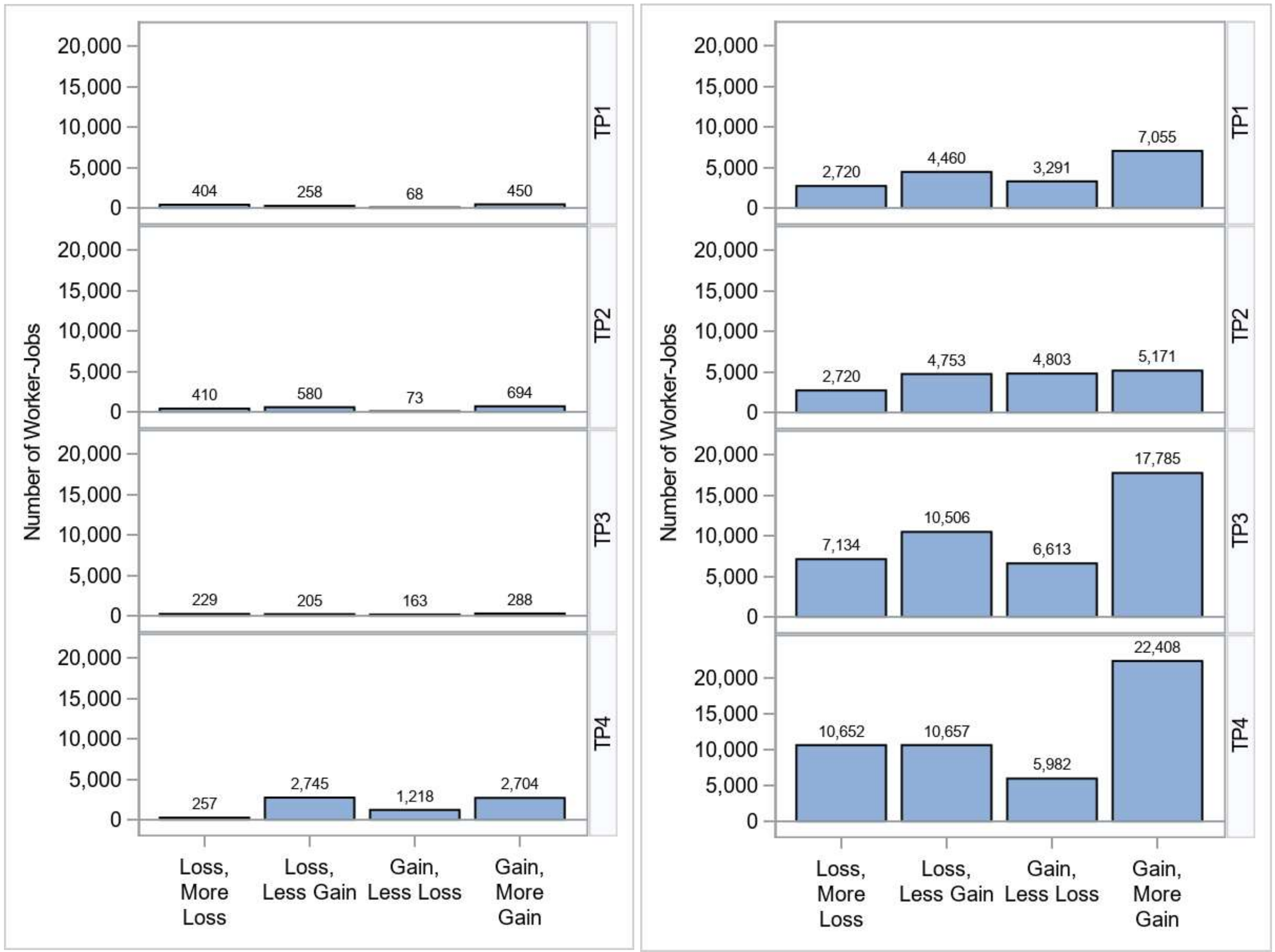


Figure 7. Simulated Worker-Job Annual Earnings by Net Effect Type for 2022-2025 (Left Panel) and 2022-2050 (Right Panel)

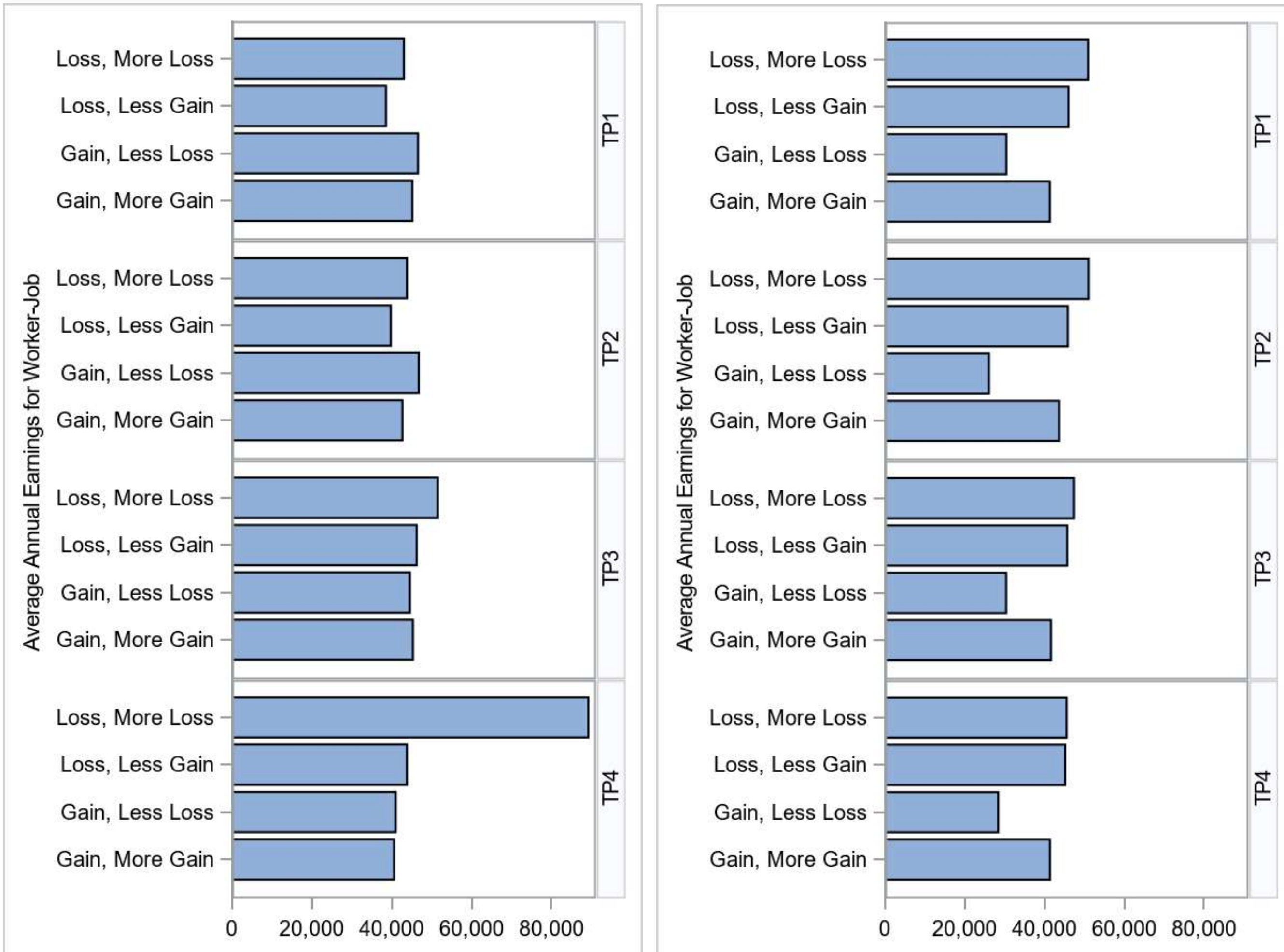


Figure 8. Cumulative Net Effects by 1-digit Industry for Draft Advice, 2022-2050

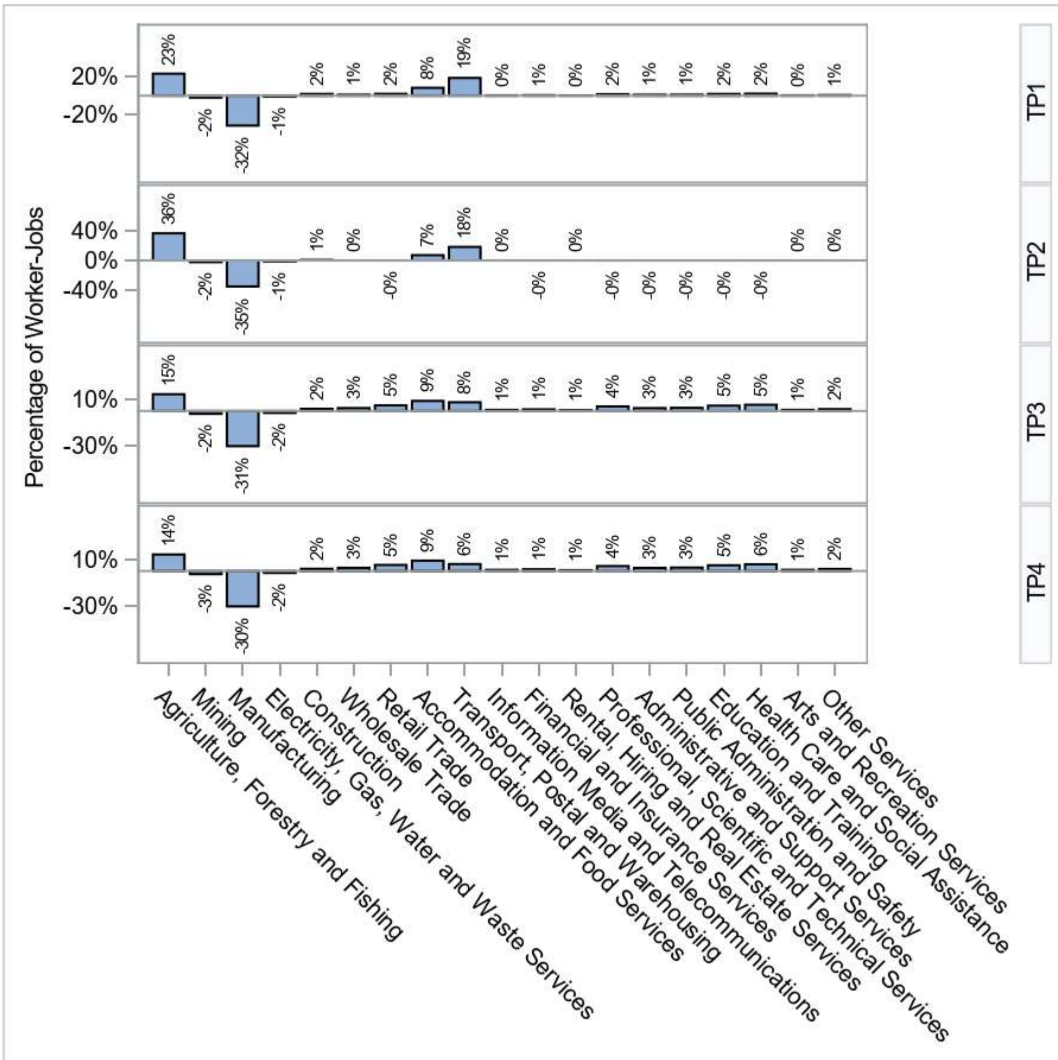


Figure 9. Share of Net Worker-Jobs by Highest Qualification for 2022-2025

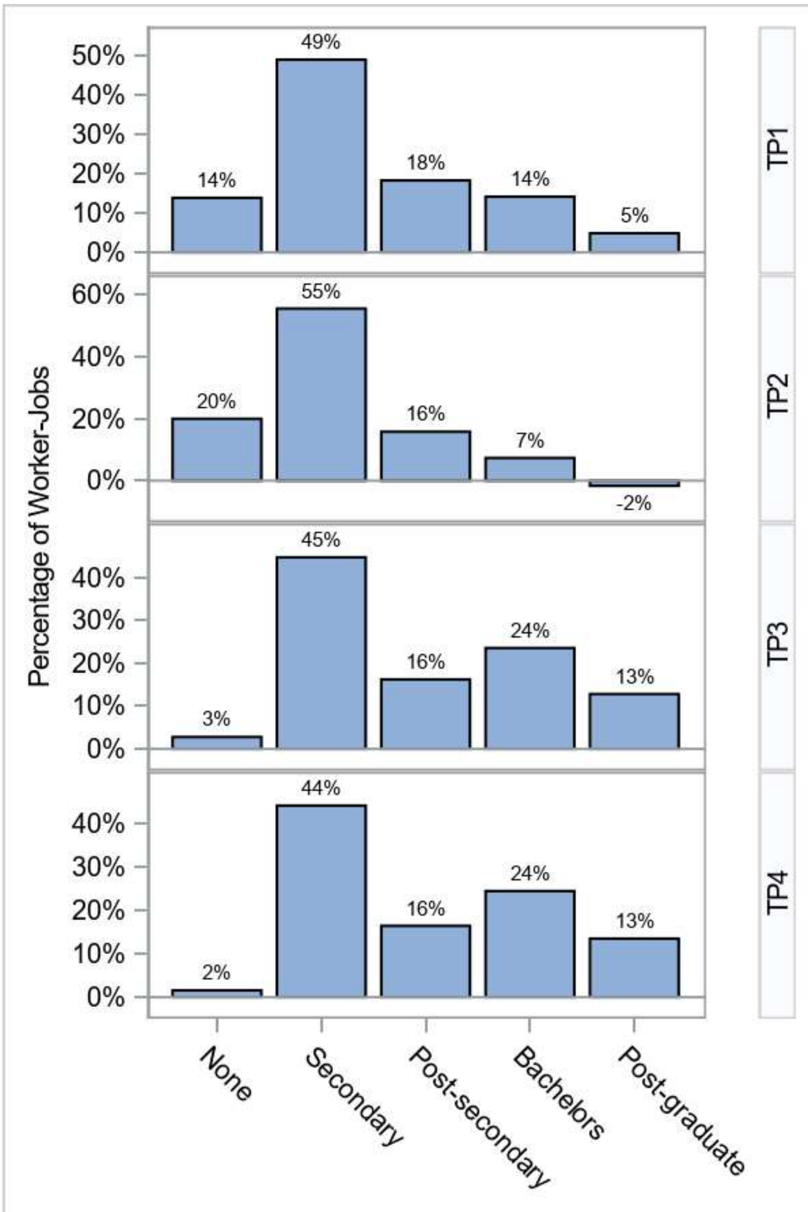
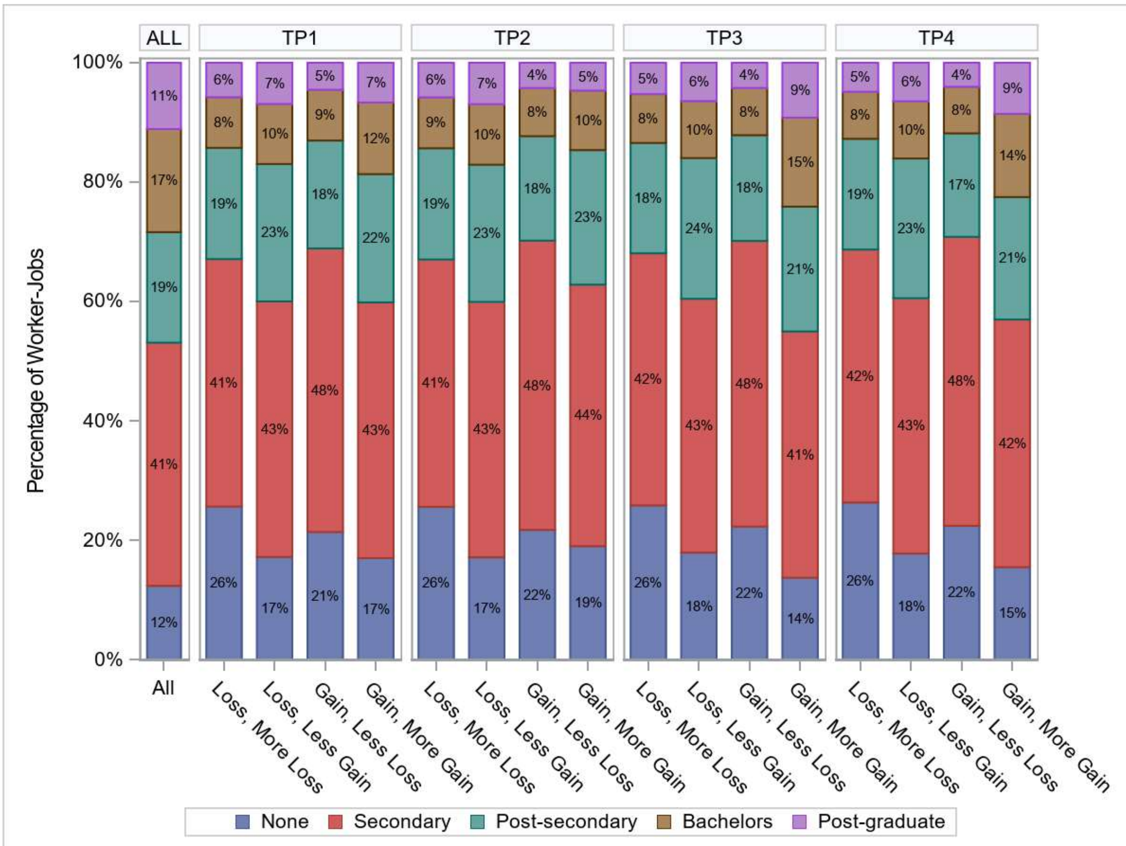


Figure 10. Detailed Shares of Net Effects by Highest Qualification for 2022-2050



9. Appendix

A1. Table of ANZSIC06 to GTAP Sectors

ANZSIC06 Code	ANZSIC Sector Description	GTAP Code	GTAP Sector Description
011	Nursery and Floriculture Production	hor	Horticulture
012	Mushroom and Vegetable Growing	hor	Horticulture
013	Fruit and Tree Nut Growing	hor	Horticulture
014	Grain, Sheep and Beef Cattle Farming	b_s	Beef and Sheep Farming
015	Other Crop Growing	hor	Horticulture
016	Dairy Cattle Farming	rmk	Dairy Farming
017	Poultry Farming	oap	Other Animal Products
018	Deer Farming	oap	Other Animal Products
019	Other Livestock Farming	oap	Other Animal Products
020	Aquaculture	fsh	Fishing
030	Forestry and Logging	frs	Forestry
041	Fishing	fsh	Fishing
042	Hunting and Trapping	fsh	Fishing
051	Forestry Support Services	frs	Forestry
052	Agriculture and Fishing Support Services	rmk b_s oap hor fsh	Dairy Farming, Beef and Sheep Farming, Other Animal Products, Horticulture Fishing
060	Coal Mining	col	Coal
070	Oil and Gas Extraction	cru gas	Oil and Gas
080	Metal Ore Mining	oxt	Mining of Metal Ores
091	Construction Material Mining	oxt	Mining of Metal Ores
099	Other Non-Metallic Mineral Mining and Quarrying	oxt	Mining of Metal Ores
101	Exploration	cru gas oxt	Oil, Gas and Mining of Metal Ores
109	Other Mining Support Services	cru gas oxt	Oil, Gas and Mining of Metal Ores
111	Meat and Meat Product Manufacturing	mtp	Meat Products
112	Seafood Processing	ofd	Other Food Processing
113	Dairy Product Manufacturing	mil	Dairy Products
114	Fruit and Vegetable Processing	ofd	Other Food Processing
115	Oil and Fat Manufacturing	ofd	Other Food Processing
116	Grain Mill and Cereal Product Manufacturing	ofd	Other Food Processing
117	Bakery Product Manufacturing	ofd	Other Food Processing
118	Sugar and Confectionery Manufacturing	ofd	Other Food Processing
119	Other Food Product Manufacturing	ofd	Other Food Processing
121	Beverage Manufacturing	ofd	Other Food Processing

122	Cigarette and Tobacco Product Manufacturing	ofd	Other Food Processing
131	Textile Fibre, Yarn and Woven Fabric Manufacturing	omf	Other Manufacturing
132	Leather Tanning and Fur Dressing	omf	Other Manufacturing
133	Textile Product Manufacturing	omf	Other Manufacturing
134	Knitted Product Manufacturing	omf	Other Manufacturing
135	Clothing and Footwear Manufacturing	omf	Other Manufacturing
141	Log Sawmilling and Timber Dressing	w_p	Wood, Wood Products, Paper and Paper Products
149	Other Wood Product Manufacturing	w_p	Wood, Wood Products, Paper and Paper Products
151	Pulp, Paper and Paperboard Manufacturing	w_p	Wood, Wood Products, Paper and Paper Products
152	Converted Paper Product Manufacturing	w_p	Wood, Wood Products, Paper and Paper Products
161	Printing	w_p	Wood, Wood Products, Paper and Paper Products
162	Reproduction of Recorded Media	w_p	Wood, Wood Products, Paper and Paper Products
170	Petroleum Refining and Petroleum and Coal Product Manufacturing	oil	Petroleum Products
181	Chemical Manufacturing	crp	Chemical Rubber and Plastic Products
182	Basic Polymer Manufacturing	crp	Chemical Rubber and Plastic Products
183	Fertiliser and Pesticide Manufacturing	crp	Chemical Rubber and Plastic Products
184	Pharmaceutical and Medicinal Product Manufacturing	crp	Chemical Rubber and Plastic Products
185	Cleaning Compound and Toiletry Preparation Manufacturing	crp	Chemical Rubber and Plastic Products
189	Other Basic Chemical Product Manufacturing	crp	Chemical Rubber and Plastic Products
191	Polymer Product Manufacturing	crp	Chemical Rubber and Plastic Products
192	Natural Rubber Product Manufacturing	crp	Chemical Rubber and Plastic Products
201	Glass and Glass Product Manufacturing	nmm	Non-Metallic Maniufacturing
202	Ceramic Product Manufacturing	nmm	Non-Metallic Maniufacturing
203	Cement, Lime, Plaster and Concrete Product Manufacturing	nmm	Non-Metallic Maniufacturing
209	Other Non-Metallic Mineral Product Manufacturing	nmm	Non-Metallic Maniufacturing
211	Basic Ferrous Metal Manufacturing	i_s	Iron and Steel
212	Basic Ferrous Metal Product Manufacturing	i_s	Iron and Steel
213	Basic Non-Ferrous Metal Manufacturing	nfm	Non-Ferrous Metals

214	Basic Non-Ferrous Metal Product Manufacturing	nfm	Non-Ferrous Metals
221	Iron and Steel Forging	i_s	Iron and Steel
222	Structural Metal Product Manufacturing	fmp	Fabricated Metal Products
223	Metal Container Manufacturing	fmp	Fabricated Metal Products
224	Other Sheet Metal Product Manufacturing	fmp	Fabricated Metal Products
229	Other Fabricated Metal Product Manufacturing	fmp	Fabricated Metal Products
231	Motor Vehicle and Motor Vehicle Part Manufacturing	mvh	Motor Vehicles and Parts
239	Other Transport Equipment Manufacturing	mvh	Motor Vehicles and Parts
241	Professional and Scientific Equipment Manufacturing	omf	Other Manufacturing
242	Computer and Electronic Equipment Manufacturing	omf	Other Manufacturing
243	Electrical Equipment Manufacturing	omf	Other Manufacturing
244	Domestic Appliance Manufacturing	omf	Other Manufacturing
245	Pump, Compressor, Heating and Ventilation Equipment Manufacturing	omf	Other Manufacturing
246	Specialised Machinery and Equipment Manufacturing	omf	Other Manufacturing
249	Other Machinery and Equipment Manufacturing	omf	Other Manufacturing
251	Furniture Manufacturing	omf	Other Manufacturing
259	Other Manufacturing	omf	Other Manufacturing
261	Electricity Generation	ecoa egas ehyd ewin esol eoth	Coal Electricity, Gas Electricity, Hydro Electricity, Wind Electricity, Solar Electricity and Geothermal Electricity
262	Electricity Transmission	tnd	Transmission and Distribution
263	Electricity Distribution	tnd	Transmission and Distribution
264	On Selling Electricity and Electricity Market Operation	tnd	Transmission and Distribution
270	Gas Supply	gas	Gas
281	Water Supply, Sewerage and Drainage Services	ser	Services
291	Waste Collection Services	ser	Services
292	Waste Treatment, Disposal and Remediation Services	ser	Services
301	Residential Building Construction	cns	Construction
302	Non-Residential Building Construction	cns	Construction
310	Heavy and Civil Engineering Construction	cns	Construction
321	Land Development and Site Preparation Services	cns	Construction
322	Building Structure Services	cns	Construction

323	Building Installation Services	cns	Construction
324	Building Completion Services	cns	Construction
329	Other Construction Services	cns	Construction
331	Agricultural Product Wholesaling	ser	Services
332	Mineral, Metal and Chemical Wholesaling	ser	Services
333	Timber and Hardware Goods Wholesaling	ser	Services
341	Specialised Industrial Machinery and Equipment Wholesaling	ser	Services
349	Other Machinery and Equipment Wholesaling	ser	Services
350	Motor Vehicle and Motor Vehicle Parts Wholesaling	ser	Services
360	Grocery, Liquor and Tobacco Product Wholesaling	ser	Services
371	Textile, Clothing and Footwear Wholesaling	ser	Services
372	Pharmaceutical and Toiletry Goods Wholesaling	ser	Services
373	Furniture, Floor Coverings and Other Goods Wholesaling	ser	Services
380	Commission Based Wholesaling	ser	Services
391	Motor Vehicle Retailing	ser	Services
392	Motor Vehicle Parts Retailing	ser	Services
400	Fuel Retailing	ser	Services
411	Supermarket and Grocery Stores	ser	Services
412	Specialised Food Retailing	ser	Services
421	Furniture, Floor Coverings, Houseware and Textile Goods Retailing	ser	Services
422	Electrical and Electronic Goods Retailing	ser	Services
423	Hardware, Building and Garden Supplies Retailing	ser	Services
424	Recreational Goods Retailing	ser	Services
425	Clothing, Footwear and Personal Accessories Retailing	ser	Services
426	Department Stores	ser	Services
427	Pharmaceutical and Other Store-Based Retailing	ser	Services
431	Non Store Retailing	ser	Services
432	Retail Commission Based Buying and/or Selling	ser	Services
440	Accommodation	afs	Accommodation and Food Services
451	Cafes, Restaurants and Takeaway Food Services	afs	Accommodation and Food Services
452	Pubs, Taverns and Bars	afs	Accommodation and Food Services
453	Clubs (Hospitality)	afs	Accommodation and Food Services
461	Road Freight Transport	rtp	Road Transport
462	Road Passenger Transport	rtp	Road Transport

471	Rail Freight Transport	rtp	Road Transport
472	Rail Passenger Transport	rtp	Road Transport
481	Water Freight Transport	wtp	Water Transport
482	Water Passenger Transport	wtp	Water Transport
490	Air and Space Transport	atp	Air Transport
501	Scenic and Sightseeing Transport	rtp atp wtp	Road transport, Air Transport and Water Transport
502	Pipeline and Other Transport	rtp	Road Transport
510	Postal and Courier Pick-up and Delivery Services	ser	Services
521	Water Transport Support Services	wtp	Water Transport
522	Air Transport Support Services	atp	Air Transport
529	Other Transport Support Services	ser	Services
530	Warehousing and Storage Services	ser	Services
541	Newspaper, Periodical, Book and Directory Publishing	ser	Services
542	Software Publishing	ser	Services
551	Motion Picture and Video Activities	ser	Services
552	Sound Recording and Music Publishing	ser	Services
561	Radio Broadcasting	ser	Services
562	Television Broadcasting	ser	Services
570	Internet Publishing and Broadcasting	ser	Services
580	Telecommunications Services	ser	Services
591	Internet Service Providers and Web Search Portals	ser	Services
592	Data Processing, Web Hosting and Electronic Information Storage Services	ser	Services
601	Libraries and Archives	ser	Services
602	Other Information Services	ser	Services
621	Central Banking	ser	Services
622	Depository Financial Intermediation	ser	Services
623	Non-depository Financing	ser	Services
624	Financial Asset Investing	ser	Services
631	Life Insurance	ser	Services
632	Health and General Insurance	ser	Services
633	Superannuation Funds	ser	Services
641	Auxiliary Finance and Investment Services	ser	Services
642	Auxiliary Insurance Services	ser	Services
661	Motor Vehicle and Transport Equipment Rental and Hiring	ser	Services
662	Farm Animals and Bloodstock Leasing	ser	Services
663	Other Goods and Equipment Rental and Hiring	ser	Services

664	Non-Financial Intangible Assets (except Copyrights) Leasing	ser	Services
671	Property Operators	ser	Services
672	Real Estate Services	ser	Services
691	Scientific Research Services	ser	Services
692	Architectural, Engineering and Technical Services	ser	Services
693	Legal and Accounting Services	ser	Services
694	Advertising Services	ser	Services
695	Market Research and Statistical Services	ser	Services
696	Management and Other Consulting Services	ser	Services
697	Veterinary Services	ser	Services
699	Other Professional, Scientific and Technical Services	ser	Services
700	Computer Systems Design and Related Services	ser	Services
721	Employment Services	ser	Services
722	Travel Agency Services	ser	Services
729	Other Administrative Services	ser	Services
731	Building Cleaning, Pest Control and Gardening Services	ser	Services
732	Packaging and Labelling Services	ser	Services
751	Central Government Administration	ser	Services
752	State Government Administration	ser	Services
753	Local Government Administration	ser	Services
754	Justice	ser	Services
755	Government Representation	ser	Services
760	Defence	ser	Services
771	Public Order and Safety Services	ser	Services
772	Regulatory Services	ser	Services
801	Preschool Education	ser	Services
802	School Education	ser	Services
810	Tertiary Education	ser	Services
821	Adult, Community and Other Education	ser	Services
822	Educational Support Services	ser	Services
840	Hospitals	ser	Services
851	Medical Services	ser	Services
852	Pathology and Diagnostic Imaging Services	ser	Services
853	Allied Health Services	ser	Services
859	Other Health Care Services	ser	Services
860	Residential Care Services	ser	Services
871	Child Care Services	ser	Services
879	Other Social Assistance Services	ser	Services
891	Museum Operation	ser	Services

892	Parks and Gardens Operations	ser	Services
900	Creative and Performing Arts Activities	ser	Services
911	Sport and Physical Recreation Activities	ser	Services
912	Horse and Dog Racing Activities	ser	Services
913	Amusement and Other Recreation Activities	ser	Services
920	Gambling Activities	ser	Services
941	Automotive Repair and Maintenance	ser	Services
942	Machinery and Equipment Repair and Maintenance	ser	Services
949	Other Repair and Maintenance	ser	Services
951	Personal Care Services	ser	Services
952	Funeral, Crematorium and Cemetery Services	ser	Services
953	Other Personal Services	ser	Services
954	Religious Services	ser	Services
955	Civic, Professional and Other Interest Group Services	ser	Services
960	Private Households Employing Staff	ser	Services