A Decomposition and Microsimulation Analysis of Occupational Wage Growth in Australia, 2010-2017

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Dynamic historical and comparative static decomposition CGE simulations are a powerful tool for understanding structural change and its impacts. In this paper, we examine the impact on wages of three sets of structural drivers: macroeconomic factors, qualification supply, and technical change.

To the CGE analysis, we add a microsimulation analysis. Microsimulation addresses a shortcoming in CGE modelling, which is that the household sector is represented by one or several representative agents. With the representative agent treatment, CGE modelling is unable to capture all of the diversity in the household sector in relation to the levels of income, sources of income, and composition of expenditure by different households.

Over the study period of 2010 to 2017, average growth in real wages in Australia was weak. Growth in high-wage occupations was generally stronger than growth in low-wage occupations, resulting in a widening gap between the wages of the highest- and lowest-paid workers. Over the period, key results from our research indicate that:

- Macroeconomic factors played a role in determining overall wage growth, but did not explain the disparity between wage growth at the occupational level;
- Strong growth in the supply of qualifications at the level of bachelor degree level and above detracted from wage growth in the high-skill occupations;
- Skill-biased technical change in favour of the high-skill occupations led to relatively strong growth in the wages of high-skill occupations, an effect that dominated the results; and
- Relatively strong growth in the wages of high-skill occupations added disproportionately to the incomes of high-income households and led to an increase in household income disparities and an increase in the relative poverty rate. However, this result did not take into account possible changes in occupation by households over the study period. With the wages of low-skilled occupations falling further below average, a change of occupation, rather than a pay-rise in their existing occupations, was a better prospect for low-income households to avoid falling into absolute or relative poverty.

The decomposition analysis could be extended to a broader analysis of structural change in the Australian economy, and may be the subject of future research. The links built for this analysis between CGE modelling and microsimulation also suggest scope for future research.

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JEL: J11, J24, J31, C68, D58

Key words: CGE decomposition, microsimulation, wages, technical change

Contents

1 Introduction

Over the last seven years, growth in real wages has been weak, averaging less than 1 per cent per annum. But some workers have fared better than others: while those in high-paid occupations, such as managers, engineers and doctors, experienced real annual wage growth averaging 1.4 per cent, lower-paid workers, including cleaners, sales assistants and labourers, on average haven't received a real wage rise at all. Disparities in wage growth contribute to inequality, challenging our traditional notion of a fair go for all. Ongoing increases in inequality may eventually detract from economic growth.

We use the CGE decomposition technique popularised by Dixon and Rimmer (2002) to separate out three sets of influences on recent wage growth: first, macroeconomic factors; second, the impact of skill-biased technical change in demand for occupations and in the qualifications that make up the occupations; and third, changes in the level of education of the workforce. Linking the CGE model to a microsimulation model, we draw some links between inequality in wage growth and household inequality more generally.

Macroeconomic factors such as economic growth, changes in household consumption, demand for imports and exports, and movements in the exchange rate have had a positive effect on wage growth. These factors have affected the occupation groups fairly uniformly, and so do not explain the divergence in wage growth.

Instead, our results indicate that the second effect – changes in the types of workers demanded by industry – explains strong growth in wages of the highest-paid occupations, and weak growth in most of the middle- to low-paid occupations.

The relative increase in demand for high-paid occupations reflects the impact of automation, which displaces low-paid workers while making high-paid workers more productive. For example, we were able to download all the data we used for this project quickly and easily ourselves, whereas once upon a time we would have employed a data-entry clerk to type it in for us.

Although there has been weak demand for most low-wage occupations, "caring" occupations, such as child carers, personal carers and education aides, are somewhat immune to the displacement effects of technological change. Regulatory requirements and the nature of the work generally require certain ratios of staff to children or patients that are not easily reduced.

We find that within every occupation, industries are gradually requiring more highly qualified workers. For example, there has been a gradual shift towards accountants with post-graduate qualifications rather than with bachelor degrees; and in childcare, there has been a shift away from workers with no post-school qualifications towards workers with certificate qualifications.

The occupation and qualification demand effects together mean that the most highly qualified workers in the highest-paid or highest-skilled occupations are the big winners in the digital age.

The third influence on wage growth is the overall change in the level of education or qualifications held by the workforce. In recent years there has been a large influx of workers holding degrees and certificates, while older workers, who are more likely to have no post-school qualifications are gradually retiring from employment. On its own, this effect reduces the wage premium associated with a high level of education, which is no longer the preserve of the elite. In other words, growth in the supply of highly-qualified workers has dampened, but not eliminated, the disparity in wage growth.

What does this mean for income distribution? Despite some exceptions, overall growth in low-skilled wages is has been slower than growth in high-skilled wages, so we have seen an increasing gap in wage income between Australia's richest and poorest households. However, official measurements of the Gini coefficient, a measure of income inequality, do not indicate that household income inequality has changed much this century. In part, this is because when people from low-income households move into better-paid occupations, income disparities are reduced.

Australia's Gini coefficient is not high by international standards – we have a more equal income distribution than most and it has remained steady for some time. Despite this, we must not downplay the importance of growing wage inequality in Australia. While innovations such as automation and other labour-saving technology are crucial to economic growth, they have contributed to a growing wage gap between the highest- and lowest-paid workers. The good news is that the increase in education levels in the workforce has worked in the opposite direction, dampening what otherwise would have been an even wider spread in wage growth.

The remainder of this paper is arranged as follows. In section 2 we describe the CGE model, data sources and decomposition technique, and in section 3 we describe the microsimulation model and links to the CGE model. The results from the model are discussed in section 4, and concluding remarks and avenues for further research are suggested in section 5.

2 The VU model

The VU model is a dynamic, detailed computable general equilibrium (CGE) model of the Australian economy in the style of the MONASH model (Dixon and Rimmer 2002). VU identifies 115 industries undertaking production and capital creation, as well as households and government and a foreign sector which supplies imports and purchases exports.

The VU model has a particularly detailed labour market, in which 97 occupations are identified, and labour is supplied to these occupations by workers classified into 56 categories according to educational qualifications. The labour market is described in more detail in section 2.1 below.

As with all models in the MONASH and ORANI tradition, representative agents choose inputs according to the constrained optimisation problems originally described in Dixon et al (1982). The initial database, based on ABS supply-and-use input-output tables, is assumed to provide a solution to the model, thereby providing initial values for the unobservable variables that describe structural features of the economy such as tastes, technology, and the positions of export demand curves. The model is solved using GEMPACK (Harrison and Pearson, 1996), a purpose built software package for solving CGE models.

The aim of this study is to uncover the structural changes that drove occupational wage growth from 2010 to 2017. The remainder of this section is therefore devoted to the two features of the VU model that are most relevant to this aim: first, the representation of the labour market in the VU model, and second, a description of the CGE decomposition technique that enables the attribution of historical patterns of change to the structural factors underlying them.

2.1 The labour market in the VU model

Demand for labour in the VU model follows the standard MONASH model specification, which has its roots in the ORANI model (Dixon et al 1982). Industries choose inputs to solve a cost-minimisation problem, in which the production function consists of several nests of composite inputs. At the top level, industries choose between commodity inputs and a primary factor composite according to a Leontief production function. At this level, each commodity is a composite of imported and domestic varieties, which are treated as imperfect substitutes. The imported and domestic varieties are combined in a CES nest.

The primary factor composite consists of a capital, land and a composite labour input. Inputs to the primary factor composite are chosen by industries minimising costs subject to a CES production function. In a dynamic year-on-year simulation, capital stocks are typically fixed according to the previous year's investment, and wages are assumed to be sticky; as a result this process determines the level of employment, and the rental returns to capital and land.

The composite labour input comprises 97 occupations, aligned with the ANZSCO minor group classification. Again, industries choose inputs (occupations) according to a cost-minimisation problem, seeking to minimise the cost of a bundle of labour subject to a CES production function in the formation of the composite labour input. All other things equal, therefore, industries will substitute towards occupations for which there has been a fall in the wage relative to other occupations.

Each occupation is then a composite of qualification types. The workforce in the VU model is divided into 56 qualification groups, consisting of 5 qualification levels in 11 qualification fields, and a final group for those with no post-school qualification. Again, inputs (qualifications) are chosen according to a cost-minimising problem, now seeking to minimise the cost of a bundle of occupation-specific labour subject to a CES production function. All other things equal, industries will substitute towards qualifications for which there has been a fall in wages relative to other qualifications.

Early versions of Australian CGE models did not contain an explicit specification of labour supply. Either a quantity or price needed to be set exogenously for every occupation. The current version of the VU model builds on this, by assuming instead that workers decide to supply labour to the occupations by solving a constrained revenue-maximisation problem subject to a CET transformation frontier. Each of the 56 qualification groups has a unique occupation profile, providing the initial solution to this constrained revenue-maximisation problem. Supply of each qualification is determined exogenously to the model.

The full lists of industries, occupations and qualifications are given in the appendix.

2.2 Decomposition simulation

Dixon and Rimmer (2002) first formualted the technique of historical decomposition in the watershed MONASH model of the Australian economy. A CGE decomposition simulation enables the separate attribution of any naturally endogenous economic variable, such as output, prices, employment or wages, to changes in structural variables such as productivity, technical change, changes in tastes and changes in foreign demand.

In this paper we base our decomposition on results from the VU model of the Australian economy, run over the period 2009-10 to 2016-17. The model has a particularly detailed labour market, and the decomposition is aimed primarily at explaining disparities in wage growth over the occupations.

The decomposition simulation relies on two prior simulations for its inputs. Firstly, a recursive dynamic historical simulation was run over the period 2009-10 to 2016-17. The aim of this simulation was to reproduce as historical observations over the period of as many economic variables as possible. The simulation is described in J.Dixon (2017). Solutions for these economic variables are accommodated in the model by endogenising corresponding structural change variables. For example, GDP is set exogenously by endogenising economy-wide productivity growth. The full set of exogenous economic variables and corresponding endogenously determined structural variables is given in the appendix.

Key features of this simulation with respect to the labour market are that:

- employment by qualification, a naturally exogenous variable, follows observations of employment by qualification field and level taken from the Survey of Education and Work (ABS 2016);
- employment by occupation, a naturally endogenous variable, is made exogenous and follows observations of occupational employment from the Labour Force Survey (ABS 2017c). These observations are accommodated by endogenising occupation-specific technical change in the labour composite nest;
- employment by industry, a naturally endogenous variable, is made exogenous and follows observations of occupational employment from the Labour Force Survey (ABS 2017c). These observations are accommodated by endogenising labour-saving productivity change in some industries, and in others by endogenising determinants of demand (e.g. taste changes) for industry output;
- wages by occupation, a naturally endogenous variable, are made exogenous and follow observations of occupational wages from Employee Earnings and Hours (ABS 2017a). These observations are accommodated by endogenising worker preferences in the labour supply transformation frontier; and
- for any occupation, wage growth is assumed to be uniform over all qualifications. This assumption is accommodated by endogenising qualification-specific technical change in the occupation composite nest.

Second, a comparative static historical simulation was run. This simulation is similar to the recursive dynamic historical simulation, in that it reproduces the same set of historical observations, and solves for the same set of structural variables. The simulation adopts some features of a typical long-run comparative static closure, including exogenous rates of return and endogenous capital stocks. Solutions for the rates of return from the dynamic model are exogenously imposed on the historical comparative static simulation, as are solutions for accumulation variables including foreign debt and government debt.

This comparative static historical simulation is not strictly necessary, but it is useful in the testing and verification of the final decomposition simulation.

The decomposition simulation is run with a typical long run comparative static closure; that is, structural variables are exogenous, employment is exogenous and wages are endogenous, and rates of return are exogenous and capital stocks are endogenous. All exogenous variables are assigned numerical shock values which are taken from the historical simulation. The decomposition simulation thus endogenously reproduces all historical observations of economic variables originally imposed on the historical simulation.

While the full set of shocks to the exogenous variables leads to the exact reproduction of observed results for the economic variables, the beauty of the decomposition simulation is that it makes it possible to examine the impacts of shocks to subsets of the exogenous variables: the "decomposition" feature of the simulation. The exogenous variables are assigned to three sets, as listed in Table 1 below.

Table 1: Components of the sets of exogenous shocks

Set	**Components**
Macroeconomic factors	Aggregate employment (persons and hours worked), population, land, rates of return, foreign debt, government debt, inflation, positions of export demand curves (commodity specific), household savings rate and commodity preferences, economy-wide preferences for imported and domestic varieties of commodities (commodity specific), investment confidence, government expenditure
Skill supply	Supply of labour by qualification
Overall and skill-biased technical change	Technical change in determining the occupation mix of employment, and the qualification mix within occupations, and overall multi-factor productivity growth

The solution to the decomposition simulation is computed using Harrison et al's (2000) method for decomposing simulation results with respect to exogenous shocks. Implementation in the GEMPACK software is straightforward.

3 Microsimulation model

The VU model is a powerful analytical tool for the analysis of economy-wide effects of structural changes in the economy. However, the VU model contains only one representative household. This limits the extent to which the impacts of structural changes in the economy on incomes and welfare between and within groups of population can be examined. We overcome this limitation by linking the VU model to a micro-simulation (MS) model.

For this paper, the MS model is constructed using data from the Household, Income and Labour Dynamics in Australia (HILDA) survey for the year 2011 (Summerfield et al. 2016). HILDA is a rich source of information on household demography, family dynamics, economic and subjective well-being, and labour market dynamics. The database for 2011 contains unit records for over 9,300 households[1], with over 23 thousand individuals representing over 21 million Australians. The MS module contain detailed income sources for each individual and household, such as:

- the number of hours worked and employment income, by occupation and industry,
- income from own-unincorporated businesses, by industry
- income from other types of investment
- welfare payments from the government
- transfers from other households/individuals
- private pension and foreign pensions,
- irregular income (such as inheritances, redundancies, lump-sum workers compensation payouts); and
- direct taxes paid on regular and irregular incomes.

It also contains individual and household demographic, educational and labour market characteristics, such as age, sex, region of residence, education level, non-school qualification level, labour force status, year of arrival in Australia, and family composition. This data provides the initial or base year income distribution.

3.1 Linking CGE and microsimulation models:

We link the CGE and MS models using a top-down approach. That is, results from relevant variables in the CGE simulation are used to update the microsimulation database to move it from the initial year to the final year of the period under investigation. Specifically, in the microsimulation model:

- Wage and salary incomes are updated using changes to wage rates and number of working hours by industry and occupation from the CGE results;
- Business incomes are updated using changes to gross operating surplus, by industry;
- Investment incomes are updated using changes to average return to capital and land.
- Government pensions are updated using changes to average wage rates
- All other income sources (namely, private pensions, private transfers, other government allowances and welfare payments, foreign pensions and irregular incomes) are updated using the CPI.
- Personal income taxes are updated, using the assumption that the average income tax rates for each household remain unchanged over the period.[2]

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[1] We only keep households with non-zero weights. (Some households have zero weights because after wave 1 residents in the households have moved to institutions, or non-private dwellings, or to remote and sparsely populated areas.)

[2] In future research, we plan to model income taxes and welfare payments using the actual parameters of these policies.

In moving from year to year, it is possible that not only the level of each household's income could change, but also that the contribution of each income source to total household income could change. By accounting for changes in income by source for each individual and thus each household, the MS module allows for us to analyse the impacts of structural changes on income distribution and/or poverty measures at both a between group (inter-group distribution) and a within group (intra-group) level.

4 Results

The decomposition simulation produces many results, including output and prices for the 115 industries in the model, rates of return and investment for all industries, expenditure by household and governments, imports and exports, employment and wages, and macroeconomic aggregates. The decomposition simulation breaks each of these results into its separate structural drivers, such as those listed in Table 1 above. In this paper, we focus on drivers of wage growth, in aggregate, by occupation, and by level of qualification. Results for other variables are only reported where relevant to wage results.

The remainder of this section describes, in turn, wage growth in aggregate, wage growth by occupation, and wage growth by qualification.

4.1 Drivers of aggregate wage growth

Overall, macroeconomic factors, technical change and skills supply all make a positive contribution to growth in real wages, which are defined as person-weighted nominal wages per hour worked, deflated by the CPI.

The impacts of macroeconomic factors, technical change and skills supply on real wages are shown in Table 2 below. The terms of trade and GDP are also included in the table because the effects on these variables are a useful link in understanding the results for the real wage.

Table 2: Impact on real wage and other economic indicators of changes in structural variables, 2010-2017

Impact (%) on… *of changes in…*	Real wage	Terms of trade	GDP
Macroeconomic factors			
Employment and population growth	-3.90	-2.61	8.56
Other macroeconomic factors	9.88	2.18	-1.71
Technical change			
Multifactor productivity	-0.53	0.10	-0.46
Labour-capital twist	-0.52	-0.23	7.70
Skill-biased technical change	7.17	2.14	2.44
Qualification supply effect	-6.11	-3.33	3.20
Net impact	**6.01**	**-1.76**	**19.72**

Macroeconomic factors

We begin with the impact of overall growth in employment and the population. In the absence of productivity growth, changes in the positions of export demand schedules, or changes in the savings rate, growth in employment and the population led to a fall in real wages. This subset of shocks reveals a decline in the terms of trade, which, other things equal, reduces the real wage by eroding the purchasing power of the local currency.

Although employment and population growth naturally induce some growth in capital stocks, we observe that the actual growth in capital stocks over the study period exceeded this. At the beginning of the period, in 2010, there was a significant backlog of investment in the mining industry that was not yet operational. Over the study period, the VU model accounted for this as an increase in capital that came about without commensurate investment, as much of the investment expenditure had been incurred prior to the study period and had a gestation period of several years. This unusual situation led to a large "free" injection of capital stock, which, all other things equal, underpinned an increase in the real wage. This was the main macroeconomic factor underlying the increase in the real wage.

Technical change

There are three broad elements to the technical change result: multi-factor productivity, a technical change twist capturing the relative changes in labour- and capital-specific productivity (holding aggregate productivity fixed), and a second level of technical change twists capturing relative productivity growth between occupations (holding aggregate labour productivity fixed). We refer to this set of changes as "technical change" or "occupation and qualification demand".

Impact of multifactor productivity

In general, multifactor productivity growth leads to an increase in GDP and real wages. Over the study period however, multifactor productivity growth was actually slightly negative, leading to a slight fall in real wages.

Impact of technical change twist in capital-labour mix

Abstracting from multi-factor productivity, we find that there is a technical change twist against labour, to accommodate the observed increase in the capital to labour ratio. This "twist" is implemented as a labour-saving productivity improvement combined with an exactly offsetting productivity decline in capital. In practice, this makes production more capital-intensive. This type of twist leads to a fall in the real wage.

The mechanism is as follows. With labour inputs fixed, and more efficient, there is an increase in the physical capital stock. The increase in the capital stock leads to an increase in output. Note that, in this subset of results, there is no overall productivity improvement, so the increase in output is derived only from the increase in capital inputs.

The increase in output leads to a real devaluation. With rates of return fixed in this subset of results, the devaluation is entirely absorbed by reduced labour costs, hence the fall in the real wage.

Impact of skill-biased technical change

Although skill-biased technical change is calculated in such a way that it has no impact on economy-wide productivity, the impacts on industry-specific productivity vary.

In making up the composite labour input, industries require more input from high-skilled occupations and less from medium and low-skilled occupations. In effect, industries that use more high-skilled occupations therefore experience a productivity decline, requiring more labour per unit of output.

Prices of services requiring the inputs of high-skilled labour, such as education, health, government administration and professional services, increase significantly relative to the prices of construction and most manufactured goods, which require the inputs of tradespeople and machinery operators.

Demand for services is less price elastic than demand for the trade-exposed manufactured goods. With the productivity decline in sectors with inelastic demand, and the productivity improvement in sectors with elastic demand, there is an increase in the domestic price level, leading to real appreciation in the domestic currency. This increases the purchasing power of the wage relative to the consumer price index, which includes a significant component of imports. Therefore, we find that the real wage increases as a result of skill-biased technical change.

Skill supply effect

Over the simulation period, we observe an increase in the proportion of the population with post-school qualifications, in particular, qualifications at or above the level of Bachelor degree. The *skill supply effect* shows that if, measured in persons or hours, aggregate employment was fixed, the increase in qualifications leads to an increase in effective employment. “Effective” employment refers to total labour input, or employment aggregated with wage-bill weights rather than volume weights based on headcounts or hours. An increase in hours worked in higher-wage occupations adds more to effective employment than an increase in hours worked in lower-wage occupations. For a given increase in aggregate hours worked, a compositional shift towards higher-wage occupations will cause in increase in effective employment.

This effect is akin to an increase in productivity, which has a small positive influence on the real wage.

4.2 Occupational wage disparities

The VU model identifies 97 occupations. Results for occupation wages are summarised here into five skill groups, based on the ANZSCO assignation of occupations to skill levels (ABS 2013a). To give a flavour for the skill classifications, very brief descriptions of the skill levels are given in Table 3 below, with slightly longer descriptions provided in the appendix.

Table 3: Occupational skill levels

Level 1	Managerial, professional
Level 2	Lower managerial and professional
Level 3	Trades
Level 4	Carers
Level 5	Sales assistants, cleaners, labourers

Figure 1 and Table 4 illustrate wage growth in each of the 5 occupation levels, with the coloured bars in Figure 1 indicating the contributions of the three main structural effects: macroeconomic factors, labour demand effects arising from technical change, and qualification supply effects. The net effects are based on observation of occupational wage movements, and show that wage growth has been higher for occupations that are higher up the skill hierarchy.

We find that *macroeconomic factors* have had positive effect on wage growth at all skill levels, and that the impact has been fairly uniform. To the extent that macroeconomic factors cause discrepancies in wage growth, trades occupations had above-average growth, balanced by below-average growth in the managerial and professional occupations. Underpinning the above-average wage growth in the trades occupations is relatively strong growth in the construction and mining sectors.

Qualification supply effects, all other things equal, have a negative effect on the wages of high-skilled occupations. Over the study period, the proportion of the workforce with qualifications at the bachelor degree level and above increased, leading to an increase in supply to the high-skilled occupations.

Technical change effects explain most of the disparity in occupational wage growth. Over the study period, the composition of the workforce shifted towards a higher proportion of high-skilled occupations. Removing the macroeconomic and qualification supply effects, the decomposition analysis shows that for occupations with relatively large employment growth, there was also relatively high wage growth. Furthermore, the occupations with the relatively large employment growth tended to be higher up the skill hierarchy.

If growth in high-skilled employment had occurred as a result of only the increase in the supply of high-qualified workers, we would have observed a fall in the relative wages of high-skilled occupations. The observed increase in the relative wages of high-skilled occupations suggests instead that demand curves for high-skilled occupations moved outwards relative to those for low-skilled occupations. Moreover, because the net effect on wages was an increase in wages for occupations in which there was also an increase in employment, the simulation shows that the demand effects outweigh the supply effects. That is, strong demand for high-skilled occupations has only partially been fulfilled by an increase in the supply of highly qualified workers.

The simulation shows that technical change has the largest positive effect on Level 1 occupations, and a smaller but positive effect on Level 2 occupations. There is a negative effect on wages in Levels 3, 4, and 5, with Level 5 the most adversely affected. This pattern suggests that the lower the skill level, the more vulnerable is an occupation to displacement by technical changes such as automation. However, we find that the negative effects on Level 4 occupations are less pronounced than impacts on either Levels 3 or 5, despite requiring a similar level of skills. Level 4 occupations include the carer and hospitality occupations, jobs which are less susceptible to displacement by automation than either Level 3 (trades) or Level 5 (sales). This suggests that the nature of work, and not just the level of training or experience required in an occupation, has a bearing on the threat posed by displacement by automation.

Table 4: Impact on occupational wages of structural change, 2010-2017

Impact (%) on wages of… of changes in…	Level 1	Level 2	Level 3	Level 4	Level 5
Macroeconomic factors	3.43	6.30	9.07	6.07	6.83
Technical change	27.82	2.82	-11.70	-9.27	-16.32
Qualification supply effect	-16.55	-0.32	7.67	6.43	12.76
Net impact	**14.70**	**8.80**	**5.04**	**3.23**	**3.27**

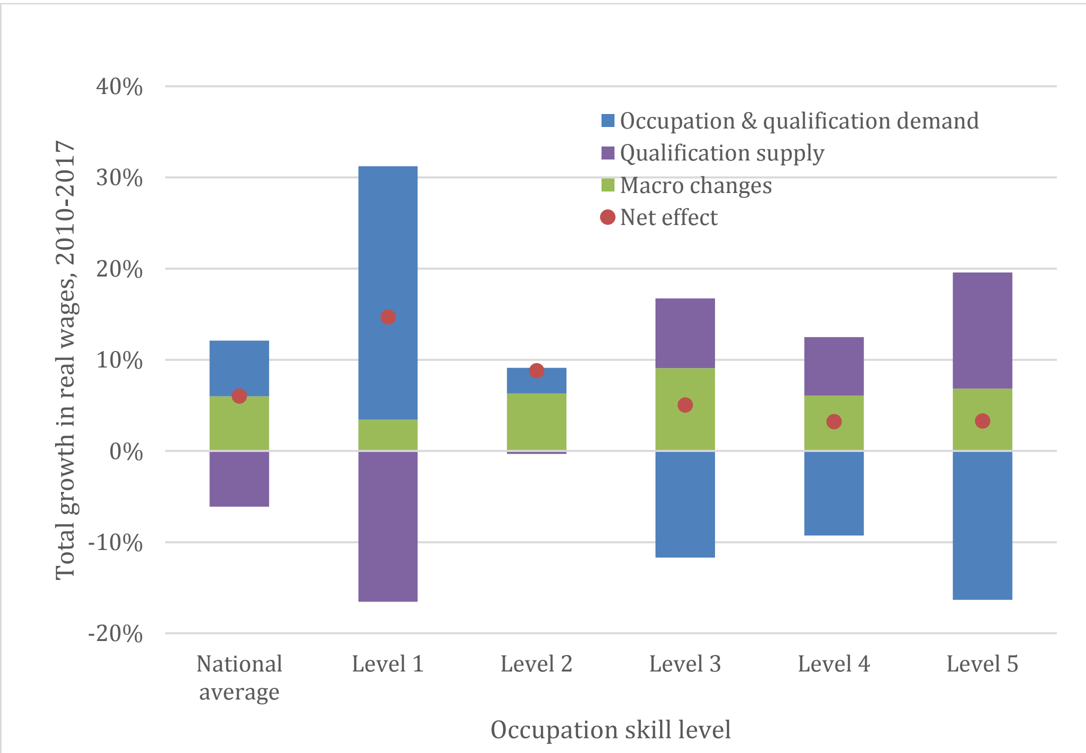


Figure 1: Impact of structural change on occupational wages, 2010-2017

4.3 Qualification wage disparities

As there is a strong correlation between qualifications and occupational skill levels, wage growth by qualification group follows a similar pattern to wage growth by occupational skill group, which can be seen in Table 5 and Figure 2 below. Again, macroeconomic factors have a fairly uniform and positive impact on wage growth for all qualification types.

Qualification supply effects, all other things equal, erode the wage premium enjoyed by highly-qualified workers. Between 2010 and 2016, the proportion of the workforce with a degree-level qualification or higher grew from 22.5 per cent to 26.6 per cent, while the proportion with no post-school qualification fell from 46.9 per cent to 41.9 per cent (ABS 2016). As highly-qualified workers become more commonplace, they also shuffle down the occupational ladder. For example, it is increasingly commonplace for people in managerial and professional occupations to have post-graduate qualifications rather than bachelor degrees. As a result, not only do the wages in high-skilled occupations grow more slowly, but also the occupations performed by high-qualified workers change, further eroding the wage premium of high-qualified workers.

Technical change, or occupation and qualification demand effects, work in the opposite direction, having a positive impact on wages of highly-qualified workers, which diminishes with the level of qualification to a negative impact on Certificates I-IV and no post-school qualifications. This is mainly because industry demands have driven changes in the occupational composition of the workforce. However, industry demands also drive changes in the qualification composition of each occupation, boosting the relative wages of high-qualified workers despite the increase in supply of these workers.

The net impact of the qualification supply effect and the technical change effect is an increase in the relative wages of wages for high-qualified workers, diminishing with the level of qualification. Wages of workers with Certificate I-IV or no post-school qualification fall relative to the national average.

Table 5: Impact of structural change on qualification wages, 2010-2017

Impact (%) on wages of… *of changes in…*	Post-grad	Grad. Dip.	Bach. Deg.	Adv. Dip.	Cert. I-IV	No post-school
Macroeconomic factors	4.80	0.09	3.78	5.13	7.83	7.00
Technical change	35.43	37.07	23.61	11.22	-5.61	-18.96
Qualification supply effect	-30.76	-27.67	-19.85	-10.00	0.55	13.31
Net impact	**9.47**	**9.49**	**7.54**	**6.35**	**2.77**	**1.34**

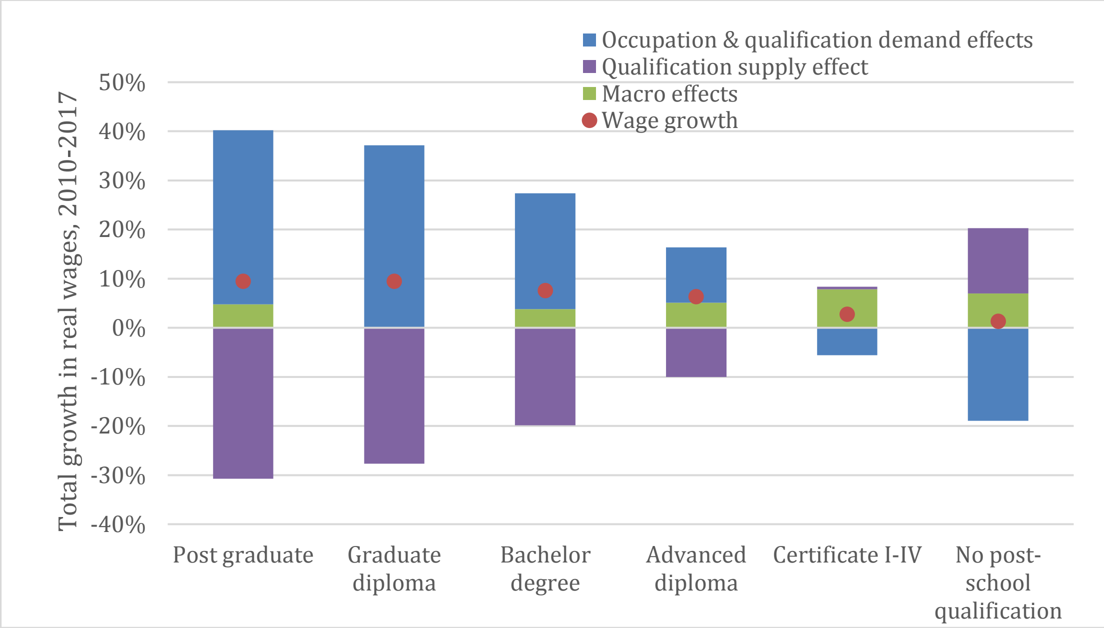


Figure 2: Impact of structural change on qualification wages, 2010-2017

4.4 The link between wage disparities and household income

As the MS model contains detailed information on household demographic, educational and labour market characteristics, it can be used to analyse income distribution and poverty measures by different population groups, differentiated by characteristics such as sex, age, occupation, qualification, region, ethnicity, etc.

In this paper we focus on changes in poverty rates by different skill groups, i.e. the groups of households represented by occupation skill level of the reference person. We choose the reference person as one with the highest income in the household, or, if there are two or more people with the same level of income, the oldest one.[3]

Poverty rate is defined as the percentage of the population living in households with equivalised disposable income of below certain poverty thresholds or poverty lines. The equivalised disposable income is the total after-tax income of a household, divided by the number of household members converted into equivalised adults, using OECD equivalence scale of 1.0 for the first adult, 0.5 for the other persons aged 15 and over, and 0.3 for each child aged under 15 (ABS 2017b).

Following Wilkins (2017), we use two poverty lines: anchored and relative. The anchored poverty line is the income level required to purchase a fixed basket of goods and services as that purchased by the household with an income of 50% of the mean income in 2001. To account for inflation, the anchored poverty line is indexed to the CPI. In 2011 and 2017, the anchored poverty lines were $15,665 and $16,366 respectively.

The relative poverty line is defined as 50% of median income. In 2011 and 2017, the relative poverty lines were $20,450 and $25,031 respectively.

[3] We borrowed this definition from Prof. Roger Wilkins, Melbourne University, whom we thank for sharing with us his computer code for processing HILDA data (Wilkins, 2017).

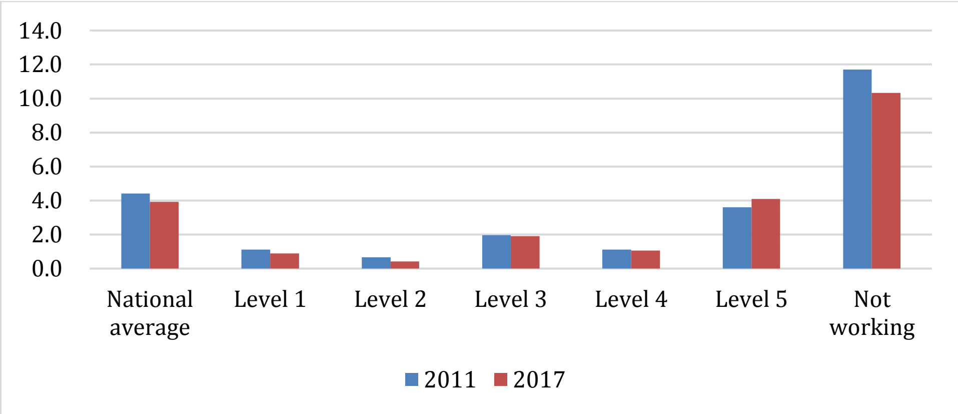
Wilkins (2017) finds that both the anchored and relative poverty rates have declined over the study period. Our study finds a much smaller decline in the anchored poverty rate, and an increase in the relative poverty rate. Part of this difference may be due to our treatment of welfare payments, which at this stage of development treats tax and benefit rates as static. However, a key reason for the difference is that our microsimulation study tracks wages by occupation rather than wages by household. At this stage of development, our microsimulation module does not account for household wage growth derived from switching occupations, instead accounting only for wage growth derived from pay increases in existing occupations.

4.4.1 Anchored poverty rates

Figure 3 reports the anchored poverty rates by occupational skill level for 2011 and 2017. As can be expected, in both years the poverty rates are relatively low for skill levels 1 to 4. Poverty rate is highest in the "Not working" group, which comprises of households with the reference person either not in the labour force or unemployed.

Over the period, the anchored poverty rates have declined for the economy as a whole and for all skill groups, except for skill level 5.

Figure 3. Anchored poverty rate, by occupation skill level (%)



To understand these results, we need to look at (i) changes in factor returns and other variables affecting household incomes due to each set of structural changes discussed earlier (Table 6); and (ii) the income structure of each skill group in the initial year (Table 7).

Column 4, Table 6, shows that over the period real GDP grew faster than the population, i.e. real per capita income increased. This largely explains the general reduction in the anchored poverty rates (Figure 3). Table 6 also shows that real hourly wage rates increased the most for skill levels 1 and 2, and increased less for skill levels 3-5. As wage income was the largest source of income for all skill levels, real wage results largely explain the reduction in the poverty rates of almost all skill groups. The exception is Level 5, whose poverty rate has increase slightly over the period. This was because of three main reason. First, level 5 saw only a small increase of their wage income (row 11, Table 6). Second, they had a relatively lower shares of business and investment income, and higher share of government allowances compared with other groups (Table 7). Over the period, capital and land income has grown at a faster rate than wage income and GDP. Thus, this group benefited relatively less than other groups from this growth. Third, this group had a relatively higher reliance on government allowances, which was indexed to the CPI, and thus grew at a lower growth rates than GDP and factor income.

The ‘Not working’ group has relatively large reduction in their anchored poverty rate. This is because wages, business and investment income and government pension contributed were the biggest sources of this group’s income. Simulation results show that the wage income for this group grew in line of national average.[4] Government pension grew with national average wage rates, and capital and land income grew faster than other income sources, and thus benefited this group.

Table 6. Decomposition of changes in selected variables over the 2011-2017 period (%)

	Macro changes	Qualification supply	Occupation and qualification demand	Net effect
	(1)	(2)	(3)	(4)
1. Real GDP	6.8	3.2	9.7	19.7
2. Average real (CPI-deflated) wage rate	6.0	-6.1	6.1	6.0
3. Aggregate employment (wage-bill weighted)	9.3	4.3	0.4	13.9
4. Aggregate real wage bill	16.0	-2.2	7.1	20.7
5. Aggregate real capital income	30.0	4.2	20.2	53.4
6. Aggregate real land income	32.3	28.5	6.1	65.5
7. Wage income, skill level 1	8.8	-12.5	33.8	29.1
8. Wage income, skill level 2	13.4	-1.3	4.8	16.7
9. Wage income, skill level 3	16.4	7.4	-22.0	2.4
10. Wage income, skill level 4	11.7	4.2	-6.7	9.3
11. Wage income, skill level 5	13.2	9.1	-20.1	2.8

Table 7. Income structure of occupation skill levels, 2011, %

Income source	Level 1	Level 2	Level 3	Level 4	Level 5	Not working	National average
Wages	80.5	83.1	77.4	80.2	72.8	36.7	71.1
Business and investment income	12.3	7.5	14.8	7.3	7.3	14.5	11.6
Other private sources	5.3	5.3	3.2	5.2	5.7	19.3	7.9
Government pension	0.4	0.7	0.9	1.7	4.7	21.3	5.1
Government allowances	1.5	3.4	3.7	5.6	9.5	8.2	4.3
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0

4.4.2 Relative poverty rates

Figure 4 reports the poverty rates by occupational skill level in 2011 and 2017. Given CGE results and assumptions about income taxes and welfare movements discussed earlier, our analysis with the micros-simulation model indicates that relative poverty rates have generally increased over the period. As indicated by Figure 5, the main cause of the increase in relative poverty is the technical change that saw a strong demand for higher occupation and qualification skill levels relative to demand for lower skill levels. Although this skill-bias factor also affect the anchored poverty rates, its influence is

[4] The reference person in this group are not working, but there are members in the group’s households who are working at different skill level.

stronger for the relative poverty rates, which are evaluated not against a fixed, but a movable threshold of 50% of median income.

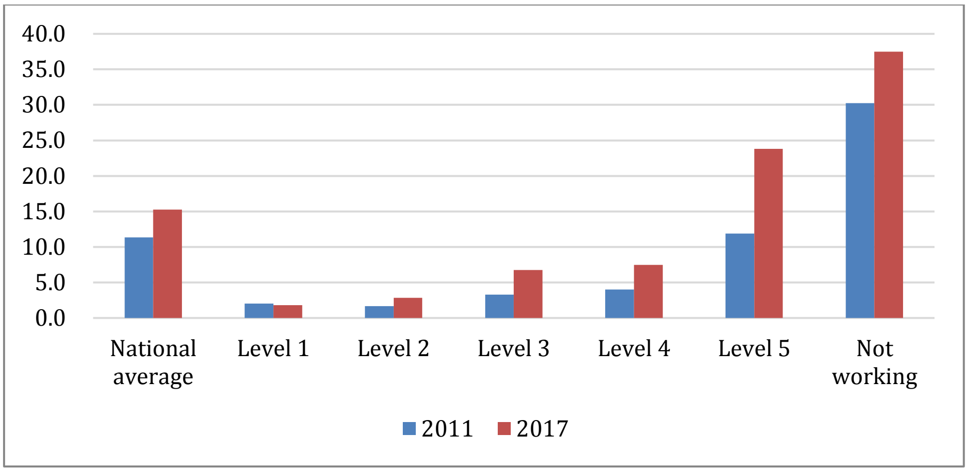


Figure 4. Relative poverty rate, by occupational skill level (%)

Macro changes in the economy also increased the relative poverty rate for almost all skill levels. This is because, can be seen from column 1, Table 6, returns to capital and land grew faster than return to labour, which benefited capital and land owners, who tend to be the richer households, and raised the poverty threshold. Simulation results show that the poverty threshold increased by about 16% under this group of shocks.

The factor that reduces income inequality is the increase in the supply of higher qualifications. This factor lowered the wage income by the higher skill groups, and raised the wage income by lower skill groups (see column 2, Table 6). In this column, rates of return on capital are fixed by assumption, so there is little impact on capital income. Together, these effects raised the poverty rates of the higher skill groups and lower the poverty rates for the lower skill groups.

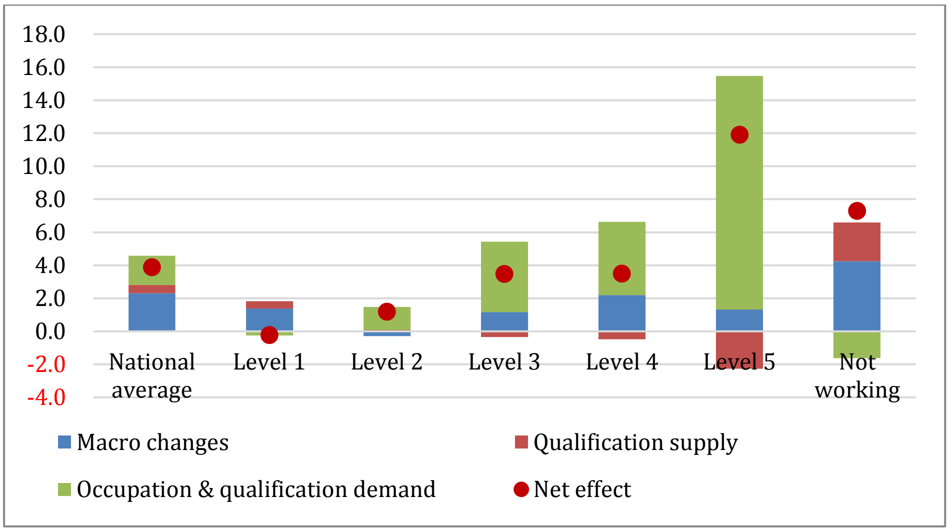


Figure 5. Contributions to changes in relative poverty rate, by occupational skill level (%)

5 Conclusions

Dynamic historical and comparative static decomposition CGE simulations are a powerful tool for understanding structural change and its impacts. In this paper, we confine our examination to the impact on wages of three sets of structural drivers: macroeconomic factors, qualification supply, and technical change. This analysis could be extended to a broader analysis of structural change in the Australian economy, and may be the subject of future research.

In this paper we add a microsimulation analysis to the CGE analysis. Microsimulation addresses a shortcoming in CGE modelling, which is that the household sector is represented by a single representative agent. With a single representative agent, CGE modelling is unable to capture the diversity in the household sector in relation to the levels of income, sources of income, and composition of expenditure by different households.

Over the study period of 2010 to 2017, average growth in real wages was weak. Growth in high-wage occupations was generally stronger than growth in low-wage occupations, resulting in a widening gap between the wages of the highest- and lowest-paid workers. Over this period, key results from our research indicate that:

- Macroeconomic factors played a role in determining overall wage growth, but did not explain the disparity between wage growth at the occupational level;
- Strong growth in the supply of qualifications at the level of bachelor degree level and above detracted from wage growth in the high-skill occupations;
- Skill-biased technical change in favour of the high-skill occupations led to relatively strong growth in the wages of high-skill occupations, an effect that dominated the results; and
- Relatively strong growth in the wages of high-skill occupations added more to the incomes of high-income households and led to an increase in household income disparities and an increase in the relative poverty rate. However, this result did not take into account possible changes in occupation by households over the study period.

This study has quantified the important elements of structural change that have driven occupational wage disparities over the last seven years. The decomposition simulation illustrates that technical change has been the main driver of increasing occupational wage disparities, while macroeconomic factors have a relatively uniform impact on wages at all occupational skill levels. With the wages of low-skilled occupations falling further below average, a change of occupation, rather than a pay-rise in their existing occupations, was a better prospect for low-income households to avoid falling into absolute or relative poverty.

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7 Appendix

7.1 VU model industries

The industry classification in the VU model is based on the ABS input-output industry groups (ABS 2013b).

Sheep, Grains, Beef and Dairy Cattle
Poultry and Other Livestock
Other Agriculture
Aquaculture
Forestry and Logging
Fishing, hunting and trapping
Agriculture, Forestry and Fishing Support Services
Coal mining
Oil and gas extraction
Iron Ore Mining
Non Ferrous Metal Ore Mining
Non Metallic Mineral Mining
Exploration and Mining Support Services
Meat and Meat product Manufacturing
Processed Seafood Manufacturing
Dairy Product Manufacturing
Fruit and Vegetable Product Manufacturing
Oils and Fats Manufacturing
Grain Mill and Cereal Product Manufacturing
Bakery Product Manufacturing
Sugar and Confectionery Manufacturing
Other Food Product Manufacturing
Soft Drinks, Cordials and Syrup Manufacturing
Beer Manufacturing
Wine, Spirits, Other Alcoholic Beverages, and Cigarette and Tobacco Product Manufacturing
Textile Manufacturing
Tanned Leather, Dressed Fur and Leather Product Manufacturing
Textile Product Manufacturing
Knitted Product Manufacturing
Clothing Manufacturing
Footwear Manufacturing
Sawmill Product Manufacturing
Other Wood Product Manufacturing
Pulp, Paper and Paperboard Manufacturing
Paper Stationery and Other Converted Paper Product Manufacturing
Printing (including the reproduction of recorded media)
Petroleum and Coal Product Manufacturing
Human Pharmaceutical and Medicinal Product Manufacturing
Veterinary Pharmaceutical and Medicinal Product Manufacturing
Basic Chemical Manufacturing
Cleaning Compounds and Toiletry Preparation Manufacturing
Polymer Product Manufacturing
Natural Rubber Product Manufacturing
Glass and Glass Product Manufacturing
Ceramic Product Manufacturing
Cement, Lime and Ready-Mixed Concrete Manufacturing
Plaster and Concrete Product Manufacturing
Other Non-Metallic Mineral Product Manufacturing
Iron and Steel Manufacturing
Basic Non-Ferrous Metal Manufacturing
Forged Iron and Steel Product Manufacturing
Structural Metal Product Manufacturing
Metal Containers and Other Sheet Metal Product manufacturing
Other Fabricated Metal Product manufacturing
Motor Vehicles and Parts; Other Transport Equipment manufacturing
Ships and Boat Manufacturing
Railway Rolling Stock Manufacturing
Aircraft Manufacturing
Professional, Scientific, Computer and Electronic Equipment Manufacturing

Electrical Equipment Manufacturing
Domestic Appliance Manufacturing
Specialised and other Machinery and Equipment Manufacturing
Furniture Manufacturing
Other Manufactured Products
Electricity Generation
Electricity Transmission, Distribution, On Selling and Electricity Market Operation
Gas Supply
Water Supply, Sewerage and Drainage Services
Waste Collection, Treatment and Disposal Services
Residential Building Construction
Non-Residential Building Construction
Heavy and Civil Engineering Construction
Construction Services
Wholesale Trade
Retail Trade
Accommodation
Food and Beverage Services
Road Transport
Rail Transport
Water and Other Transport
Pipeline Transport
Air and Space Transport
Postal and Courier Pick-up and Delivery Service
Transport Support services and storage
Publishing (except Internet and Music Publishing)
Motion Picture and Sound Recording
Broadcasting (except Internet)
Internet Service Providers, Internet Publishing and Broadcasting, Websearch Portals and Data Processing
Telecommunication Services
Library and Other Information Services
Finance
Insurance and Superannuation Funds
Auxiliary Finance and Insurance Services
Rental and Hiring Services (except Real Estate)
Ownership of Dwellings
Non-Residential Property Operators and Real Estate Services
Professional, Scientific and Technical Services
Computer Systems Design and Related Services
Employment, Travel Agency and Other Administrative Services
Building Cleaning, Pest Control and Other Support Services
Public Administration and Regulatory Services
Defence
Public Order and Safety
Primary and Secondary Education Services (incl Pre-Schools and Special Schools)
Technical, Vocational and Tertiary Education Services (incl undergraduate and postgraduate)
Arts, Sports, Adult and Other Education Services (incl community education)
Health Care Services
Residential Care and Social Assistance Services
Heritage, Creative and Performing Arts
Sports and Recreation
Gambling
Automotive Repair and Maintenance
Other Repair and Maintenance
Personal Services
Other Services

7.2 VU Model occupations (equivalent to ANZSCO minor groups)

ANZSCO	Description	Predominant skill level
111	Chief Executives, General Managers and Legislators	1
121	Farmers and Farm Managers	1
131	Advertising, Public Relations and Sales Managers	1
132	Business Administration Managers	1
133	Construction, Distribution and Production Managers	1
134	Education, Health and Welfare Services Managers	1
135	ICT Managers	1
139	Miscellaneous Specialist Managers	1
141	Accommodation and Hospitality Managers	2
142	Retail Managers	2
149	Miscellaneous Hospitality, Retail and Service Managers	2
211	Arts Professionals	1
212	Media Professionals	1
221	Accountants, Auditors and Company Secretaries	1
222	Financial Brokers and Dealers, and Investment Advisers	1, 2
223	Human Resource and Training Professionals	1
224	Information and Organisation Professionals	1
225	Sales, Marketing and Public Relations Professionals	1
231	Air and Marine Transport Professionals	1
232	Architects, Designers, Planners and Surveyors	1
233	Engineering Professionals	1
234	Natural and Physical Science Professionals	1
241	School Teachers	1
242	Tertiary Education Teachers	1
249	Miscellaneous Education Professionals	1
251	Health Diagnostic and Promotion Professionals	1
252	Health Therapy Professionals	1
253	Medical Practitioners	1
254	Midwifery and Nursing Professionals	1
261	Business and Systems Analysts, and Programmers	1
262	Database and Systems Administrators, and ICT Security Specialists	1
263	ICT Network and Support Professionals	1
271	Legal Professionals	1
272	Social and Welfare Professionals	1
311	Agricultural, Medical and Science Technicians	2
312	Building and Engineering Technicians	2
313	ICT and Telecommunications Technicians	2
321	Automotive Electricians and Mechanics	3
322	Fabrication Engineering Trades Workers	3
323	Mechanical Engineering Trades Workers	3
324	Panelbeaters, and Vehicle Body Builders, Trimmers and Painters	3
331	Bricklayers, and Carpenters and Joiners	3
332	Floor Finishers and Painting Trades Workers	3
333	Glaziers, Plasterers and Tilers	3
334	Plumbers	3
341	Electricians	3
342	Electronics and Telecommunications Trades Workers	3
351	Food Trades Workers	3
361	Animal Attendants and Trainers, and Shearers	3
362	Horticultural Trades Workers	3
391	Hairdressers	3
392	Printing Trades Workers	3

393	Textile, Clothing and Footwear Trades Workers	3
394	Wood Trades Workers	3
399	Miscellaneous Technicians and Trades Workers	3
411	Health and Welfare Support Workers	2
421	Child Carers	4
422	Education Aides	4
423	Personal Carers and Assistants	4
431	Hospitality Workers	4, 5
441	Defence Force Members, Fire Fighters and Police	2, 3
442	Prison and Security Officers	4, 5
451	Personal Service and Travel Workers	3, 4
452	Sports and Fitness Workers	3, 4
511	Contract, Program and Project Administrators	2
512	Office and Practice Managers	2
521	Personal Assistants and Secretaries	3
531	General Clerks	4
532	Keyboard Operators	4
541	Call or Contact Centre Information Clerks	4
542	Receptionists	4
551	Accounting Clerks and Bookkeepers	4
552	Financial and Insurance Clerks	4
561	Clerical and Office Support Workers	5
591	Logistics Clerks	4
599	Miscellaneous Clerical and Administrative Workers	3, 4
611	Insurance Agents and Sales Representatives	3, 4
612	Real Estate Sales Agents	3
621	Sales Assistants and Salespersons	5
631	Checkout Operators and Office Cashiers	5
639	Miscellaneous Sales Support Workers	3, 4, 5
711	Machine Operators	4
712	Stationary Plant Operators	4
721	Mobile Plant Operators	4
731	Automobile, Bus and Rail Drivers	4
732	Delivery Drivers	4
733	Truck Drivers	4
741	Storepersons	4
811	Cleaners and Laundry Workers	5
821	Construction and Mining Labourers	4, 5
831	Food Process Workers	4, 5
832	Packers and Product Assemblers	5
839	Miscellaneous Factory Process Workers	4, 5
841	Farm, Forestry and Garden Workers	5
851	Food Preparation Assistants	5
891	Freight Handlers and Shelf Fillers	5
899	Miscellaneous Labourers	4, 5

7.3 VU Model Qualifications

In the VU Model, there are 56 qualifications, defined by level of qualification and field of qualification. Listed below are the 5 levels of qualification and the 11 fields of qualification, equivalent to ASCED definitions at the broad level. The cross-classification of qualifications by field and level leads to 55 qualification categories. The 56th category in the VU model is "No post-school qualification".

ASCED code	Level of Qualification	ASCED code	Field of Qualification
1	Postgraduate degree level	01	Natural and physical sciences
2	Graduate diploma and graduate certificate level	02	Information technology
3	Bachelor degree level	03	Engineering and related technologies
4	Advanced diploma and diploma level	04	Architecture and building
5	Certificate level	05	Agriculture, environmental and related studies
		06	Health
		07	Education
		08	Management and commerce
		09	Society and culture
		10	Creative arts
		11	Food, hospitality and personal services

7.4 Dynamic, historical and decomposition Closure

Below we list the closure status of *selected* model variables.

Shocks to exogenous variables in the historical simulation are equal to results from the dynamic simulation. Shocks to exogenous variables in the decomposition simulation are equal to results from the historical simulation.

X=exogenous; N=endogenous	dim	Simulation			Decomp category
		Dynamic	Historical	Decomp	
macro variables					
aggregate employment		X	X	X	Macro
GDP		X	X	N	
multi-factor productivity		N	N	X	Tech ch
average real wage		X	X	N	
labour-capital technical change twist		N	N	X	Tech ch
Consumption		X	X	N	
Average propensity to consume		N	N	X	Macro
Government expenditure		X	X	X	Macro
Investment		X	X	N	
Risk premium on investment		N	N	X	Macro
Terms of trade		X	X	N	
General shift in export demand schedules		N	N	X	Macro
Imports		X	X	N	
General shift in import-domestic twist		N	N	X	Macro
Net foreign liabilities		N	X	X	Macro
Industry variables					
rates of return	IND	N	X	X	Macro
selected exports	COM*	X	X	N	
commodity-specific position of export demand schedule	COM*	N	N	X	Macro
selected imports	COM*	X	X	N	
commodity-specific import-domestic twist	COM*	N	N	X	Macro
selected industry output	IND*	X	X	N	
labour-saving technology	IND*	N	N	X	Tech ch
Employment variables					
industry employment	IND	X	X	N	
commodity demand shifters	COM	N	N	X	Macro
occupation employment	OCC	X	X	N	
occupation technical change twist	OCC	N	N	X	Tech ch
qualification employment	QUAL	X	X	X	Qual sup

* indicates partial set