Did tax-transfer policy change New Zealand disposable income inequality between 1988 and 2013?

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Abstract

This paper investigates the role tax and transfer policies changes played in the increase in disposable income inequality over the 1988-2013 period. Utilising the Household Economic Survey (HES) and a behavioural microsimulation model (Treasury's TAXWELL-B) the relative contributions of tax policy and changes in various sociodemographic characteristics (age, highest educational attainment, and employment status) to the change in inequality are estimated.

Tax and transfer policy changes are found to have had a major role in the increase in income inequality, accounting for around a third of the observed increase. Furthermore, non-policy related changes in the employment distribution also increased income inequality. However, increases in tertiary educational attainment and the proportion of workers in their prime earning years were both factors that were reducing income inequality over this same period. With these factors pushing in separate directions, this research also indicates that there are significant unobserved determinants of the rise in income inequality that cannot be attributed to the static role of tax-transfer policy, age, education, or employment status distributions.

Statistics New Zealand disclaimer

Acknowledgements

1 Introduction

Numerous measures of disposable income inequality in New Zealand increased in the late 1980s and early 1990s, and have remained elevated since. The purpose of this paper is to investigate the role changes in tax and transfer policies played in this increase.

Although Nolan (2018a) established that the redistributive effect of the tax-transfer system declined over this period, the impact of tax-transfer policy cannot be described by comparing the change in the redistributive effect alone. Changes in the structure of the population between two periods of time can change the redistributive properties of the tax-transfer system, even if the underlying policies remain unchanged.

As a result, in order to describe how changes in tax and transfer policies specifically influenced disposable income inequality outcomes, it is necessary to model how these payments are made. In this paper, a behavioural tax-transfer microsimulation model is used to model this process. This model allows for the calculation of tax-transfer payments and labour supply responses for a given tax-transfer system. By using such a model, counterfactual scenarios can be created that apply the tax-transfer system of one year onto the population of another year. Given these scenarios and the associated disposable income inequality measures for these scenarios, any change in the income distribution can be decomposed into policy and non-policy related contributions. These scenarios are constructed and analysed for two pooled sets of years: 1988-91 and 2010-13.

This type of decomposition between population and tax-transfer determinants of changing income inequality gives differing results depending on the sequencing of the counterfactuals. As a result, since no ordering is more economically intuitive than another ordering for the analysis at hand, the Shapley value is used to estimate an average marginal effect of policy as motivated by Shorrocks (2013). This process mirrors the analysis undertaken by Bargain (2012) for the United Kingdom and Herault and Azpitarte (2016) for Australia.

The population effect on income inequality can be further decomposed, in order to describe the relative roles of changing observed population characteristics in the evolution of income inequality over this period. Each of these population factors influences the potential orderings available for the policy effect thereby changing the estimated impact of policy. The changes in population characteristics that will be evaluated in this paper

are the age, employment, and highest qualification level distributions.

In order to evaluate the role of these population factors the semi-parametric approach of DiNardo et al. (1996) is utilised. This approach reweights the weighted sample of a given year to represent the population characteristic of interest for a different year. The change in the disposable income inequality measure due to this reweighting then provides an estimate of the role the change in the population characteristic had on disposable income inequality.

By combining the role of changing population characteristics with a structural model of tax-transfer policy settings, this paper intends to give a clearer understanding of how tax-transfer policy changes in New Zealand since 1988 have influenced disposable income inequality outcomes. Both by providing a quantitative estimate of the role of tax-transfer policies, and by offering a comparison to the role played by other factors during that time period.

The paper is organised as follows: Section 2 motivates the investigation of the role tax and transfer changes played in changing inequality outcomes. Section 3 provides a literature review about decompositional methods. Section 4 covers the data sources used including imputation of missing data. Section 5 provides a methodological outline of microsimulation modelling and the use of weighting and labour supply estimation to improve the ability to use microsimulation to make inferences about tax-transfer questions.

Given this background section 6 introduces the decomposition method for the effects of tax-transfer policy on the income distribution. Section 7 then outlines the changes in some population characteristics and how this can be incorporated in a decompositional analysis. Section 8 provides the results of the decomposition while section 9 concludes.

2   New Zealand Decomposition motivation

The increase in income inequality measures during the mid-1980s and early 1990s, followed by the persistence of those higher inequality measures through into the 2000s, has been widely documented (Perry 2017, Ball and Creedy 2015, Jeram and Wilkinson 2016).

In this paper, the role tax and transfer payment changes played in the in-

crease in disposable income inequality is investigated using a tax-transfer microsimulation model. By using such a model to create counterfactual scenarios that represent the role of tax-transfer policy, it is possible to decompose the change in inequality into policy and non-policy related contributions.

The purpose of such a decomposition is to investigate the first order effect that tax-transfer policy changes had on the income distribution during this time, with the direct change in payments and the indirect labour supply response to these changes both modelled.

The unit of analysis in this paper is the individual. The inequality of individual incomes is represented using the Gini coefficient, as shown in Figures 1 and 2. Here market income refers to the gross income of individuals excluding transfer payments, while disposable income includes transfer payments and subtracts tax payments. The income measure used is income per adult equivalent person using a parametric scale which is parametrised to be close to the Jensen (1988) scale. The data come from Statistics New Zealand's Household Economic Survey, however tax and transfer payments have been imputed using a microsimulation model instead of taken directly from survey results. Furthermore, the calibrated weights applied in Ball and Creedy (2015) are used in these figures to reweight the HES to represent the New Zealand population in each HES year.
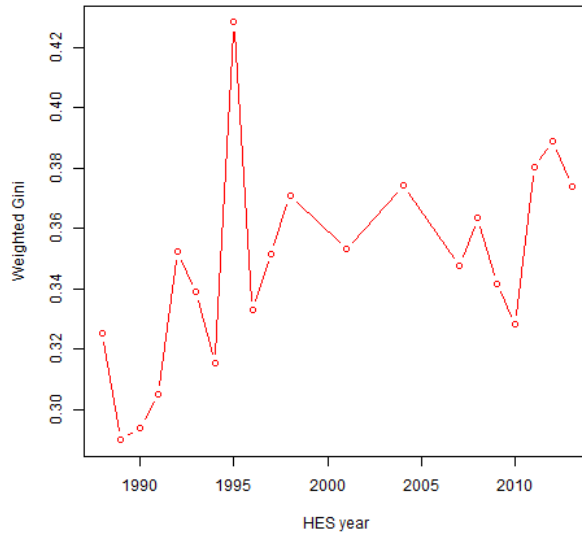
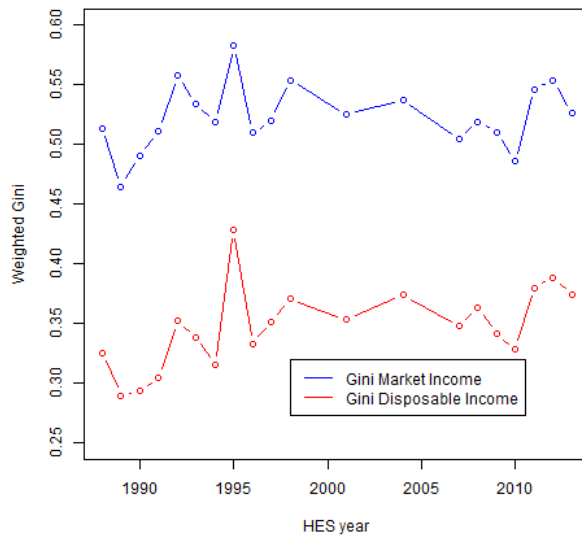Figure 1: Gini coefficient for equivalised Disposable Income

Figure 2: Market vs Disposable Income Gini coefficients

Figure 1 shows the increase in disposable income inequality between 1988 and 2013 in terms of adult equivalent income per person. Although there is significant variation in the Gini coefficient over this time period, for the weighted sample investigated in this paper the Gini coeffcent climbs from just over 30 to nearly 38 between 1988 and 2013.

However, this fact alone does not indicate that policy was the reason for rising inequality outcomes. Figure 2 suggests that market income and disposable income moved together over most of the 1988-2013 period. As a result, it is unlikely that changes in the tax-transfer system alone can explain why inequality in disposable income increased.[1]

Over the same period, other characteristics of the population changed in ways that may have influenced the distribution of income. The age distribution, education distribution, and employment status distribution all shifted - with the population ageing, average highest educational achievement rising, and an increasing number of individuals moving into part time work.

Changing characteristics of the population, along with the complexity of the interaction between the population and the tax-transfer system, implies that the decline in the redistributive effect between 1988 and 2013 is not sufficient to estimate the role of policy.

When analysing the role policy played in the change in income inequality New Zealand Podder and Chatterjee (2002a) provided a description based on decompositional analysis of factor incomes to discuss how rising inequality was the result of policy changes. However, this analysis had two key issues for such an interpretation: it did not model the tax and transfer payments in a way that allows for clear counterfactual analysis regarding what factor incomes would have looked out in the absence of the reform (both due to changing characteristics and behaviour), and it relied on household survey data for tax and transfer payments which are unreliable for these income measures as noted in Ball and Ormsby (2017).

There have also been studies investigating the role that changing population characteristics played in the rise in income inequality outcomes in New Zealand, specifically by Ball and Creedy (2015) and Hyslop and

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[1]Changes in the tax-transfer system may have led to a corresponding change in market incomes. Outside of changes in market incomes associated with adjustments in hours of work, the assumption of *fixed incomes* as in Kasten et al. (1994) is still maintained in this paper. The shortcomings associated with such an assumption are discussed in detail when the decomposition method is outlined.

Mare (2005). However, these analyses did not model what the income distribution would have been if another year's tax and transfer system had been applied to the population of a given year, and so were unable to provide estimates of the role of tax-transfer policies played in inequality outcomes.

The analysis in this paper expands on both the factor share and characteristics based decompositions of the increase in New Zealand income inequality by offering a structural analysis of tax-transfer policy, including endogenous labour supply responses to these changes in policy.

3   Literature review

Decomposition of income inequality indices, as summary measures of an income distribution, are an important part of distributional analysis in economics. Shorrocks wrote two of the seminal papers on decomposition of general inequality indices, considering (additive) decomposition by population subgroup (Shorrocks 1984) and decomposition by factor income (Shorrocks 1982). The conclusion from Shorrocks (1988) was that such a decomposition was non-interpretable a position that Cowell (2009) notes is still widely held. Here non-interpretability implies that rising inequality in one factor/subgroup does not logically contributes to rising inequality overall.

Podder and Chatterjee (2002b) and Podder and Chatterjee (2002a) suggested that it was possible to perform an interpretable decomposition of an inequality index (in this case the Gini coefficient) based on a single factor. The authors then used a decomposition by income source to discuss the role of policy changes on income inequality in the New Zealand context. However, Jurkatis and Strehl (2013) argue against the interpretability of the decomposition given in these papers, instead suggesting that research focuses on marginal effects stemming from the estimated Gini elasticity with respect to income source (which is closely related to the semi-elasticity method used in the Podder and Chatterjee papers) for trying to understand factor income decompositions of the Gini coefficient.

Without the ability to link the inequality of income from some subgroup directly to aggregate inequality, it is necessary to clearly model the income distribution in terms of factors of interest in order to allow for clear counterfactual analysis. As a result, in this paper the focus is on constructing

counterfactual distribution to perform multi-dimensional decompositions of the type suggested by Shorrocks (2013). Here a series of counterfactual models are defined that represent the change of a given factor that determines the income distribution and thereby income inequality.

When the change in an inequality index is decomposed on the basis of more than one factor the estimated marginal effect of a factor can vary based upon its ordering in the sequencing of the decomposition. If there is no reason why a researcher would expected one effect to come before another in the sequencing of analysis Shorrocks (2013) suggested that you could calculate all the possible sequences and average the marginal effects to get an estimate of the true marginal effect. This logic was based on the Shapley value from cooperative game theory Shapley (1953).

Hyslop and Mare (2005) and Daly and Valletta (2000) offered this form of decomposition, using the semi-parametric method of DiNardo et al. (1996) to estimate counterfactuals. This form of counterfactual construction made the differences between types of sequencing clear. If a factor is sequenced first, for example age, then the estimated marginal effect is that of age. If a factor is sequenced second - for example age after household structure - then the marginal effect is that of age conditional on the change in household structure. In this way, if there is a relationship between these factors this will be captured in their ordering.

Jenkins and Kerm (2005) applied a similar method. However, instead of decomposing the distribution on the basis of changes in the distribution of other factors, the authors considered the ways the shape of the distribution changed through time. These corresponded to a *sliding*, a *stretching*, and a *squashing* of the estimated probability distribution function.

All these methods are non-causal, but provide a clear description of the way the income distribution has changed and what other population factors have been correlated to this movement.

In the New Zealand context, Hyslop and Mare (2005) offered a description of how important characteristics of the population were related to the change in income inequality between households in terms of gross income between 1984 and 1998. Household structure was a major contributor to the rise in household income inequality, with employment status and socio-demographic attributes also contributing. As is the general case with this method, a large proportion of the change in income inequality (around half) remained unexplained.

A second way of constructing counterfactual distributions for decomposi-

tion of an aggregate index such as inequality is through direct imputation using a microsimulation model. An example of this type of counterfactual stems from Bargain (2012). Unlike the semi-parametric approach, these papers tend to focus on disposable income rather than gross or market income as the tax-transfer structure has been modelled allowing for the construction of counterfactual disposable incomes.[2]

The full technique used in this paper combines these two approaches and is based on Herault and Azpitarte (2016). In Herault and Azpitarte (2016) the microsimulation decomposition of Bargain (2012) is combined with a semi-parametric decomposition based on DiNardo et al. (1996). Both microsimulation and semi-parameteric methods are ways of creating counterfactual income distributions which allow the decomposition of catalysts for changing income inequality based on what if analysis.

In the New Zealand context, Creedy and Eedrah (2014) decomposed the change in income inequality between 2007 and 2011 into policy and non-policy effects using Treasury's microsimulation model (TAXWELL). Over this period income inequality was virtually unchanged. However, policy changes were estimated to have increased inequality while non-policy effects were reducing these measures. In terms of reweighting, Ball and Creedy (2015) investigated the influence of various population factors in the change in disposable and market income inequality in the 1983-2013 period by using a set of calibrated weights that kept population characteristics constant across the period.

Combining the microsimulation and semi-parametric approaches, Nolan (2016) performed an analysis of the change in disposable income inequality in New Zealand (using the Gini coefficient) over the 1995-2013 period. These results showed that the combination of policy changes had no impact on income inequality once labour supply responses were taken into account, and that an ageing population had put upward pressure on inequality during this period. This age effect was similar to the results found for gross households income in Hyslop and Mare (2005) where socio-demographic characteristics increased income inequality. However, Hyslop and Mare (2005) also indicated that employment status had played an important role in increasing income inequality, a relationship that is investigated here over a longer time horizon.

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[2]Using a microsimulation model only allows the distribution of gross income to vary in so far as labour supply changes. This assumption is discussed more when the method is outlined.

4 Data and data treatment

The data used for this analysis comes from Statistics New Zealand's Household Economic Survey (HES). Two sets of pooled years are compared: the period including the HES88 survey until the HES91 survey and the period including the HES10 survey until the HES13 survey. The first set of pooled years are termed HES91 and the second set HES13 for brevity.

These periods were selected as the goal is to explain the increase in disposable income inequality that occurred between these years. The two four year periods are the same length and as a result allow for the construction of counterfactual tax-transfer systems based on the equivalent period in the other set of pooled data.

Another reason for selecting these specific pooled years is because both periods involve a similar change in economic and labour market conditions. HES91 refers to the period following *Black Monday/Tuesday 1987*, with the associated fall in economic output and sharp increase in unemployment in New Zealand. HES13 refers to the period following the initial shock of the *Global Financial Crisis* which also led to a decline in economic activity and rising unemployment. As discussed in Nolan (2018d) the downturn experienced in the earlier period was more severe, both in terms of the decline in GDP and employment and the increase in unemployment. As a result, although both periods refer to economic downturns there is a relevant difference in the intensity of the change which must be considered when comparing the two periods.

Furthermore, the entire income distribution is not considered in this paper. Gini coefficients cannot be calculated for those with negative incomes while some populations (eg students and dependants) are commonly excluded from analysis as they receive zero income even though they still have access to resources. As a result, all families with an disposable income below $5,000 in June 2013 prices, or with negative market incomes, are excluded from analysis. This also makes the sample used consistent with that used in Nolan (2018a) and in prior research using TAXWELL-B (eg Creedy and Mok 2015).

4.1 Imputation

4.1.1 Wages

When counterfactual years are defined for analysis the real imputed wage for a given HES year is left fixed. Alternatives to this are discussed in Nolan (2018b), however each of these alternatives involves a large or currently impractical extension of the underlying microsimulation framework. As a result, fixed gross wages are used.

A fixed gross wage allows the construction of both the current budget constraint for individuals, and alternative budget constraints they would face when the tax-transfer system changes. This allows for counterfactual analysis both through the calculation of how direct tax-transfer changes are allocated to households (eg tax incidence falls entirely on the worker), and through any effect it has on the behavioural response of individuals to changes in the tax-transfer system.

Given that the technique assumes a fixed gross wage at all possible hours to construct these budget constraints it is necessary to calculate the available wage for every adult in the sample. For individuals, the **wage measure** used in this paper is the implied wage from wage and salary income in the HES data. This is equal to total current weekly wage and salary earnings from the individuals primary job divided by the number of hours worked per week in their primary job.[3]

However, for individuals who are not working but are able to participate in wage and salary work it is not possible to calculate a wage rate in this way. As a result, it is necessary to impute wages for those who are not working. The wage imputation process and results for the periods of interest are reported in Nolan (2018d).

In Bourguignon et al. (2008) and Jessen (2016) further use is made of this imputed wage to perform further decompositional analysis. A counterfactual wage is estimated using these imputed wages, and counterfactual income distributions are created using the wage distribution generated from the wage equation for a different year. However, given the large amount unobserved heterogeniety in wage rates, issues of comparability

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[3]The earnings from prior jobs, self-employed work, and secondary jobs are ignored when calculating the wage. The primary job is defined as the wage and salary job the individual is currently employed in that offers the largest average weekly income at current hours of work.

of certain relevant characteristics across the surveys (ethnicity, occupation, industry), and the already significant number of decomposition paths investigated in this paper this is not a direction that will be taken further in this paper.

4.1.2 Tax-transfer imputation

A tax-transfer microsimulation model allows an analyst or researcher to impute values for tax and transfer payments for a given tax-transfer system and an agent with a set of characteristics. The HES data provides individuals with characteristics, and as a result such a model can be used to impute tax and transfer payments for a variety of counterfactual tax-transfer systems.

However, in order to make comparisons to a given base year the modelled tax-transfer system that transforms market into disposable income has to be consistent with the data. At this point there is a modelling dilemma - the model could be used to describe the change in tax-transfer payments from their observed level, or the reported tax-transfer payments could be fully replaced by imputed values.

In this instance, reported HES data on the modelled tax and transfer payments is removed from the data and replaced by imputed values. The reason for this is the lack of reliability regarding household survey based tax and transfer payments and the ability to replace these values with estimates from a microsimulation model as discussed in Figari et al. (2012). The specific lack of reliability of household survey data on benefits is discussed in the New Zealand context by Hyslop and Mare (2005) and Ball and Ormsby (2017).

Observed transfer payments are still used to determine who receives additional unmodelled payments and who is eligible for benefits that require specific characteristics (eg the Invalid's Benefit during this time period - now referred to as the Supported Living payment).

The full set of policies modelled and the nominal values for the years of interest are given in Nolan (2018c), along with hyperlinks to the relevant legislative documentation. These values and policies were coded into Treasury's tax-transfer microsimulation model (TAXWELL) thereby increasing the period where tax-transfer payments could be imputed in this model from 2007-2013 to 1988-2013. This extension allows for the imputation of alternative tax-transfer systems which was not possible when Ball and

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Creedy (2015) investigated income inequality trends with the same underlying HES data.

5   Methodology and simulation

Economic modelling involves the construction of counterfactual worlds, which allows the researcher to deduce conclusions about a specific fictional world - this is also known as the creation of *what-if scenarios*. A model can be seen as useful for policy analysis if it is *credible*: data and this counterfactual scenario can be used to inductively reach conclusions about the real world Sugden (2001).

When it comes to looking at the impact of policy change Spadaro (2007) discusses three outcomes of value in a model:

- Simplicity of use and interpretation.

- An ability to describe the complexity of the socioeconomic structure.

- The ability to capture the heterogeneity of agents.

However, there is no one model that is dominant over all three outcomes, and as a result modellers face a trade-off between these outcomes when picking a modelling technique. Typically *representative agent* models focus on the first outcome, while models that ignore the first element too much (thereby giving results that are hard to explain or causally link) tend to be termed *black box* approaches to analysis.

While a representative agent model limits the degree of heterogeneity in modelled agents, it is both clear to interpret and is able to incorporate substantial behavioural elements. In some sense, this allows modellers to answer the *Lucas Critique* Lucas (1976) when observing the impact of policy.

However, by excluding heterogeneity this approach is unable to fully deal with the Lucas Critique - as the heterogeneity of agents in terms of their characteristics (and the behavioural responses this entails) is policy rele-

vant information that influences the impact of policy.[4]

In this the Lucas Critique is stating that there needs to be appropriate behavioural structure in order to estimate the impact of policy through the lens of historic data. As a result, when trying to look at the impact of policy, a modelling approach (or approaches) that satisfies this requirement as much as possible is preferable. Furthermore, there should be clarity about the ways the model does not capture this structure.

For an investigation of the role of tax-transfer policy a tax transfer microsimulation model offers this clarity and allows for the introduction of important behaviour.

A microsimulation model requires three broad elements for its construction Spadaro (2007):

- A microdata set containing the economic and sociodemographic characteristics of individual agents.

- An institutional framework. This is the rules of the policies to be simulated and income generating process inherent in the economy (e.g. budget constraints).

- A theoretical model representing the behaviour of agents.

A microsimulation model takes microdata and rules/policy, then applies the behaviour of individuals in order to simulate the economy as a function of policy. Given this, it is possible to discuss the impact of a policy based on the different characteristics of individual agents - where the heterogeneity of individual agents is described through difference in the agents measured characteristics.

Any *counterfactual analysis* preformed with an *Arithmetic Microsimulation model* involves fully modelling the institutional structure but not behaviour

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[4]Looking at the macroeconomy, representative agent models rose in popularity out of criticism of large-scale econometric models on the basis of the mathematical/logical link between aggregate variables. In a similar way, the mathematical link between the primitives of individuals and macro-aggregates, is often not available or cannot be defined. This is discussed in Orcutt (1957), Goldman and Uzawa (1964), and Shafer and Sonnenschein (1982) with regards to individuals to macro theory, Mas-Colell (1989) for the capital controversy, and Hoover (2001) for the relation between macro and micro economics. A series of related essays can be found in Hahn and Petri, eds (2004). The key point in what we are discussing is that the behaviour of groups can often not be sufficiently described as a mathematical function of the behaviour of a representative individual for many questions of interest.

- it implicitly assumes that labour supply and gross wages are unchangeable. In this way, the impact of policy measured in such an analysis is often termed a *morning after effect*.

More broadly such changes can be termed the *direct effect of tax-transfer policy changes* in the analysis performed in this paper.

When it comes to individual behaviour, labour supply choices are included in the analysis in this paper. As a result, the full form of the microsimulation model used is a static *Behavioural Microsimulation model*. The policy effect from such a model includes the direct effect of policy and an associated change in labour supply behaviour - which is termed the *indirect effect* of policy in this paper.

By using varying combinations of behaviour and policy a decomposition between the direct and behavioural effects of policy can be made. Following Herault and Azpitarte (2016) the labour supply behaviour of individuals in a given year is subject to their expectations regarding their tax liability and transfer payments. For example, someone in 2013 may expect the tax-transfer system of 1991 and behave in a way that is consistent with this. If this behaviour is modelled only the direct effect of the change in tax-transfer settings between 1992 and 2013 will occur.

5.1 Deflators, annual comparisons, and equivalent policies

Two different deflators are used in this paper in order to make the data comparable for the question at hand.

The first deflator is the Consumer Price Index including interest payments (CPI).[5] The CPI is used to set pooled years to the same base year, with all nominal sums set to the a given quarters price level. This implies that the HES91 period has been shifted to March 1992 prices, while HES13 is shifted to June 2013 prices.

When it comes to setting up counterfactual policies it may also seem appealing to deflate the payments and thresholds in the tax-transfer system by CPI for creating the counterfactual years. The results reported by Nolan (2016) used this method.

However, as Bargain and Callan (2010) argue, in order to keep the policies *distributionally neutral* they would need to rise or fall with average

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[5]This series started in March 1994 and is back indexed using the standard CPI.

growth in the income distribution. As a result, deflating tax-transfer rates and thresholds by a wage/income index is required to prevent making normative assumptions about counterfactual policies as stated in Bargain (2014). In this way a government's decision to not increase tax-transfer thresholds and transfer rates as quickly as average wage/income growth is seen as a direct policy choice to cut these payments. This assumption is also consistent with a view regarding the affordability of the tax-transfer system, where the ability to fund redistribution rises as average incomes increase. As a result, Average Weekly Earnings (including overtime) from the Quarterly Employment Survey is used to deflate tax-transfer policies between the two periods.[6]

Compared to results that use CPI to deflate policies in a nation experiencing economic growth, a wage/income index will naturally suggest that a tax-transfer system that indexes against CPI inflation is inequality increasing.

5.2 Weights and the treatment of tax and transfers in simulation

Although the Household Economic Survey (HES) data are used for analysis, making any inference about how this survey relates to the New Zealand population requires a series of initial assumptions.

Statistics New Zealand first applies judgement to the HES when they clean up data responses and offer sampling weights based on calibration to population parameters as stated in Statistics New Zealand (2001). The purpose of weights is to make the sample representative of the New Zealand population as a whole. Initially Statistics New Zealand did not offer sampling weights for the HES (pre-1988), but then introduced sampling weights based on the inverse probability of the unit (in this case the household) being sampled in that given year. In 2001 Statistics New Zealand changed to calibrated weights (Statistics New Zealand 2001) which uprate the sample to make it representative of a set of known aggregate characteristics of the population (population size, ethnic make-up, age composition).

As well as weighting assumptions, the timing of collection matters. Each

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[6]The QEX series only began in 1989, and directly replaced a similar quarterly employment survey In order to link the two series, wage growth is assumed to equal consumer price growth between December 1988 and March 1989. Furthermore, wage growth is assumed to be generally comparable between the two indices.

reported income series is split into 24 *spells*, or two week periods. The household can be surveyed at any point in the HES period (running from July to June).[7] When surveyed HES asks households about their income during the entire prior year. In this way, income data for the HES as a whole refers to earnings for the two years prior to the survey end date.

TAXWELL takes this HES data and applies two clear adjustments/assumptions:

1. New calibrated weights to match the number of beneficiaries by benefit type. The standard HES data undersamples beneficiaries (largely due to their higher non-response rate). As a result, new calibrated weights are estimated given population information on beneficiary numbers from the Ministry of Social Development. This is discussed in Aziz et al. (2013) and Creedy and Tuckwell (2003).

2. The replacement of primary transfers and tax payments based on observed eligibility, rather reported benefit and tax income alone.

The second assumption is a central part of what is required for simulating alternative income distributions in the face of changes in policy settings. By directly attributing transfers and taxation on the basis of eligibility, this deals potential measurement errors due to recall bias and to avoid the issue of approximate imputation in survey data. The reason for imputing data rather than using reported survey data in these instances is justified in Figari et al. (2012). Most secondary and tertiary payments remain unmodelled, and their values are taken directly from the HES survey (eg Emergency benefit payments).

However, such an assumption is not necessarily innocuous due to the fixed cost of benefit take-up and the potential for individuals and households to avoid taxation - and the fact that recall bias exists for the characteristics we determine eligibility from. However, it does give an idea of how the distribution of income is likely to change in the face of policy changes - subject to the still strong assumption that rates of take-up and tax avoidance do not shift too sharply.

The behavioural microsimulation model (TAXWELL-B) does not deal with the same detail in the data - taking the income and benefit eligibility of the family in the final spell and annualising it, rather than considering income and benefit status in each spell (two week period) reported for the period. As a result, TAXWELL-B implicitly assumes that the family has supplied

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[7]The July-June year began with the HES01 survey. Prior surveys had been based on a April-March year

labour and received transfer income in the same way all year that they have over the reported period (the final spell is annualised)[8]. This is the final data used for the analysis in this paper.

The calibrated weights are used in the construction of the Gini coefficients in this paper. The Gini's were calculated using the R package IC2 Plat (2015). The details of constructing Gini coefficients using weights can be found in Creedy (2015) while a full discussion of measuring and measurement Gini coefficients is given in Yitzhaki and Schechtman (2013).

5.3 Behavioural policy responses

Changes in the tax-transfer system would be expected to have consequences in terms of the choices made by individuals. As a result, a behavioural component is added to Treasury's arithmetic microsimulation model (TAXWELL) to account for how these changes in available net incomes lead to a labour supply response. This model is termed TAXWELL-B.

Taking gross wages as fixed, a behavioural model takes changes in policies (which are defined through the use of procedures and the parameters they define) and allows them to influence net wages available at different discrete hours of work (the budget constraint). This in turn influences labour supply choices through individual preferences over income and leisure.[9]

The leisure-consumption preferences of individuals for this analysis come from Nolan (2018b). Utilising the discrete hours random utility framework of van Soest (1995), a quadratic utility function for families with preference parameters that are a function of family characteristic are estimated.

When incorporated into TAXWELL-B, the labour supply choice of each family is calibrated to match the observed choice. In this case, random terms are drawn from the error term (which is assumed to follow an extreme value distribution) and added to the utility for each hours value. If the hours level selected matches what is observed then this error term is

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[8]This also implies that TAXWELL-B only looks at reported income for the year of the survey.

[9]This is still a comparative static model. As a result, the labour supply change is not necessarily representative of the change in long-run labour supply. This framework is discussed in Jia and Vattø (2013), but the convergence to the static result found by the authors stems from myopia on the part of the modelled agents - in the face of rational expectations equilibrium employment would differ.

kept for future simulations - if not the error term is redrawn. This process continues 100 times and if no error term gives the observed choice by this point the individual is thrown out. Virtually no individuals were removed from the data set due to this. The calibration process is discussed with examples in Creedy and Kalb (2005).

Two different estimates of the preference parameters are used in this paper - one referring to the 1988-1993 period and one referring to the 2009-2013 period. When the HES91 data is referred to labour supply behaviour is based on the preference parameter model of HES88-93. Similarly when the HES13 data is referred to is is based on a preference parameter model of that period.

As a result, the behavioural response depends not just on the tax-transfer policy period but on the population period that is being analysed - due to the fact that the HES88-93 and HES09-13 preference parameter estimates were quantitatively very different.

6   Decomposition method: The role of tax-transfer policies

6.1   The policy model

The microsimulation model utilised allows the construction of scenarios that consider what economic outcomes would have looked like in a given year if the tax-transfer system had taken a different value. A decomposition process involves constructing counterfactuals that isolate the specific effect of a given tax-transfer policy change.

As a result, when asking what effect tax and transfer payments had on income inequality it is possible to use a microsimulation model to ask what income inequality would have been in a given year if the tax-transfer system of a different year had been applied - but the other given population characteristics remained fixed. It is these counterfactual scenarios that provide the what if questions that allow for the decomposition.

The procedure that outlines this process formally is given by Bargain and Callan (2010), based a non-behavioural (arithmetic) microsimulation model. At a point in time t the income distribution, or an aggregate measure of the distribution (such as an inequality index, I_t), can be thought of as some

function of the characteristics of individuals in the sample[10] ($\mathbf{X_t}$) and the policy parameters of the tax-benefit system $\gamma_\mathbf{t}$. As a result the measure of interest at time t can be written as:

$$I_t = I[d_t(\mathbf{X_t}, \gamma_\mathbf{t})]$$

Where d_t represents a tax-benefit function that transforms market incomes into disposable incomes, termed by Bargain (2012) as the tax-benefit structure. As a result, the change in inequality between two periods of time (say 0 and 1) can be written as:

$$\Delta = I(d_1(\mathbf{X_1}, \gamma_\mathbf{1})) - I(d_0(\mathbf{X_0}, \gamma_\mathbf{0})) \tag{1}$$

The goal is to calculate the relative impact that shifts in these characteristics and tax-benefit policies had in changing this index between the two points in time. In this framework, the two points in time represent two mutually exclusive groups and the question is how differences in the relative effect of the characteristics of these groups (the tax benefit system, the attributes of individuals/families, and the structure of the implied income generating function) contribute to explaining the difference in the index I.

The relative contribution of these different factors can be calculated by considering what if questions such as "what would the income inequality index be if the period 1 population characteristics were in place, but the (appropriately deflated) tax-benefit policy parameters and structure from period 0 held". This counterfactual is represented by $I(d_0(\mathbf{X_1}, \alpha\gamma_\mathbf{0}))$.

Following Bargain and Callan (2010) a non-behavioural microsimulation model can be used to define the counterfactuals necessary to estimate a *policy effect*. A key advantage of using a microsimulation model to construct these counterfactual scenarios is the fact that it captures the full detail of the tax-benefit system and the vastly different impact policy changes have on the net incomes of the variety of individuals in society. For example, one way of structuring the decomposition in this instance is the following:

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[10]Eg Age, labour supply. These are weighted up to represent the overall population.

$$\begin{aligned}
\Delta =& \{I[d_1(\gamma_\mathbf{1}, \mathbf{X_1})] - I[d_0(\alpha_1\gamma_\mathbf{0}, \mathbf{X_1})]\} \quad \text{Policy effect} \\
&+ \{I[d_0(\alpha_1\gamma_\mathbf{0}, \mathbf{X_1})] - I[d_0(\alpha_1\gamma_\mathbf{0}, \alpha_1\mathbf{X_0})]\} \quad \text{Population effect} \\
&+ \{I[d_0(\alpha_1\gamma_\mathbf{0}, \alpha_1\mathbf{X_0})] - I[d_0(\gamma_\mathbf{0}, \mathbf{X_0})]\} \quad \text{Income growth}
\end{aligned}$$

When constructed this way γ_t and d_t change subscript together, as the policy effect captures the full change in policy parameters and the structure of the tax system.

The above equation states that, starting at $t = 1$ the change in an aggregate index between two periods can be defined as a sequence of counterfactuals involving period 0 (deflated) policy applied to the period 1 population characteristics (eg the weighted period 1 sample), and the index observed in period $t = 0$. There is an additional term in the above equation due to the deflating of the policy and population variables moving from $t = 1$ to $t = 0$. For a relative income inequality index this *income growth* effect should be zero, and so can safely be ignored.[11]

When decomposing the difference between an index value at $t = 1$ and $t = 0$ either the policy effect or the population effect can be estimated first, giving two potential orderings to consider. Because of its sequential nature (the policy effect or the population effect could be estimated first), and the fact that the sequence does influence the estimate of the marginal effect, there needs to be some way to choose between these two potential orderings - or to set a weighted average of the orderings.

Shorrocks (2013) considered this problem and used the Shapley value from cooperative game theory to justify using an average of the possible decompositions - as there is no reason to favour one ordering above another.

6.2 Income counterfactuals and take-up rates

The construction of counterfactual tax-transfer settings relies on assumptions about the tax up rate of transfers and the payment of taxes relative to the base data. As survey data is used, then any difference between modelled tax and transfer payments and the survey data would need to

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[11]This is termed the assumption of *linear homogeneity*. If this assumption fails then this characteristic makes up part of the residual term.

be taken into consideration when forming counterfactual income distributions.

In this paper, modelled transfer payments and tax liabilities are applied to the base data and as a result the modelled tax system can be applied without change to counterfactual years. This involves assuming full take-up of primary transfer payments and full payment of income tax liabilities in both the base and counterfactual scenarios. As a result, the take-up behaviour of individuals is not modelled.

There are situations where these take-up assumptions are violated as discussed by Keane and Moffitt (1998) and Wiemers (2015), which would be relevant for the distribution of observed income. However, in the analysis of this paper the primary benefits modelled already have high take-up rates in both periods. As a result, the take-up assumption appears reasonable and is unlikely to influence the change in the income distribution which is the focus of analysis here.

6.3 The behavioural response to policy

In order to allow for the labour supply changes that follow from adjustments to tax-transfer policies, Bargain (2012) changes the Bargain and Callan (2010) framework by allowing characteristics to change. Specifically, this involves taking the data matrix X_t, and considering how policy transforms it. Previously, a change in policies did not directly influence X_t as varying γ_t did not lead to a change in gross incomes. However, when labour supply is allowed to change both hours of work and gross income will also change. As a result, the data matrix at period t facing the policy settings of period l can be written as X_t^l. With this counterfactual for the data matrix, and keeping $X_t^l = X_t$ when $t = l$ for simplicity, the example decomposition extends to:[12]

$$
\begin{aligned}
\Delta = & I[d_1(\gamma_\mathbf{1}, \mathbf{X_1})] - I[d_0(\alpha_1\gamma_\mathbf{0}, \mathbf{X_1})] && \text{Policy effect} \\
& + I[d_0(\alpha_1\gamma_\mathbf{0}, \mathbf{X_1})] - I[d_0(\alpha_1\gamma_\mathbf{0}, \alpha_1\mathbf{X_0^1})] && \text{Population effect} && (2) \\
& + I[d_0(\alpha_1\gamma_\mathbf{0}, \alpha_1\mathbf{X_0^1})] - I[d_0(\alpha_1\gamma_\mathbf{0}, \alpha_1\mathbf{X_0})] && \text{Behavioural effect}
\end{aligned}
$$

Here labour supply behaviour is estimated on $t = 0$ period data, and the behavioural effect is simulated by comparing the index value with labour

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[12]Assuming the income effect is zero.

supply on the $t = 0$ sample with the policies of $t = 1$ to the index value with labour supply observed at $t = 0$.

Although it initially appears that there are six possible decompositions between the *direct policy*, *behavioural* (indirect), and *population* effects there are in fact only four: as this represents a further decomposition of the *population* effect from Bargain and Callan (2010) where the *direct policy* effect had already been identified, it implies to the authors that the *population* and *behavioural* effects must be positioned consecutively.

This argument admits that the potential for ordering does matter, as Sastre and Trannoy (2002) point out when discussing the Owen value and Nested Shapley value. This becomes important when looking at any breakdown of the initial decomposition. Specifically Sastre and Trannoy (2002) state:

> The contribution of any given factor to overall inequality can be interpreted as the expected marginal impact of the factor when the expectation is taken over all the possible elimination sequences. Thus, it is important that the elimination sequences or, equivalently, the subsets of components considered in the calculation, have an economic appeal.

Implying that any decomposition that is provided needs to be based on only selecting counterfactuals that make economic sense.

Bargain (2012) recognised that, although the direct effect of policy was identified in the initial Bargain and Callan (2010) framework, the indirect effect of policy changes on labour supply was not. Instead, any change in the summary index which was due to changes in labour supply was being included in the population effect category.

In this paper this view about the economically appropriate counterfactuals is not applied, and all orderings of population, behavioural, and direct policy decompositions are used. Each time an individual characteristic (such as employment behaviour) is changed the marginal effect of direct tax policy is changed in a way that is economically meaningful. As a result, the exclusion of these counterfactuals based on Sastre and Trannoy (2002) is not applied here.

The final results of this paper can be viewed as an extension of Bargain (2012) in order to analyse the *population* effect in more detail. The Bargain and Callan (2010) and Bargain 2012 decomposition method has been applied to a number of high income countries (Bargain et al. 2013, Matsaganis and Leventi 2014) implying that a more detailed decomposition

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would have value for analysing inequality trends around the world.

6.4   Interpreting the results of this method

The decomposition process described in this paper takes a counterfactual where the tax transfer system of one year (eg HES91) is applied to the population of another year (eg HES13). Full take up of transfer payments, and full payment of tax liabilities, is assumed and changes in labour supply choices given new net incomes in the counterfactual scenario are estimated.

As a result, the output for this form of analysis should be interpreted as a first-order approximation of the role tax-transfer played in changing income inequality - with adjustments in production and consumption patterns, as well as individual characteristics (apart from labour supply), not accounted for.

Although this method provides a clear description of a type of policy effect on income inequality, there are other channels that tax-transfer changes could influence the distribution of income which are not included in this estimate such as:

- Policy's impact on market incomes (Gross wages, employment opportunities, general equilibrium effects).

- Policy's impact on individual/population characteristics (Educational attainment, family and household structure, migration).

Given that these channels will be relevant for the large tax-transfer policy changes during this period, the policy effect estimated in this paper likely differs from the full dynamic effect of varying tax-transfer policies. For example, changes in tax rates relative to other countries may change the incentive for skilled migrants to come and work in a country - changing both the population and the characteristics of the population. Furthermore, without labour demand or general equilibrium effects a microsimulation model does not provide a closed system. As a result, the non-closure inherent in this model can provide implausible results - especially if the underlying system is not fiscally neutral.

In the scenarios modelled here the HES91 tax-transfer system is not a revenue neutral change, with the increase in spending on transfers and the decline in tax income from lower aggregate labour supply exceeding the tax

revenue raised from higher average tax rates. Given this, if the periods being compared involve questions about the affordability of the tax-transfer system then it needs to be made clear that the unaffordable tax-transfer system is not a reasonable counterfactual for tax-transfer purposes.

It is possible to consider whether the change in taxes and transfers increased income inequality between HES88 and HES09 by applying the opposite tax-transfer system to each year. But if the HES88 system was viewed as unaffordable or unsustainable then this places a question mark over using the HES88 tax-transfer system as a benchmark for changing income inequality outcomes.

Prior to HES88 and over the HES88-91 period, the constant fiscal deficits, increasing benefit expenditure as a percentage of GDP (McClure 1996), and 1991 credit rating cut by S&P were all factors that suggest the tax-transfer system in HES91 was seen as fundamentally unaffordable. As a result, even though the change in the tax-transfer structure may have changed outcomes in terms of the distribution of income reversing any perceived negative changes is more complex than reinstituting the old tax-transfer regime.

However, since HES91 there have been cuts to average tax rates as well as reductions in certain benefit categories (Nolan 2018c) - implying that the fundamental nature of the tax-transfer changes reduced the magnitude of any income redistribution through the tax-transfer system. This is shown directly in Nolan (2018a).

7 Decomposition method: The role of other factors

The effect of tax and transfer policies on inequality measures depend on the underlying population, and therefore depend upon the characteristics of the individuals being analysed. In the prior decompositional method, all characteristic/population changes and their influence on the income distribution are bundled into a single residual term.

In order to account for other factors the weighted sample data of a given year is reweighted to more closely represent the population of an alternative year. This method was applied to Australian survey data in Herault and Azpitarte (2016), and is related to estimates performed in the New

Zealand context in Hyslop and Mare (2005). Hyslop and Mare (2005) estimated the influence of general changes in employment and socio-demographic characteristics, but focusing on a different income unit (household income).

In this paper, three other factors beyond the static role of policy are considered when looking at the change in income inequality: Changes in the distribution of *employment status*, *age*, and *highest educational attainment*.

Why have these changes been selected? It has been suggested that the changing age structure of the population can influence the income distribution in a number of ways (Goldstein and Lee 2014): The changing age structure, capital intensity, and increasing longevity (and associated lifecycle effects). In this paper, the question is whether the growing proportion of individuals in their prime working age has contributed to the observed increase in income inequality. As a result, it is not the full effect of age that is investigated but instead a narrower question regarding changing age structure alone.

Varying employment status is also likely to generate differences in income inequality measures. Although both periods of analysis refer to recessions (New Zealand's recession of the early 1990s and the Global Financial Crisis), the deterioration of the labour market in 1988-1991 was worse than that experienced in 2010-2013 - both in terms of the magnitude of the decline and the relative timing in the economic cycle. However, the nature of the labour market had also changed substantially between those two periods - with part time work becoming more common. As a result, the distribution of employment status differed in a way that will influence income inequality outcomes between HES91 and HES13.

Finally, changes in the distribution of highest educational attainment have been linked to a changing dispersion of income (eg Coady and Dizioli 2017). Not only does this provide an additional mechanism with which the income distribution may have changed, it is also not likely to be independent of the nature of tax-transfer policy changes. As a result, the role of educational attainment is important to include in this analysis.

Several other distributional factors may have been relevant for the change in the income distribution but are not considered here: Wages, returns on characteristics, ethnicity, industry of work, and occupation.

Changes in the wage distribution are likely to have been an important determinant of the lift in income inequality, as outlined in Hyslop and Yahanpath (2005). As mentioned in the imputation section decompositions based on counterfactual wage distributions have been performed

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within this framework previously in the literature (eg Jessen 2016). Using the wage equations from the wage imputation procedure for non-workers counterfactual wage distributions can be formed to allow for this analysis.

This form of analysis appears problematic at first due to the large unobserved heterogeniety in the data. A solution to this is to keep unobserved error terms in the wage rate to for simulation. However, the underlying characteristics in the wage equation rely on characteristics that were not necessarily comparable over time due to changes in definitions (ethnicity, industry, occupation) and in many cases had to be imputed using correspondence tables. As a result this form of decomposition was rejected.

A replacement for wage distribution analysis is the return to characteristics approach of Hyslop and Mare (2005). However, Hyslop and Mare (2005), Dixon (1998), and preliminary analysis of the distribution performed for this paper suggested that the changes in return to characteristics have played a limited role in changing inequality outcomes. With important characteristics unreliable this form of decomposition was also not undertaken.

Ethnicity, industry of work, and occupation are also characteristics of the population that changed and will be related to inequality outcomes. With the structure of the economy changing, industry and occupation were of special interest for this analysis. However, these three characteristics that were not necessarily comparable over time due to changes in definitions. Industry and occupation had to be imputed using correspondence tables, while ethnicity categories remained incomparable between the wage equation years estimated. As a result, decomposition based on these factors was inappropriate.

In the New Zealand context this paper can also be seen as an extension of Hyslop and Mare (2005) - by incorporating the impact of tax-transfer policies into the counterfactual decomposition analysis, and shifting the analysis from household income to individuals and families.

7.1 The method for investigating changing characteristics

To extend the Bargain (2012) method Herault and Azpitarte (2016) separates out the employment effect into policy related and non-policy related

changes in employment. They use the methodology of Bover (2010), which is essentially the DiNardo et al. (1996) method as applied by Hyslop and Mare (2005) and Daly and Valletta (2000).

As discussed in Fortin et al. (2011), the DiNardo et al. (1996) reweighting method for estimating counterfactual distributions is essentially a propensity score reweighting method, with the reweighting factor based on the estimation of a logit/probit model.

In this context, time is treated as a state/treatment variable. The impact of a specific factor on a distribution (eg the wage distribution in the case of DiNardo et al. 1996 or income distribution in the case of Hyslop and Mare 2005) can then be given by assuming the distribution of the factor is fixed over time (the assumption of the *invariance of conditional distributions*).

However, as noted in Fortin et al. (2011) this requires the strong economic assumptions that there are no general equilibrium effects and no selection based on unobservables. Both these assumptions, and thereby the assumption of conditional independence, are likely to be violated when considering an income distribution. As a result, the process of reweighting the data to make the distribution of one factor similar in one time period to another period should be seen as an exploratory form of analysis - not causal. For example, if a change in the education distribution explained a large section of the change in the relative density of income this does not tell us why both distributions changed and does not imply that an exogenous increase in education levels would lead to the given change in the density of income.

Under this methodology, the counterfactual scenarios are defined in the following way over the entire income distribution. Assume there are N individuals/income units, where the $i \in \{1, ..., N\}$. Partition the data matrix, $\mathbf{X_t}$ into $\mathbf{y_t}$ (which represent the income of all income units) and $\mathbf{z_t}$ (which represents the attributes of all income units). An individual observation in the data set can be thought of as a vector $(y_i, \mathbf{z_i}, t)$, where y_i is income of the income unit, $\mathbf{z_i}$ is a vector of attributes, and t is the time variable. Each of these observations belongs to a joint distribution of incomes, attributes, and dates $F(y, z, t)$ - therefore the joint distribution of incomes and attributes at a point in time is the conditional distribution $F(y, z|t)$.

Assume that the distribution is also dependent on some policy variable, γ. Then the joint density of income and attributes at one point in time is

$f_t(y) = f(y, z|t; \gamma_t)$. The density of wages at a point in time, $f_t(y)$, is the integral of the density of income conditional on a set of individual attributes at a date t_y[13] ($f(y|z, t_y; \gamma_t)$) over the distribution of individual attributes at time t_z[14] ($F(z|t_z)$), with Ω_z the domain of individual attributes. This gives:

$$f_t(y) = \int_{z \in \Omega_z} dF(y, z|t_{y,z} = t; \gamma_t)$$
$$= \int_{z \in \Omega_z} f(y|z, t_y = t; \gamma_t) dF(z|t_z = t)$$
$$= f(y; t_y = t, t_z = t, \gamma_t)$$

Under the strong (especially in the case of income) assumption that the structure of income ($f(y|z, t_w = t; \gamma_t)$) does not depend on the distribution of attributes, the situation where $t_z \neq t_w$ can be defined. Then the "density that would have prevailed in 2013 if attributes had remained at their 1992 level and income had been shared according to the income schedule in 2013" ($f(y; t_w = 13, t_z = 92, \gamma_{13})$) is:

$$f(y; t_y = 13, t_z = 92, \gamma_{13}) = \int f(y|z, t_y = 13; \gamma_{13}) dF(z|t_z = 92)$$
$$= \int f(y|z, t_y = 13; \gamma_{13}) \psi_z(z) dF(z|t_z = 13)$$

Where $\psi_z(z) = \frac{dF(z|t_z=92)}{dF(z|t_z=13)}$ is a reweighting function.

As a result counterfactual scenarios can be created by estimating the reweighting function and applying it to the sample weights that are attached to the HES data. However, this begs the question of how to practically estimate $\psi_z(z)$. DiNardo et al.'s innovation was to apply Bayes' Rule to the problem, which implies that:

$$\widehat{\psi_z}(z) = \frac{P(t_z = 92|z)}{P(t_z = 13|z)} \cdot \frac{P(t_z = 13)}{P(t_z = 92)} \tag{3}$$

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[13]The time period of the income vector.
[14]The time period of the attributes matrix.

Then the data set can be reweighted with the relevant relative probabilities, estimated with standard logit models as described in Cameron and Trivedi (2005), in order to form the counterfactual density.

As mentioned above, each counterfactual must be introduced sequentially (while holding other factors constant), as a result the estimated contribution of the factor associated with that counterfactual depends on the ordering of estimation.

Ordering matters as the characteristics the result is conditional on changes as the ordering change - and as a result, the later the ordering is the more other changes/factors the result is conditional on. When the effect of a factor first is estimated first, it is the unconditional contribution of that factor. Second it is the contribution of that factor, conditional on the first factor. With no reason to prefer a given ordering of the factors the Shapley value us applied to find the marginal effect of that factor.[15]

As a result, the number of counterfactuals needed to average over to estimate the marginal effect of the policy is $C!$ where C is the number of contributing factors used.

As noted when discussing Herault and Azpitarte (2016), the counterfactual corresponding to employment outcomes can be neatly fit within the microsimulation decomposition framework of Bargain (2012). Furthermore, Herault and Azpitarte (2016) goes on to analyse changes in the distribution of specific factors (age, education, distribution of income unit type and size, wage income, capital income).

An example of the estimation procedure with regards to the employment status characteristic is as follows. Take the data for HES91 and HES13 and pool it, adding a dummy variable to each dataset that represents that year (yd). For each family an employment status dummy is provided ES, these are:[16]

- $ES = 0$: For both not employed.

- $ES = 1$: For one adult in part time work.

- $ES = 2$: For one adult in full time work.

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[15]This can be thought of as the average of the marginal effects from each ordering - hence why it corresponds to the *fair* value associated with the Shapley value.

[16]Part time work is defined as working less than 30 hours per week - note that this is the same definition as household surveys, but differs from the in-work tax credit where eligibility starts at 20 hours.

- $ES = 3$: For one adult in full time work and one adult in part time work, or for two adults in part time work.

- $ES = 4$: For both adults in full time work.

Given these dummies and the year status of each family, the reweighting factor for the jth family type (in this case either single adult or couple) is estimated using the probability that a given family belongs to $yd = 1$. As a result, the reweighting factor for the jth family type will take the form:

$$\psi_E(E) = \frac{P(t = 1|E)}{P(t = 0|E)} \cdot \frac{P(t = 0)}{P(t = 1)}$$

Which for notational simplicity can be written as:

$$\psi_E(E) = \frac{P_1(E)}{P_0(E)} \cdot \frac{P_0}{P_1} \tag{4}$$

Where $P_t(E)$ is the probability of being in time period t given employment status E, and P_t is the unconditional probability of being in time period t.

In this case, for the jth subgroup, take the discrete set of employment outcomes - where $m = 0, ..., 4$ represents the employment status described above. Defining $e_m = 1$ if the household has employment outcomes m and $e_m = 0$ otherwise, then:[17]

$$\psi_E(E) = \sum_{m=0}^{M} e_m \frac{P_1(e_m = 1)}{P_0(e_m = 1)} \cdot \frac{P_0}{P_1} \tag{6}$$

Here $\frac{P_1(e_m=1)}{P_0(e_m=1)}$ can be estimated for all m by using the relevant ratios of a given subgroup that has that employment status.[18]

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[17]Or if this is ordered such that it is conditional on some other sociodemographic characteristics first this reweighting factor takes the form:

$$\psi_{E|z}(E, z) = \sum_{m=0}^{M} e_m \frac{P_1(e_m = 1|z)}{P_0(e_m = 1|z)} \tag{5}$$

[18]In the case where the decomposition involving sociodemographic characteristics takes place first, the relevant probabilities are estimated by using an ordinal logit model.

The employment decomposition is inherently different to the policy and behavioural decompositions from Bargain (2012) as the direct impact of policy is not considered separately when looking at employment status. While the Bargain (2012) method simulates a counterfactual labour supply based on an estimated response to changes in policy settings, the employment decomposition reweights the data to change employment patterns in the base data. In that way the change in the employment distribution embodies both a labour supply response to changes in tax-transfer policy settings, and an unexplained change in the employment distribution. As a result, the estimated labour supply change from a behavioural microsimulation model can be used to estimate the relative contribution of this change in the employment distribution that is due to policy effects - as well as adding a term that represents the direct effect of tax-transfer policy changes on the index value.

One issue that needs to be highlighted when interpreting the decomposition of the employment effect is the difference in the intensive margin between the behavioural model and the employment status reweighting. Employment status varies between part time and full time work, while the policy behavioural model varies on the basis of fixed numbers of a larger set of discrete hours. As a result, the employment status model may not reweight due to some set of characteristics remaining in part time work, even though the policy response will see the individual change their hours.

When incorporating changes in the age and educational attainment in the population the same reweighting method is applied.

The population groupings for age are based on a division between those in the earlier stages of their labour market involvement (15-34), prime working age (35-64), and retired individuals (65+). For highest educational attainment the groupings are split between those with a maximum of Level 3 NCEA attainment, Level 4-6 attainment, and Level 7 and higher attainment.

With education, globalisation, and technological change all seen as major contributors of changing inequality outcomes, the implied return to characteristics for individuals would be expected to change as suggested in Goldin and Katz (2010). In Hyslop and Mare (2005) the potential for changing returns to characteristics are also investigated, but their role in changing income inequality between 1984 and 1998 is limited.

Preliminary analysis for this paper using the Hyslop and Mare (2005) method-

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ology suggested that the role of changing returns to characteristics remained low during the 2000s and as a result this factor was not investigated further. However, given the potential importance of this issue - especially in relationship to the significant change in educational attainment and potential inter-relationship between these factors - this is a worthwhile direction for future research.

7.2 Changes in age, employment status, and highest educational attainment

Between HES91 and HES13 there were significant changes in the age, employment status, and highest educational attainment distributions of the respective samples as shown in Table 1.

Table 1: Proportions change

| | 1988-91 | | 2010-13 | |
	Single adult	Coupled adult	Single adult	Coupled adult
Age proportion				
15-34	54.57%	31.22%	41.50%	21.00%
35-64	26.34%	54.72%	38.14%	61.87%
65+	19.09%	14.06%	20.36%	18.14%
Highest educational attainment proportion				
Level 0-3	28.01%	28.63%	22.35%	16.88%
Level 4-6	64.35%	62.04%	48.19%	41.51%
Level 7+	7.64%	9.34%	29.46%	41.61%
Employment status proportion				
Not working	46.75%	42.04%	49.11%	46.93%
Part time	6.56%	10.49%	13.21%	10.83%
Full time	46.69%	47.47%	37.68%	42.24%

With the baby boomer generation nearing or entering retirement age while fertility rates declined in New Zealand the age distribution has shifted right over the past three decades. However, for the purpose of adjusting the age distribution the key proportions of interest are those between 15 and 34, those aged between 35 and 64, and finally those aged 65 and over.

Between the HES91 and HES13 periods the proportion of individuals aged between 15 and 34 declined sharply, falling by over 13 percentage points for single people and 10 percentage points for coupled individuals. Although this corresponded to an uptick in individuals over retirement age

(especially for coupled people) most of the increase in the density of the age distribution has been in the 35-64 age group.

Educational attainment increased markedly for both single and coupled people between HES91 and HES13, with the proportion of people with Level 7 and above qualifications quadrupling.

Both 1988-91 and 2010-13 involved recessions and marked increases in unemployment in New Zealand. However, in terms of the depth and length of the 1988-91 economic slowdown eclipsed that of the 2009 Global Financial Crisis for New Zealand. This led to higher unemployment during the earlier period. However, as noted in Nolan (2018b) part time employment increased sizably during this period. The change in the nature of the labour market will also have influenced inequality outcomes between HES91 and HES13.

7.3   Interpreting the results of the method

As mentioned at the start of this section, with regards to the analysis of tax-transfer policies such a decomposition makes a number of unsatisfactory assumptions if we were trying to interpret these results causally. The initial tax decomposition assumes:

1. Gross wages are fixed and labour demand is perfectly elastic.

2. No general equilibrium (change in other factor prices and quantities) or dynamic (endogenous changes in other characteristics) effects.

When decomposing on the basis of other, non-policy factors counterfactual incomes are no longer being simulated the same way. Instead, the limitations of interpretation associated with interpretation of the DiNardo et al. (1996) method as mentioned in Fortin et al. (2011) become relevant:

1. The method assumes no spillover effects from the reweighting procedure onto the rest of the distribution.

2. Omitted variable bias is ignored when estimating parameters

3. The *deep structural parameters* of the income generating process are not identified, as a result the model is non-causal - in terms of not having "pre-treatment" variables which in turn define the choice of income.

4. This method of applying a counterfactual based on the income generating process of the other time period involves mixing differences in both unobservable variables and the change in the income generating process, implying that the estimates are non-causal and depend on assumptions about the conditional distribution of unobservables. Although *ignorability* assumptions are often used to rescue these models in the case of an income generating function this assumption is likely to be violated.

The strength of these assumptions makes it non-credible to claim that such a method explains the causal impact of a given factor on the income distribution. As a result, this type of analysis needs to be justified as a *descriptive analysis* of the change in the income distribution - and more specifically the change in scalar measures of income inequality.

Another key issue is that the HES data, and the decomposition procedures that are being applied are *static* by nature - when the interest in income inequality is often driven by issues related to lifecycle and intergenerational inequality and endogenous changes in individual characteristics. As discussed in Atkinson and Bourguignon (1987) income distributions can be modelled in a variety of different ways due to the complex nature of the income generating process, each of which provide a different view on the distribution and rely on differing assumptions to achieve these results. As an overarching single model of the income distribution would be intractable, it is preferable to build a specific model for a specific question with clearly specified shortcomings - which is the goal of this paper.

This can be seen in the New Zealand context by the types of discussion that occur regarding the 1984-1993 reform program. Stillman et al. (2008) used Census data to try and understand the long-run consequences of these reforms on 140 local labour markets - coming to the conclusion that the reforms had a long-lasting impact.

The comparison of static snapshots does allow some insight into factors that are likely to be important for disparities in income opportunities over an individuals lifecycle. However, inequality at a point in time does not imply inequality or injustice over a lifecycle - and so these concepts should be taken with care when viewing estimates.

7.4 Selection of counterfactual orderings

With six different effects modelled there would be $6! = 720$ combinations of these varying effects. This can be reduced by taking into account that the behavioural response to tax-transfer policy changes and the residual change in employment status must be placed consecutively given that they correspond to a decomposition of the employment status term. As a result, there are only 5 unique terms to be decomposed, so there are $5! = 120$ combinations that must be computed and averaged to estimate an average effect of a given factor.

However, unlike Bargain (2012) and Herault and Azpitarte (2016) this paper does not keep the ordering between the residual and employment effects fixed.

As discussed in the policy decomposition section, Bargain (2012) states that "the other effects and behavioural effects must be positioned consecutively since they correspond to a split of the former other effects in primary decompositions 1 and 2". However, it is not clear that justifies fixing the ordering of the effects - for example if age is separated out it is still part of the *other effects* or residual term but it can be placed anywhere in the ordering of effects.

If instead the method had estimated a total policy response and that was being decomposed into behavioural or non-behavioural elements then the ordering would be fixed. But the residual term cannot be interpreted in the same way.

Specifically, Herault and Azpitarte (2016) discusses the behavioural term as the response of agents given the expectation they face a given tax system. If expectations provide the justification for why the policy decomposition into behavioural and non-behaviour terms makes sense then there is no economically meaningful reason to expect the behavioural and direct tax terms have to be consecutive. With all counterfactuals remaining economically meaningful, an application of the Shapley value requires that all orderings are calculated and averaged over.

8 Results of the decomposition

Unlike previous literature, this paper compares pooled sets of years due to the smaller data sets available. In this section the Gini coefficient dur-

ing the HES88-HES91 period will be compared to the HES10-HES13 period.

Both these periods followed on from the start of a financial crisis. In October 1987, a slump in global stockmarkets sparked off a broader based slowdown in the New Zealand economy. In September 2008 the failure of Lehman Brothers in the United States sparked the Global Financial Crisis which set off a broader based slowdown in the New Zealand economy.

In order to create counterfactuals the annual policy applied over a four year period are applied to the other four year period of analysis. For example, the HES88-HES91 with HES10-HES13 tax and transfer policies involves applying the policies of HES10 to HES88, the policies of HES11 to HES89, the policies of HES12 to HES90, and finally the policies of HES13 to HES91.

8.1   Equivalence Scale

This decomposition concentrates on the Gini coefficient as the key inequality measure. The value of an inequality measure depends on the unit of analysis and equivalence scale used. In this paper the individual is taken as the unit of analysis where an equivalised family income per person is attributed equally across members of the family. Although such an assumption satisfies the *principle of anonymity* the artificial construction of a family income figure implies that it does not necessarily satisfy the *principle of transfers* as discussed in Creedy (2017).

The relevant family income depends on the equivalence scale used, as this scale captures the degree of economies of scale within the family. At one extreme a *per-capita* income measure takes family income as observed and shares it equally across family members thereby assuming that there are no scale economies for larger families. At the other extreme is the *family* level income measure where full scale economies are assumed (eg there are no additional costs associated with having an extra family member) and so the overall family income is given to each individual in the family. In this instance economies of scale in the household imply that, for a given observed family income, each family member receives that income irrespective of family size. Between these two extremes is the parametric scale used in this paper, with parameters that are close to those implied by the Jensen (1988) scale.

Figure 3: Disposable income Gini varying equivalence scales.

Figure 3 illustrates the Gini measures between 1988 to 2013 for these three scales. In each case inequality measures vary for each HES year, and it is unclear whether an equivalence scale that reduces the incomes of large households more (eg per capita) reduces or increases inequality measures. These complications indicate how important clarifying the unit of analysis, economies of scale, and where appropriate income sharing in the household or family is. Similar results hold if household income sharing is used instead of income sharing solely within the family.

The analysis performed in this paper assumes that income sharing occurs between all members in the Economic Family unit (EFU). An economic family unit is made up of an adult, their partner (where a partner exists), and their children (termed dependants). Equivalised income is then given to each person in the family unit, and inequality statistics are calculated given that income distribution. Alternative Gini coefficients for per capita income per person are also provided for comparison in the results section.

The adult equivalence scale used was the parametric scale utilised in Creedy et al. (2010). This scale calculates the adult equivalent size of the family as:

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$$m = (n_a + \theta n_k)^\alpha \tag{7}$$

Where n_a is the number of adults in the family, n_k is the number of children, $0 \geq \theta \leq 1$ is the weight placed on the number of children, and $0 \geq \alpha \leq 1$ is a measure of scale economies among the family unit. Dividing family income by m gives a measure of the equivalised income of each individual in the family unit. The results below use this adult equivalent scale to compare family income.

The base comparison for this parametric scale has values of $\alpha = 0.6$ and $\theta = 0.7$ and gives results comparable to Jensen scale (Jensen 1988).

8.2 Results

In Tables 2 the Gini coefficients for counterfactual scenarios are shown. Table 2 refers to the individual as the income unit.

Table 2: Gini coefficients for each counterfactual

	1988-91		2010-13	
	Per Capita	Equivalised	Per Capita	Equivalised
Characteristics Fixed				
Status Quo Policy	36.83	30.30	40.01	36.69
Tax Change	39.24	33.80	38.62	34.67
Behavioural Change	36.61	29.72	39.89	36.12
Full Change	38.59	32.74	38.46	34.59
Age distribution changed				
Status Quo Policy	34.54	29.89	38.35	36.76
Tax Change	37.60	33.49	36.00	34.25
Behavioural Change	34.02	29.02	38.18	36.71
Full Change	36.51	32.04	35.83	34.19
Highest Qualification distribution changed				
Status Quo Policy	33.79	29.17	39.78	38.30
Tax Change	36.98	32.90	37.76	36.21
Behavioural Change	33.29	28.32	39.63	38.29
Full Change	35.89	31.43	37.60	36.16
Age and Highest Qualification distribution changed				
Status Quo Policy	33.92	28.97	40.03	38.40
Tax Change	37.27	32.97	38.10	36.41
Behavioural Change	33.42	28.11	39.91	38.39
Full Change	36.18	31.49	37.96	36.37
Employment Status distribution changed				
Status Quo Policy	33.81	29.70	37.78	37.00
Tax Change	36.90	32.96	35.09	33.99
Age and Employment Status distribution changed				
Status Quo Policy	35.61	29.89	38.35	36.76
Tax Change	38.57	33.49	36.00	34.25
Highest Qualification and Employment Status distribution changed				
Status Quo Policy	33.81	28.68	39.47	38.62
Tax Change	36.90	32.27	37.19	36.20
Age, Highest Qualification and Employment Status distribution changed				
Status Quo Policy	33.96	28.43	39.71	38.61
Tax Change	37.19	32.28	37.56	36.33

The results in Table 3 use the Gini coefficients from Table 2 where an adult equivalence scale is applied.

The decomposition of the relevant factors come from one of two directional methods: taking the HES13 base population and applying a reweighting or imputation (in the case of taxation) factor to make the population more closely represent HES91, or taking the HES91 population that has been reweighted to more closely represent HES13 and comparing that to the actual population from that time. For each factor, its order in the decomposition determines what the change is conditional on - eg if age is positioned after highest education then the age effect is conditional on the change in the highest education distribution.

The residual term comes about from changing the base year of analysis from HES13 to HES91. A *residual first* decomposition switches from the observed HES13 base year to the HES91 base year with the HES13 age, education, taxation, and employment. A *residual last* decomposition takes HES13 with the age, education, taxation, and employment properties of HES91 and compares it to HES91. In this way the base year and residual term includes three changes: the change in the preference parameters (as the labour supply model is for a given population), a change in prices, and a change in other observed and unobserved characteristics of the sample.

Table 3: Decomposition results

	Gini contribution			
	Gini points	Range	Proportion	Range
Average of all orderings				
Age	(0.065)	(0.416) - 0.525	(1.0%)	(6.5%) - 8.2%
Highest educational attainment	(1.389)	(2.203) - (0.518)	(21.7%)	(34.5%) - (8.1%)
Direct taxation	2.924	1.990 - 3.998	45.7%	31.1% - 62.6%
Behavioural response	(0.426)	(1.477) - 0.078	(6.7%)	(23.1%) - 1.2%
Total policy effect	2.497	2.019 - 3.261	39.1%	31.6% - 51.0%
Residual employment status	0.112	(0.384) - 1.442	1.8%	(-6.0%) - 22.6%
Total employment status	(0.314)	(0.834) - 0.675	(4.9%)	(13.1%) - 10.6%
Residual	5.268	4.417 - 6.311	82.3%	69.1% - 98.8%
Total change	6.391	-	-	-
Residual last ordering				
Age	(0.041)	(0.255) - 0.420	(0.6%)	(4.0%) - 6.6%
Highest educational attainment	(1.840)	(2.203) - (1.542)	(28.8%)	(34.5%) - (24.1%)
Direct taxation	2.285	1.990 - 3.006	35.8%	31.1% - 47.0%
Behavioural response	0.052	0.010 - 0.078	0.8%	0.2% - 1.2%
Total policy effect	2.337	2.034 - 3.082	36.6%	31.8% - 48.2%
Residual employment status	(0.097)	(0.384) - 0.597	(1.5%)	(6.0%) - 9.3%
Total employment status	(0.044)	(0.318) - 0.675	(0.7%)	(5.0%) - 10.6%
Residual	6.032	-	94.4%	-
Residual first ordering				
Age	(0.100)	(0.416) - 0.525	(1.6%)	(6.5%) - 8.2%
Highest educational attainment	(1.043)	(1.457) - (0.518)	(16.3%)	(22.8%) - (8.1%)
Direct taxation	3.651	3.266 - 3.998	57.1%	51.1% - 62.6%
Behavioural response	(1.061)	(1.477) - (0.585)	(16.6%)	(23.1%) - (9.2%)
Total policy effect	2.590	2.019 - 3.261	40.5%	31.6% - 51.0%
Residual employment status	0.527	(0.019) - 1.442	8.2%	(0.3%) - 22.6%
Total employment status	(0.534)	(0.834) - 0.000	(8.4%)	(13.1%) - 0.0%
Residual	4.417	-	69.1%	-

8.2.1 Average estimates

The results in Table 3 indicate that tax-transfer policy changes played a large role in the rise in income inequality between HES91 and HES13, accounting for 39% of the increase in the Gini coefficient.

The direct effect of tax and transfer changes, including growth in most of the thresholds and payments that was linked to consumer prices rather than higher average wage growth, was behind this policy increase. The direct effect alone pushed up the Gini coefficient by nearly 2.9 points or 46% of the increase in inequality during this period.

As in prior research using this method (Bargain 2012 for the UK, Herault and Azpitarte 2016 for Australia, and Nolan 2016 for New Zealand), the change in labour supply behaviour by households partially mitigated the increase in inequality due to policy change, reducing the Gini coefficient by just over 0.4 points.

Unlike Nolan (2016) the behavioural response was insufficient to fully cancel out the increase in inequality due to the change in tax-transfer policies. Although Nolan (2016) dealt with a different time period (1995-2013) the main reason for this difference was the choice of deflator for counterfactual tax-transfer thresholds and transfer payments - with that result based on a CPI deflator while this paper used average income growth.

Non-policy related changes in the employment status distribution partially cancelled out the behavioural policy response, with the change in employment status increasing income inequality. Overall, the change in employment status between these periods reduced disposable income inequality. This result was consistent with the labour force effect on disposable income estimated in Ball and Creedy (2015), but differed from the effect on gross income inequality due to employment status estimated in Hyslop and Mare (2005) for the 1984-1998 period.

The age effect on the distribution of income was muted, reducing the Gini coefficient by 0.065 points. Over an individuals lifecycle the variability in individual income explains much of the variation in income in cross sectional data (Mierau and Rockey 2014, Creedy 1992). Furthermore even within age cohorts income inequality varies - following a parabolic relationship where inequality rises into individuals prime earning years before declining (Barry Hirsch 1980).

In this paper the ageing population is captured solely by a rising propor-

tion of individuals who are in their prime working age. A priori it is not clear what effect an ageing population has on inequality. Nolan (2016) found an increase in inequality due to the ageing population using the same method that was applied in this paper.

However, both Aziz et al. (2013) and Ball and Creedy (2015) found that there was little relationship between the change in the age distribution and disposable income inequality. Furthermore, Herault and Azpitarte (2016) estimated that the ageing population in Australia lowered market income inequality but increased disposable income inequality. As a result, a limited age distribution effect is consistent with prior research using this method.

Educational attainment plays a complicated role in income inequality outcomes and the nature of the relationship has long been debated (Stack and Neubeck 1978). In order to achieve the result of higher educational attainment lowering income inequality, it usually necessary to view the change in educational outcomes as reducing inequality in educational outcomes. Given this, rising educational attainment in many countries has been associated with a reduction in income inequality (Coady and Dizioli (2017)). Similar results are found in this paper, with the change in highest educational attainment reducing the Gini coefficient by nearly 1.4 points.

In terms of overall socio-demographic characteristics, Hyslop and Mare (Hyslop and Mare) reweighted the data based on an aggregate of "age, sex, ethnicity, and education levels of adults in the household, together with the numbers of children in various age groups.". The authors found that changes in the shares of these characteristics accounted for around 10% of in the increase in income inequality between 1984 and 1998.

The Hyslop and Mare (2005) study referred to a different income unit, different income (gross as opposed to disposable) and time period. The difference between these results and the net effect of the characteristics analysed here (subtracting nearly a full point from the Gini coefficient) indicate that the role of socio-demographic characteristic changes depend strongly on the type of income unit and income type analysed.

Ball and Creedy (2015) found characteristics such as age and labour force status slightly increased inequality during this period, while the results of this paper showed a very small decrease. Overall, the characteristics based results in this paper are relatively close to those found in Ball and Creedy (2015) for the same period.

The residual effect remains substantial in this analysis, accounting for nearly

three-quarters of the increase in the Gini-coefficient between HES91 and HES13. With every additional factor beyond the direct role of taxes and transfers (employment status, age, and highest educational attainment) suggesting a reduction in income inequality when an increase was observed this indicates that other major unexplained factors exist for explaining the change in income inequality.

8.2.2 Estimate range

Although these estimates seem plausible, it is of value to look at the range of estimates that made up the average. If there are systematic differences in the estimated marginal effect of a factor due to its ordering then this can provide more information about the underlying relationship between these factors and income inequality over the 1988-2013 period.

The effect of **behavioural responses** on income inequality varied based on the HES population used. An economically significant can in the distribution of labour supply responses occurred based on the HES91 population, with virtually no distributional change when based on HES13 population. This is indicated in the above table by comparing he residual last ordering results (when the results are all based on the HES13 population) and the residual first results (where the population is shifted to the HES91 population before factors are decomposed).

Although this may in part be due to the different structures of the two populations, importantly the preference parameter models applied to the HES91 and the HES13 data were very different - as can be seen by the different structure of the HES88-93 and HES09-13 results in Nolan (2018b) which forms the basis of this analysis. Furthermore, this suggests some role for changes in the parameters of the labour supply model in explaining the change in observed behaviour.

The **age effect** estimated given different orderings varies between a 6.5% reduction in income inequality and a 8.2% increase. However, when the age effect is unconditional (the age effect occurs first or after the residual factors) the estimated effect is always within a percentage point to zero.

The range shown in overall *employment status* effects stems from the behaviour of the relative distributions to changes in employment status. Given differences in returns to employment status, reweighting a given population to have the same employment status as another population doesn't

imply the same result will hold if the process occurs in reverse.

Starting with the HES91 population gives a decomposition that suggests that employment status decreased the Gini coefficient between then and 2010-13. The average estimated effect starting from the HES91 population is a 0.53 point drop in the Gini coeffect - or about -8.4% of the increase. The range is between -13% and 0%. As a result the ordering of employment relative to the residual leads to an economically different conclusion regarding the influence employment status had on the income distribution. Given a sharper decrease in income inequality due to the labour supply responses to tax-transfer policy changes (using behaviour estimated for HES88-93), this suggests that non-policy related employment status changes led to a large increase in disposable income inequality.

Conversely, while starting with the HES13 population the change in the employment status distribution has a more mixed effect. The average estimated effect starting from the HES10-13 population is a 0.044 point decrease in the Gini coeffect - or about 0.7%. The range is between -5.0% and 10.6%. With the labour supply response to tax-transfer policy changes (using behaviour estimated for HES10-13) having very little impact on income inequality, this suggests that non-policy related employment status changes to an uncertain and likely small decrease in disposable income inequality.

The different behavioural models explain the varying behavioural effects - but not the full employment difference (which comes from the employment status reweighting exercise). As it is an inequality measure, differences in other elements (eg returns to characteristics) could drive such differences.

The **educational attainment** effect results are relatively robust to the ordering of variables, with the shift in the educational attainment distribution led to an economically significant reduction in income inequality in almost all orderings.

All ordering for **direct taxation** also gave an economically significant increase in income inequality due to the policy changes. The estimated effect ranged between 31% and 63% of the increase in income inequality irrespective of the base year used. For all orderings the direct effect is significantly larger than the behavioural effect. Including the behavioural effect, the overall role of policy was also robust to the ordering used.

One of the key reasons for expanding the number of factors analysed is to reduce the **residual term** - the change in income inequality not explained

by factors in the model. However, the residual term remained large for all decomposition orderings and at its largest neared 100% of the total increase in the Gini coefficient.

9 Conclusions

In this paper, potential reasons for the increase in income inequality between HES91 and HES13 were investigated. The change in inequality was decomposed into a variety of proximate causes based on the construction of counterfactual distributions. These distributions were created either from simulations provided from a tax-transfer microsimulation model or counterfactuals created by reweighting the data to more closely represent the age/education/employment distribution of the alternate years.

Gini coefficients were taken as the summary measure of income inequality in this analysis, with all the decomposition results based on changes in the Gini coefficient. When Gini coefficients were constructed the unit of analysis used was the individual, with each individual receiving income per adult equivalent person. The equivalence scale used was a parametric scale parametrised to be close to the Jensen (1988) scale.

Given this decomposition and data, tax and transfer policy changes accounted for nearly 40% of the increase in the Gini coefficient between HES91 and HES13. The range of estimates for this policy effect was wide (32%-51%) but the estimated role of tax and transfer policies was always positive and large.

This policy change can be further decomposed into a direct change, due to the change in payment rates and thresholds, and a behavioural change due to the labour supply responses of individuals. If no behavioural response occurred tax and transfer changes would have accounted for over 46% of the increase in income inequality - with the change in labour supply behaviour due to the change in tax and transfer settings reducing income inequality by nearly 7%.

Between HES91 and HES13 the proportion of the population with Level 7 qualifications and above rose sizeably. This change in highest educational attainment is estimated to have reduced income inequality over the period by nearly 1.4 Gini points. The ageing of the New Zealand population also reduced income inequality during this period, although the estimated reduction was very small.

Over this same period there was a shift towards part time work. This change in the distribution of the employment status reduced income inequality by a small amount. However, the change in the employment status distribution includes the behavioural response to tax and transfer policy. As a result, the underlying non-policy change in employment status between HES91 and HES13 is estimated to have increased income inequality by over 0.1 Gini points cancelling out part of the decline due to the behavioural responses to tax and transfer changes.

One of the goals of this analysis had been to explain more of the residual or unexplained change in income inequality than had been possible in prior research by introducing more potential factors. However, rather than explaining more of the residual change in income inequality between HES91 and HES13 this decomposition process suggested that unexplained factors were even more important in determining the increase in income inequality than previous studies had suggested.

The shifts in the age and highest educational attainment distributions both reduced aggregate income inequality more than the change in the employment status distribution increased it. Given that overall income inequality rose, this implies that unexplained factors had a larger role in increasing income inequality.

Given the static response to tax and transfer policies (both in terms of the way they transform market to disposable income and in terms of labour supply responses), the change in the age distribution, the change in educational attainment, and the change in employment status only around a quarter of the change in the Gini coefficient is explained. This suggests that there is scope for future research to investigate the role of other characteristics, and the return on characteristics these characteristics.

However, the primary purpose of this paper was to investigate the role tax and transfer policies played in the increase in income inequality between HES91 and HES13. By using a tax-transfer microsimulation model and taking into account labour supply responses, this method has provided a quantitative estimate of the role played by tax-transfer policies. Furthermore, given the robustness of the tax-transfer effect to varying orderings of the explanatory factors, the result that tax-transfer changes accounted nearly 40% of the increase in inequality is both economically significant and credible.

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