Inequality within and between New Zealand Urban Areas

A thesis

submitted in fulfilment

of the requirements for the degree

of

Doctor of Philosophy in Economics

at

The University of Waikato

by

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THE UNIVERSITY OF
WAIKATO
Te Whare Wānanga o Waikato

2019

Abstract

A better understanding of the drivers of changes in the distribution of personal income continues to be of interest to academics, policy makers and the general public. While the focus has often been on the role of economic factors, socio-demographic factors play an important role as well.

This thesis examines the socio-demographic determinants of changes in the distribution of income in New Zealand urban areas from 1986 to 2013, using data from the Censuses of Population and Dwellings. The thesis examines the role of changes in the age structure, immigration and patterns of educational assortative matching on the changes in the distribution of income over time and across areas.

Multiple decomposition analyses are used to examine the composition and within-group distribution effects of ageing and immigration, while a counterfactual randomisation methodology is used to examine the effect of educational assortative matching.

The results show that inequality has increased in New Zealand urban areas but there is spatial disparity in this trend and in its drivers. Across areas, most of the rise in inequality was driven by increases in the metropolitan areas. Ageing of the population had a downward effect on inequality but widening of the age group-specific distributions has led to overall inequality growth. For immigration, increases in immigrant share have an inequality-increasing effect, but changes in the immigrant group-specific distribution of income are inequality-reducing in non-metropolitan areas and inequality-increasing in metropolitan areas. With respect to the effect of patterns of partnering among male-female couples on inequality, it is shown that educational assortative matching has an inequality-increasing effect on the distribution of total income of couples. Moreover, spatial sorting on observable characteristics such as age, education and location has an inequality-increasing effect as well.

Acknowledgements

They say it takes a village to raise a child. Indeed, it has taken the help and support of a lot of people to complete this thesis.

I would like to begin by expressing my profound gratitude to my supervisors: Prof. Les Oxley, Prof. Jacques Poot, and Dr Dave Maré. I could not have had a better supervisory panel. I owe this panel a huge debt of gratitude for their ongoing support over the course of my postgraduate study. Special thanks to Prof. Les Oxley and Prof. Jacques Poot, who have both served as Chief Supervisors at different stages of this thesis. I have been very lucky to have benefited from the incredible mentorship and guidance of both Jacques and Les. My sincere thanks to Dave Maré for hosting me at Motu during the initial phase of the thesis; Dave provided incredible assistance in developing the ideas that led to this thesis and continued to provide great support over its entire duration. I also appreciate the constructive feedback provided by the external examiners: Prof. Sholeh Maani (University of Auckland) and Prof. Stephen Jenkins (London School of Economics).

I am grateful to the University of Waikato for providing financial support for my PhD through the National Institute of Demographic and Economic Analysis Doctoral Scholarship award. Sincere thanks to all members of staff of the Department of Economics and the National Institute of Demographic and Economic Analysis of the University of Waikato. Both departments provided a collegial environment and the hardworking staff in both departments served as a big inspiration. I would like to particularly thank Maria Fitzgerald for her administrative support.

I would also like to express my gratitude to staff members of Motu Economic and Public Policy Research, for hosting me, and providing excellent feedback at the initial stages of this thesis, and to the staff of Statistics New Zealand Micro-data Access team for their help with the data.

My profound gratitude goes to my family: my dad, Prof. T Alimi; my late mother, Dr.K.M Alimi; and my siblings - Abiodun, Omowumi, and Omotayo. Being away from you all during this study was very difficult but your love and unending support kept me going!

Finally, I would like to thank my friends, who are too numerous to list, for their care, encouragement and above all willingness to listen to me rambling on about my thesis.

For walking these paths before me and for your unending love and support. This thesis is dedicated to my father, and the memory of my mother.

Disclaimer

Access to the data used in this study was provided by Statistics New Zealand (SNZ) under conditions designed to give effect to the security and confidentiality provisions of the Statistics Act 1975. All frequency counts using Census data were subject to base three rounding in accordance with SNZ's release policy for census data.

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Chapter One: Introduction

This thesis examines income inequality within and between New Zealand regions and urban areas between 1981, or 1986, and 2013[1]. With respect to urban areas, a consistent set of 40 main and secondary urban areas is used, based on data from each Census of Population and Dwelling from 1986 to 2013, recoded to 2013 geographic boundaries[2].

Income inequality is an important issue on which more or less everyone has an opinion. The question of which individuals, or what segments of society, get what share of income is one that generates many viewpoints. Some of these viewpoints may be based on concepts of social justice or morality. In such cases existing inequality is viewed as undesirable when it not simply the outcome of fair differences in returns for differential skills, efforts, risks or contributions. Public opinion across the developed world reveals that the issue of widening inequality is regarded as one of the most significant social issues of our time (Sutter, 2013; Edwards, 2014). Not too long ago, former US president Barack Obama described the issue of rising inequality as the defining challenge of our time (Newell, 2013).

Though concerns about the distribution of income are not new in economics, the issue has received renewed attention in recent times partly due to world leaders being concerned about the extent to which growth following the recovery from the Global Financial Crisis has been inclusive (i.e. benefitting all groups in society), along with the contribution of works such as Thomas Piketty's (2014) *Capital in the 21st century*. The discourse on inequality has attracted interest from academics, policy analysts and world leaders. Contributions to the debate have also ranged from those from religious leaders like the Pope to heads of international agencies such as the IMF and the OECD (Goldfarb & Boorstein, 2013; Gurria, 2014; Gurria, 2015; Largarde, 2015).

Inequality has risen rather sharply since the 1980s in most OECD countries, and this has brought the need for a better understanding of its drivers and evaluation of its impact to the top of the policy and research agenda. In fact, the OECD has

[1] Chapter 2 covers the period from 1981 to 2013.
[2] Statistics New Zealand considers an urban area to be an area with a population of 1000 or more. Other factors such as remoteness and location of employment of the majority of the population are also used to further differentiate between the types of urban area. The thesis uses a set of 40 areas that are coded to 2013 urban area boundaries, consistently classified from 1986 to 2013.

estimated that, between 1985 and 2005, the average OECD country would have grown by nearly 33 per cent more had inequality not risen (OECD, 2015). At the New Zealand level, several academic articles[3], the Ministry of Social Development (MSD) monitoring reports on household incomes,[4] and books, such as Max Rashbrooke's (2013) *Inequality: A New Zealand crisis*, have also attempted to provide evidence of growing inequality and draw attention to the New Zealand case. There is also a lot of public debate on income inequality in New Zealand, with concerns about the distribution of income reported as the top economic issue facing New Zealanders[5].

Historically, New Zealand has introduced various social policies that focused on narrowing the distribution of income, although the importance given to this issue has varied over time. For example, New Zealand was the first country to introduce a minimum wage in 1894. More recently, Cabinet agreed in August 2003 to a work programme on "Reducing Inequality" (MSD, 2003) and currently, the Treasury's Living Standards framework – a descriptive framework of the factors that it considers are essential to national well-being – includes "increasing equity" as a key pillar of increasing national well-being. Though equity in the context of this framework is described as the ability of people to participate in the economy and society fully, it also broadly encompasses enhancing income mobility and reducing income inequality.

This thesis examines three socio-demographic determinants of inequality in the New Zealand context. Specifically, this study focuses on the roles of ageing, immigration and educational assortative matching on the distribution of income in New Zealand between 1986 and 2013. Over this period, New Zealand has experienced rapid rates of ageing, increased rates of immigration and increases in the proportion of couples with similar educational levels[6]. In addition to these

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[3] See Easton (2013) for a review. More recent studies include Aziz, Ball, Creedy and Eedrah (2015) and Ball and Creedy (2016).

[4] For example, see Perry (2014, 2015). Authored by Bryan Perry, MSD publishes a periodic report on the trends in inequality and hardship, measured by means of household incomes.

[5] Results from January 2017 Roy Morgan poll which seek New Zealander's views on problems facing New Zealand. Available at http://www.roymorgan.com/findings/7128-most-important-problems-facing-new-zealand-february-2017-201702271519. Concern about the distribution of income was also one of the top five big issues for the 2014 and 2017 general election (see Collins, 2014 and https://www.interest.co.nz/news/88590/new-zealanders%E2%80%99-concerns-highlighted-run-election-poverty-and-gap-between-rich-and-poor.

[6] Other notable changes over this period include: the deregulation and liberalisation of the late 1980s and early 1990s, increased educational achievement and labour force participation of women, the global financial crisis of 2007/2008 and the subsequent recovery. See Evans et al. (1996) for a review of the economic reforms of the late 1980s and early 1990s.

changes in this period, the 1980s have also been regarded as a watershed during which inequality increased in most developed countries (apart from Latin America, where inequality fell).

Most studies on inequality have focused on changes in the distribution of personal income over this period at the national level but there is recent acknowledgement that changes in inequality varies across geography and some of its drivers have occurred disproportionately in cities. (See Moretti, 2013, Baum-Snow and Pavan, 2013, Baum-Snow, Freedman and Pavan, 2018). There is a paucity of evidence at the sub-national level. A few New Zealand studies have documented a rise in inequality sub-nationally from the 1980s, but most of these studies cover the period up to the mid-90s.[7] It is important to examine more recent sub-national trends and patterns in inequality, especially with respect to what has happened since the mid-90s. This thesis fills this gap and also examines what changes in certain socio-demographic characteristics imply for the distribution of income.

Apart from the scanty evidence in the extant literature, the thesis takes a sub-national focus for some additional reasons: first, New Zealand urban areas are quite distinct in social, economic and demographic characteristics and a national focus may wash out or hide significant differences across areas. National statistics aggregate inequality within and between local areas, both of which can have different drivers. Hence income inequality studies that focus on the national scale may mask the important differences that these characteristics entail for inequality within and between areas. Second, given that the rich and the poor are not evenly distributed across the country, local inequality trends will often differ from national trends. This has implications for the consequences of inequality, which can be expected to be important locally as well as nationally. For example, Luttmer (2005) provides evidence that a self-reported measure of happiness is negatively related to the earnings of neighbours. It is expected that people will direct their displeasure or frustration about a perceived relatively lower income to neighbours rather than those living far away. Third, on the policy front, policies to address inequality at a national level might not even be appropriate at a sub-national level due to the ease of residential mobility. As stated by Glaeser, Resseger and Tobio (2009), redistributive polices to reduce national inequality

[7] Karagedikli, Maré and Poot (2000, 2003) and Martin (2000) use Census data that only cover the period up to 1996.

may not work if, when implemented at a city level, such policies lead to sorting of low and high income people into different areas. Finally, urban areas are becoming more important and are also increasingly becoming the focus of economic policies. More than half of the world's people currently live in cities and this is expected to increase further[8], even in developed countries. United Nations statistics report an urbanisation rate of 86% in New Zealand, which is projected to increase to 90% by 2050 (UN, 2014). It is important to examine inequality in the spaces people actually reside in.

The thesis extends several earlier studies, such as those of Jackson (2011), Bryant (2011), Maré and Timmins (2000) and Callister and Didham (2010, 2014), which have provided descriptive analysis of the national and sub-national trends on ageing, immigration and assortative matching in New Zealand. It goes further by examining what impact changes in these socio-demographic factors have had on the distribution of income. It contributes to knowledge by: 1) describing patterns and trends in the distribution of income of individuals as well as couples in urban areas in New Zealand; and 2) examining the distributional implications of changes in the age structure, immigration and patterns of partnering on the distribution of personal incomes and incomes of couples (in the assortative matching study). In addition to providing a descriptive analysis, this thesis answers three main research questions:

- What is the effect of changes in the age structure on income distribution in urban areas?
- What role has increased immigration played in the changes in the distribution of income in New Zealand urban areas?
- What is the impact of changing patterns of educational assortative matching on the distribution of total income of male-female couples?

Apart from in the descriptive chapter (Chapter 2), the main measure of inequality used in the thesis is the Mean Log Deviation (MLD)[9]. The MLD belongs to a class of additively decomposable inequality measures that permits inequality to be

[8] Indeed, rapid urbanisation has necessitated world leaders to explicitly focus in one of the recently adopted Sustainable Development Goals on cities. Goal 11 focuses on making "cities and human settlements inclusive, safe, resilient and sustainable".

[9] Standard errors are not calculated for the MLD estimates because the thesis focuses on population data. In the assortative matching chapter, standard error for the inequality measures are calculated for metropolitan and non-metropolitan areas and they ranged from 0.01% to 0.04% which indicates the high preciseness of the MLD estimates.

separated into between and within-group components. The MLD is preferred to other measures including other additively decomposable inequality measures such as the popular Theil measure because: 1) the change in MLD is easily decomposable to contributions from within- and between-group components as well as shared and within-group distribution components; 2) the MLD also weights the inequality measure for a group by the group's population share. Thus, MLD provides a direct evaluation of the effect of changes in age or immigration composition.3) Cowell and Flachaire (2007) show that MLD is less sensitive to uncertainty about incomes at the upper end of the distribution. This property makes it a rather appropriate choice for the analysis of New Zealand census data on income. In the census, incomes are captured in bands, with the top band open-ended and the lower bound of the upper band varying over time. In this thesis, incomes in this top band are assumed to follow a Pareto distribution[10] and the relative insensitivity of the MLD to incomes at the top of the distribution means our results will be less sensitive to changes in the top bracket.

In the ageing and immigration chapters, the thesis uses multiple decomposition techniques to decompose the level and the change in inequality, including the population sub-group decomposition method of Mookherjee and Shorrocks (1982), the density decomposition approach of DiNardo, Fortin and Lemieux (1996) and the regression decomposition approach of Fields and Yoo (2000). The thesis focuses on the effect of changing group shares (either immigrant groups or age groups) and the effect of changes in within-group income distribution. In the educational assortative matching chapter, a counterfactual randomisation methodology is used to examine the changes in the patterns of partnering in male-female couples on the distribution of total income of couples.

The focus of the thesis is on personal incomes[11]. The census captures total personal income before tax of people in the 12 months before the census night. It consists of income from all sources such as wages and salaries, self-employment income, investment income, and superannuation[12]. The focus of the thesis is on

[10] The Robust Pareto Midpoint Estimator (RPME) adopted is a nearly non-parametric estimator that, with enough bins, can fit the most income distributions, regardless of its shape. von Hippel et al. (2016) detail the advantages of this estimator.

[11] If the interest is on consumption and welfare, measuring income at the household level seems ideal since individuals share resources and costs across members of their households but for understanding the labour market, individual incomes are better. In the chapter on assortative matching, household income is proxy for by the sum of the personal income of individuals that make the couple.

[12] Wages and salaries contribute in excess of two-thirds of total income

positive income to make the analysis informative of changes in the distribution of labour market earnings. Hence zero income and negative income which are typically cases of losses incurred by businesses or farms are excluded. Over 9 in 10 New Zealanders in each census period reported positive incomes thus the analysis is informative of the changes in the distribution of income of most New Zealanders.

The rest of the thesis proceeds as follows: Chapter 2 provides descriptive evidence on sub-national inequality in New Zealand. The analysis is done at the regional level[13] and examines inequality within and between the 16 regions of New Zealand from 1981 to 2013. Multiple measures of inequality are used here, including popular measures of inequality such as the Gini coefficient and percentile ratios. Total income is a function of hours worked and due to the huge variation in the labour force participation of women[14], the analysis focuses on male incomes. In terms of the growth in inequality and the spatial trends, the conclusions on growth in inequality and the spatial trends still hold when examining all individual incomes[15]. This analysis shows that average income varies across New Zealand regions but also that there is considerable dispersion of income among individuals in the same region. There is also considerable persistence in relative positions of regions. Wellington and Auckland have the highest and second highest average incomes respectively in each census period from 1986. No region escaped the sharp growth in income inequality since 1986 but the highest growth rates of inequality were in the metropolitan regions of Auckland and Wellington. This work[16], co-authored with Emeritus Prof. Jacques Poot and Adj. Prof Dave Maré is published as a chapter in Paul Spoonley (Ed.) *Rebooting the Regions: Why low or zero growth needn't mean the end of prosperity.*

Given the evidence of increased inequality and spatial variation in this trend, the rest of the thesis examines the role of differences in age structure, immigration

[13] The focus on regions here rather than on urban areas as elsewhere in the thesis, is chosen to allow more direct comparison with earlier studies.

[14] For example, labour force participation rates for women in 1986 varied between about 47 per cent (in the Tasman, Nelson, Marlborough and West Coast regions) to about 59 per cent in Wellington, although they increased sharply subsequently everywhere (for example by as much as 19 percentage points in Southland by 2013

[15] Examining all individual incomes (male and female), we still find that inequality increased and regions like Auckland and Wellington also had the highest growth in inequality. The chapter also focused on male income to update earlier evidence from Karagedikli et al. (2000; 2003),

[16] Alimi, Maré and Poot (2016).

and assortative matching in the spatial variation along with the effect of inter-temporal changes in these variables.

A simplified spatial level of analysis is adopted in the rest of the thesis. Urban areas are divided into metropolitan and non-metropolitan areas. The justification for this is that descriptive analysis has shown that the greatest disparity is between the large metropolitan areas and elsewhere. The rest of the thesis examines the contribution of spatial and temporal variation in patterns of ageing, immigration and assortative matching to the differences in inequality between metropolitan and non-metropolitan areas. Metropolitan areas consist of all urban areas that make up New Zealand's six biggest cities[17] and non-metropolitan areas are all classified as other urban areas. The immigration and assortative matching analyses are limited to the population aged 25 to 64 earning positive income. This ensures that the focus is predominantly on labour market effects[18]. The ageing analysis is for the population aged 15 and above.

Chapter 3 focuses on changes in the age structure between 1986 and 2013. New Zealand aged over this period. The overall effect of changes in the age composition (ageing) has slowed down the growth in inequality, but the widening of the age-specific distribution explained the rise in inequality in all urban areas. This work[19], co-authored with Emeritus Prof. Jacques Poot and Dr. Dave Maré, is published as a chapter in U. Blien, K. Kourtit, P. Nijkamp and R. Stough (Eds.) *Modelling Aging and Migration Effects on Spatial Labor Markets*[20].

Chapter 4 examines how immigration affects metropolitan and non-metropolitan income distributions. Migrants are classified by skill level and length of stay. The results show that increases in immigrant share have an inequality-increasing effect, but the effect of within-immigrant group changes in the distribution of income varies across areas. Within-immigrant group change is inequality-increasing in metropolitan areas while slightly inequality-reducing in non-metropolitan areas. Overall changes in the distribution of income of the New Zealand-born non-migrants were inequality-reducing in all areas. Inequality increased in metropolitan areas because the overall inequality-increasing effects

[17] The urban areas that make up Auckland, Wellington, Christchurch, Hamilton, Dunedin, and Tauranga are classified as Metropolitan areas.
[18] Most of the under 25 age group are either in education or training while the 65s and over age group will largely be out of the labour force as the retirement age is 65 in New Zealand.
[19] Alimi, Maré and Poot (2018a).
[20] A revised version of this chapter is forthcoming in the New Zealand Population Review.

(composition and within-group changes) of immigrants are larger than the inequality-reducing changes for the New Zealand-born non-immigrants. This is however different in non-metropolitan areas: the overall inequality-reducing changes for the New Zealand-born were larger than the inequality-increasing change from immigrants hence inequality fell. This work[21], co-authored with Prof. Jacques Poot and Dr. Dave Maré is published as an IZA working paper.

In Chapter 5, the level of analysis shifts from individuals to couples working full-time and the effects of educational assortative matching among male-female couples on the distribution of total income of couples in metropolitan and non-metropolitan areas are examined. The results show that educational assortative matching increased but, contrary to some evidence from overseas, the increase was driven by those in the middle of the education distribution. However, it had an inequality-increasing impact on the distribution of total income of couples. Assortative matching was found to have considerable potential to influence the distribution of income, and sorting on observable characteristics such as age, education and location, is inequality-increasing. This work[22], co-authored with Prof. Jacques Poot and Dr. Dave Maré is published as a Motu working paper.

Chapter 6 concludes the thesis by highlighting its contributions, discussing its limitations and presenting opportunities for further research.

[21] Alimi, Maré and Poot (2018b).
[22] Alimi, Maré and Poot (2018c).

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Chapter Two: Article 1 - Income inequality within and between New Zealand regions[23,24]

Omoniyi Alimi, David C. Maré and Jacques Poot

2.1 Introduction

In the eyes of the rest of the world Aotearoa New Zealand is a strikingly beautiful country with safe cities and friendly people who have a high level of prosperity that is shared fairly. This image was first shaped more than a century ago when the country led the way globally with progressive policies such as giving women the vote in 1893 and introducing minimum wages in 1894. Nowadays, tourists visiting the country's top attractions on organised tours and business people staying in the comfort of Auckland's and Wellington's four-star hotels will find this perception mostly confirmed, or at least find any signs of poverty and inequality less pervasive than at home. But those who venture off the beaten tracks of metropolitan centres and main tourist destinations see a different New Zealand. Yes, the scenic beauty and the friendliness of the people are ubiquitous and enduring, but prosperity may be hard to detect when travelling through depopulated towns with dilapidated storefronts and dwellings.

This sharp contrast between the glitzy CBDs and peeling paint of small-town buildings has of course not gone unnoticed in analyses of regional trends in recent years. It is indeed one of the triggers of this book. Eaqub (2014) compares median household income in New Zealand regions with GDP per capita of countries. That puts Auckland and Wellington firmly in the Western Europe

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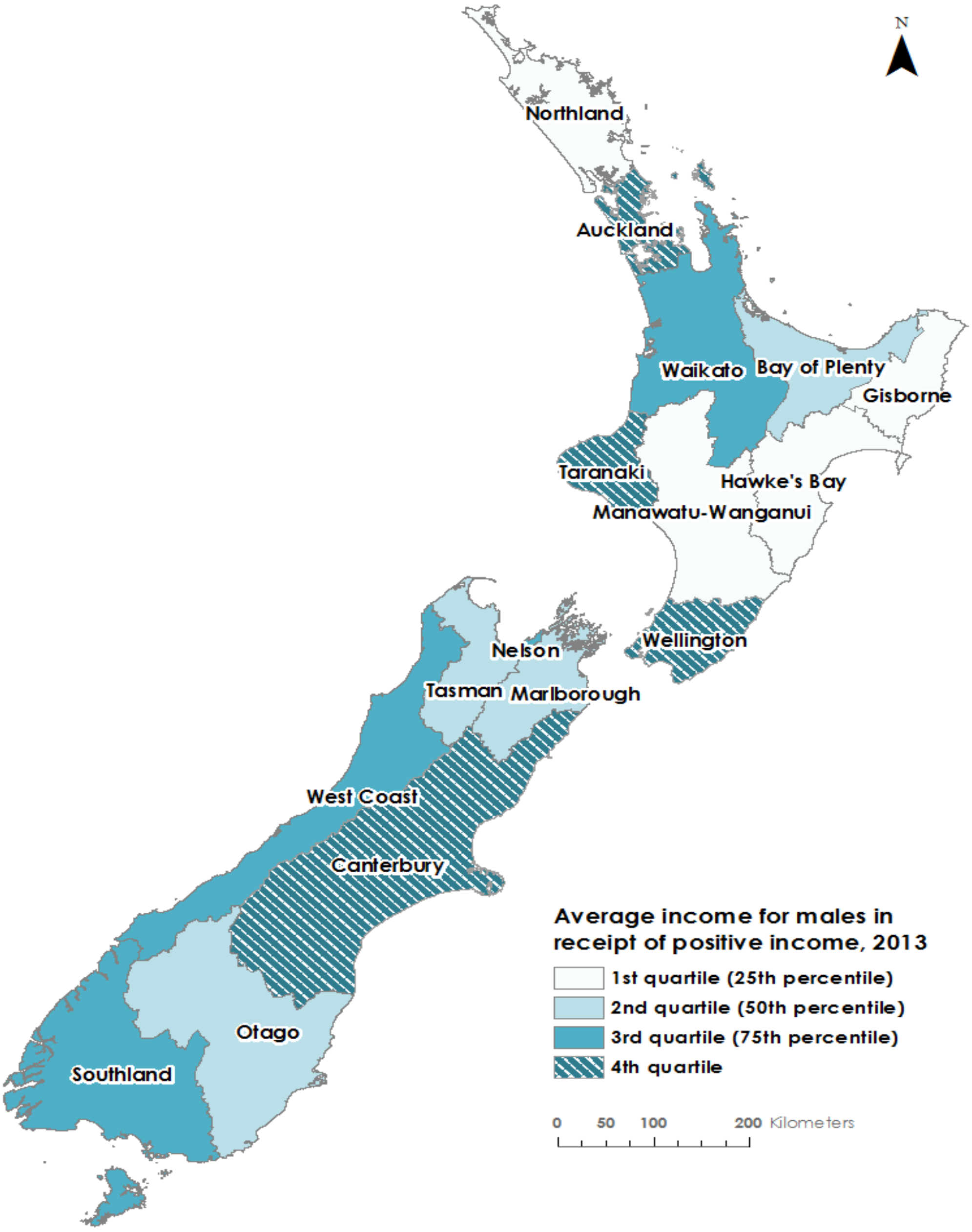
[23] Alimi, Maré and Poot (2016) - This work co-authored with Emeritus Prof. Jacques Poot and Dr. Dave Maré is published as a chapter in Paul Spoonley (Ed.), *Rebooting the Regions: Why low or zero growth needn't mean the end of prosperity*. Auckland: Massey University Press.

[24] This study has been supported by the 2012–2014 *Nga Tangata Oho Mairangi* (NTOM) project, funded by Ministry of Business, Innovation and Employment (MBIE) grant CONT-29661-HASTR-MAU and the 2014–2020 *Capturing the Diversity Dividend of Aotearoa New Zealand* (CaDDANZ) project, funded by MBIE grant UOWX1404. Access to the data used in this study was provided by Statistics New Zealand under conditions designed to give effect to the security and confidentiality provisions of the Statistics Act 1975. All frequency counts using Census data were subject to base three rounding in accordance with Statistics New Zealand's release policy for census data. The views, opinions, findings and conclusions or recommendations expressed in this chapter are strictly those of the authors and do not necessarily represent, and should not be reported as, those of Statistics New Zealand or the organisations at which the authors are employed.

league, but leaves regions such as Hawke's Bay, Gisborne and Manawatu–Wanganui more on a par with Greece, and Northland with Timor Leste. This last may appear somewhat far-fetched; but few would argue that the big city–hinterland gap has not widened in New Zealand, as it has in many developed countries. Of course, there have always been big differences between income and prosperity across geographical space, sufficiently so to generate a separate field of economics to explain the causes of such differences. And the explanation has always been, and remains, complex and debatable. Consequently, regional and urban economics was a rather unloved field of the economics profession for much of the last century, at least until the 1990s, when mainstream economists developed some new tools that enabled more rigorous explanations (see e.g. Krugman, 1998).

Depending on the geographical scale applied, spatial differences may have increased more in New Zealand than in many other countries, given New Zealand's long history of uniform prices and national wage determination until the reform years of the 1980s. Williamson (1965) compared regional income inequality across a range of countries and found that in the 1950s Australia and New Zealand had the lowest regional inequality of the 24 countries examined. But we have to be careful not to glamorise that 'golden age' of New Zealand's egalitarian economy, protected behind high walls of import tariffs and quotas. Jensen (1969) calculated that in fiscal year 1964/65 gross personal income in the city with the highest income per capita (Invercargill at that time, with Wellington in second and Auckland in third place) was 37 per cent higher than in the poorest city (Greymouth). Compare that with 2014 regional data and Johnson (2015: 48) finds that the median personal income of those employed is 29 per cent higher in the highest-ranking region (Wellington) compared with the lowest (Manawatu–Wanganui). Eaqub (2014: 12) finds a much greater gap of 63 per cent in 2013 median household income between the highest (Auckland) and lowest (Northland) regional scores. Figure 2.1 shows how average personal income (as defined below) varied across New Zealand regions in 2013.

Figure 2.1: Average personal income for males in New Zealand regions, 2013



Source: Statistics New Zealand, 2013 Census of Population and Dwellings

Such calculations show that there has always been a notable gap in income per capita between the richest and poorest regions of New Zealand, even if it was historically less so than in other developed countries. Additionally, due to higher average rents and house prices in metropolitan centres, the cost of living is much greater in such cities than in the provinces, so that the spatial gap in *real* average income between high-income cities and low-income hinterland is actually much less than it is in nominal terms. Indeed, real income differences between regions may be declining today, when house prices in high-income cities such as

Auckland and Wellington are increasing faster than elsewhere. This observed decline is consistent with the prediction from economic theory that real income per capita differences between large regions should over time become smaller, provided that such regions, first, have access to the same technologies; second, are linked through trade; and, third, have unrestricted flows of capital and labour (see e.g. Le Gallo and Fingleton, 2014 for a review of the international evidence).

Accurately accounting for the way in which regional differences in prices partially or fully offset the observed gaps in nominal income between regions is quite complicated and will not be attempted in the present chapter. Statistics New Zealand does not calculate regional–spatial price indexes because it concluded, based on a lack of submissions received after seeking public consultation, that there appears to be little interest in knowing whether a dollar of income buys you more in one region than another (Statistics New Zealand 2014: 12). We disagree with this assessment and plan to report regional–spatial price indexes in another publication. Incorporating regional differences in prices would, however, not weaken the main conclusion of this chapter, which is that there have been within all regions sharp increases in income inequality among individuals between 1986 and 2013, with the exception of the 2001–2006 phase of rapid economic growth. Additionally, differences between the average or median nominal incomes observed across regions are already small compared with the differences in income between those receiving the highest and the lowest incomes within each region. In simple terms, an individual's personal characteristics, such as education and experience, play a much bigger role in predicting personal real income than their location, although the latter is by no means irrelevant.

The issue, therefore, is not primarily one of growing differences in average income between regions, but one of increasing inequality within regions and the ways in which this growing intra-regional inequality manifests itself differently in different places. The latter is aptly shown by Johnson (2015), who concludes that the main underlying driver of unequal opportunities across individuals is that of agglomeration: the concentration of people and capital in modern, globally connected, knowledge-intensive and services-driven cities versus the relative population decline of the provinces. This process, lucidly explained in Glaeser's (2011) *The Triumph of the City*, implies that spatial differences in average income are becoming less meaningful for understanding the changes in economic fortunes of individuals who have increasingly diverse backgrounds and face a growing diversity of circumstances.

In this chapter we therefore focus predominantly on how income inequality within each of the regions has increased. We do this by updating, by means of post-millennium data, Karagedikli et al.'s (2000) analysis of income inequality between and within New Zealand's 16 regions. In the next section we show how each region has fared in terms of average personal income relative to the nation. This is followed by a discussion, by means of several measures, of how regions have differed in terms of changes in their distribution of personal incomes. In the final section we draw some broad conclusions and reinforce our main point: that comparing the average income of regions is less helpful for understanding the mixed fortunes that individuals in different regions (and different parts of regions) face than understanding their widely varying backgrounds and the circumstances they face. Indeed, growing intra-regional inequality is a big issue all regions have experienced, albeit not uniformly. Despite the decline in the real cost of communication and transportation, location and distance paradoxically matter more now for opportunities of some population sub-groups than in the past, particularly those with lower skills and at older ages. As such, growing intra-regional income inequality is unlikely to be effectively addressed with 'space-blind' policies. Recent policies 'nudging' migrant settlement and new investment in non-metropolitan areas in order to boost demand there appear consistent with that perspective.

2.2 Average personal income: differences between New Zealand regions

As noted above, New Zealand income inequality has been historically modest by international standards — across both people and space. Since the mid-1990s, several studies have focused on how the post-1984 economic reforms and other socio-economic trends impacted on the distribution of personal and household income in New Zealand. These studies include Easton (1996), Dixon (1999), Podder and Chatterjee (2002), Hyslop and Maré (2005), Hyslop and Yahanpath (2006), Gould (2008), Papps (2010), OECD (2011), Rashbrooke (2013), Perry (2014) and Ball and Creedy (2016). While such studies differ in methodology, period covered and the level of detail regarding individuals and households, they all conclude that income and earnings inequality increased markedly from the late 1980s until the mid-1990s, with some finding inequality growing further until the start of the new millennium. New Zealand income inequality measured by the Gini coefficient moved sharply from being below average in the OECD to being above average between the mid 1980s and the mid 1990s.[25] Subsequently, the 'rising tide' of economic boom years until the global financial crisis (GFC) of 2008 'lifted all boats', leading to declines in inequality. However, inequality increased further since the GFC and, according to some measures, reached levels not observed previously. By 2010, New Zealand's Gini coefficient was 13th highest in the OECD (Perry, 2014).

Regional differences in income inequality trends have received remarkably little attention until fairly recently. This is partly due to a difficulty of obtaining reliable data at a sub-national level, particularly when the source is a survey with a relatively small number of respondents, such as the Household Economic Survey (HES). Inland Revenue Department data yield information on taxable income of everyone, but these data provide few personal characteristics of the taxpayers. Since recently, the Integrated Data Infrastructure (IDI), which links various sources of public data, is an alternative source of information for analysing the distribution of income, but the population census remains the preferred source of data for sub-national income differences. However, the census has the disadvantage that the available information refers to aggregate income from all sources. Smith (2000), Martin (2000), Karagedikli et al. (2000, 2003) and Pool et al. (2005) track income changes between and within regions during the years of economic reforms. The publications by Eaqub (2014) and Johnson (2015) have given regional differences a much more central place in the recent income inequality debate. In a technical sense, the present chapter updates the analysis of 1981–96 regional income changes reported by Karagedikli et al. (2000), extending it to 2013.

[25] The Gini coefficient has been one of the most popular measures of income equality since it was introduced by the Italian statistician and sociologist Corrado Gini in a 1912 paper. It measures the extent to which an observed Lorenz curve (a plot of the cumulative share of income of group of people against the cumulative share of that group in the population, starting with the group with the lowest income) deviates from the 45° line, which indicates perfect income equality. The Gini coefficient equals twice the area between the 45° line and the Lorenz curve. A Gini coefficient of zero signals perfect equality and a value of one represents maximum inequality (one person has all the income).

It should be noted that most research on income distribution takes a cross-sectional perspective. This does not take account of the possibility that, while the poor are getting poorer and the rich are getting richer, individuals who are in the lowest income deciles may have opportunities to increase their own income over time through investments in education or training, or through labour mobility across occupations, industries or regions. Using the longitudinal Survey of Families, Income and Employment (SoFIE), Carter and Imlach Gunasekara (2012) found that individuals often experience changes in income, both up and down the income scale. There is nonetheless also considerable persistence of low income. Personal income change over the life course cannot be addressed in this chapter.

Table 2.1 shows average personal income in New Zealand in March year 2013 prices (i.e. the observed incomes have been deflated by the national Consumer Price Indexes [CPIs]). Table 2.1 also shows relative income in each of the regions for all of the censuses since 1981. Relative income is defined as the average income in each region divided by the corresponding national level. The measure of income used here is before-tax income from all sources (including interest, dividends and social security transfer payments) for males earning positive income. The focus is on positive income to make the analysis informative of changes in the distribution of labour market earnings, because zero income and negative income are typically cases of losses incurred by businesses or farms and do not reflect labour earnings. We also follow Karagedikli et al. (2000) by using male income as a proxy for labour earnings of all full-time workers simply because total income is a function of hours worked and there is much more regional variation in female than male labour force participation and hours worked. For example, labour force participation rates for women in 1986 varied between about 47 per cent (in the Tasman, Nelson, Marlborough and West Coast regions) to about 59 per cent in Wellington, although they increased sharply subsequently everywhere (for example by as much as 19 percentage points in Southland by 2013). An alternative approach would have been to calculate income for all persons working full-time (to focus more closely on labour market earnings), but then our results would no longer be directly comparable with Karagedikli et al. (2000). Because it is not the absolute dollar values of income but the relative values between and within regions, we are confident that the results reported below reflect those of labour force participants generally, irrespective of gender.

Table 2.1: Relative average personal income in New Zealand regions 1981-2013

	1981		1986		1991		1996		2001		2006		2013
STHL	1.16	WLGT	1.14	WLGT	1.21	WLGT	1.16	WLGT	1.18	WLGT	1.15	WLGT	1.15
WLGT	1.09	AUCL	1.07	AUCL	1.11	AUCL	1.12	AUCL	1.12	AUCL	1.11	AUCL	1.09
WAIK	1.04	**NZ**	**$42,708**	**NZ**	**$39,664**	**NZ**	**$43,054**	**NZ**	**$46,429**	**NZ**	**$50,178**	TARA	1.03
NZ	**$49,951**	TARA	0.99	TARA	0.96	TARA	0.98	TARA	0.96	TARA	0.96	CANT	1.00
BOPL	1.00	STHL	0.97	WAIK	0.96	WAIK	0.98	WAIK	0.96	WAIK	0.95	**NZ**	**$51,683**
AUCL	1.00	WAIK	0.97	STHL	0.94	STHL	0.96	STHL	0.95	CANT	0.94	STHL	0.95
HAWK	0.99	BOPL	0.96	CANT	0.93	CANT	0.93	CANT	0.92	BOPL	0.91	WAIK	0.94
TARA	0.99	HAWK	0.95	NELS	0.92	BOPL	0.92	BOPL	0.90	NELS	0.91	WECO	0.92
MAWA	0.97	NELS	0.94	BOPL	0.91	NELS	0.92	NELS	0.89	STHL	0.90	NELS	0.90
CANT	0.96	NTHL	0.94	MAWA	0.89	HAWK	0.87	HAWK	0.87	MARL	0.90	MARL	0.90
OTAG	0.96	CANT	0.94	HAWK	0.89	Tasman	0.86	Tasman	0.86	HAWK	0.89	BOPL	0.89
GISB	0.94	MAWA	0.92	OTAG	0.89	MARL	0.86	MARL	0.86	OTAG	0.86	OTAG	0.89
MARL	0.92	OTAG	0.91	MARL	0.88	MAWA	0.86	MAWA	0.85	TASM	0.86	TASM	0.87
NTHL	0.91	GISB	0.89	GISB	0.83	OTAG	0.85	OTAG	0.85	MAWA	0.85	HAWK	0.87
NELS	0.89	MARL	0.88	TASM	0.83	GISB	0.83	NTHL	0.82	NTHL	0.83	MAWA	0.83
WECO	0.86	WECO	0.85	WECO	0.81	NTHL	0.82	GISB	0.80	WECO	0.82	GISB	0.81
TASM	0.86	TASM	0.83	NTHL	0.81	WECO	0.82	WECO	0.79	GISB	0.81	NTHL	0.80

Abbreviations: NTHL- Northland; AUCL- Auckland; WAIK- Waikato; BOPL- Bay of Plenty; GISB- Gisborne; HAWK- Hawke's Bay; TARA- Taranaki; MAWA- Manawatu-Whanganui; WLGT- Wellington; TASM- Tasman; NELS- Nelson; MARL- Marlborough; WECO- West Coast; CANT- Canterbury; OTAG- Otago; STHL- Southland; NZ- New Zealand

Source: The source of the data is the Census of Population and Dwellings in the years listed. The reported New Zealand income refers to the average income of males in receipt of positive income. Individuals are assigned to the midpoints of the income bands. Average income in the top band has been estimated by the Robust Pareto Midpoint Estimator (RPME) described in Von Hippel et al. (2015). All nominal amounts have been deflated by the national Consumer Price Index. The reported national average personal incomes are in September Quarter 2012 dollars.

One important issue with census data is that the top income band on the census form is open-ended. For example, the top band in the 1986 Census captured everyone earning \$50,001 and above, while for the 2013 Census it was everyone earning \$150,000 and above. The proportion of the population in the top income band varies between less than 1 per cent (in 1981) and 4 per cent (in 2006). While they are a small fraction of the population, people in this group of top earners have a major impact on average income overall. This income must therefore be estimated in an appropriate manner. Statistics New Zealand has made available the likely national 'mid-point' income (i.e. the median) in the top band for each census using data from the HES, but this information is not appropriate for any sub-national analysis. Instead we make the common assumption that income at the top end of the distribution follows a Pareto distribution. In that case, the number of persons with income greater than or equal to Y is given by $AY^{-\alpha}$ where A and α are constants that can be estimated. If L is the lower bound of the open-ended income band, the implied average income of those with income greater than L can be calculated as $\alpha L/(\alpha\text{-}1)$. We use the Robust Pareto Midpoint Estimator (RPME) of von Hippel et al. (2015) to estimate the α coefficients and average income in the top band for each region and census.

The first striking feature of Table 2.1 is that real average personal income at the national level declined sharply by 15 per cent from \$49,951 in 1981 to \$42,708 in 1986. This decline continued between 1986 and 1991 (by a further 7 per cent). From 1991, real income recommenced the kind of long-run growth path expected in developed economies. As noted previously, this is based on income data for males, and Karagedikli et al. (2003) show that for females real income growth was positive throughout the 1981–96 period. However, when considering all adults in receipt of positive income, the intercensal changes are qualitatively similar to those reported in Table 2.1, confirming that the trends reported in Table 2.1 are indicative of real income change for the average New Zealander. Table 2.1 shows that it took until 2006 for real income to exceed the level reached before the economic reforms commenced in 1984. Due to the GFC, income growth remained very modest (3 per cent over six years) between 2006 and 2013.

Broadly speaking, the period between 1981 and 2013 can be divided into two phases of regional income change: 1981–91, when real income declined in all regions; and 1991–2013, when real income increased in all regions. The first of these phases captures the drastic structural changes and sweeping reforms in the New Zealand economy since 1984 (see Evans et al., 1996 for a review). It is very clear from Table 2.1 that these reforms were far more favourable to the urban populations of Auckland and Wellington than to the populations of the other regions. By 1991, average income in Wellington (top ranked) was a fifth above the national average while in the West Coast it was a fifth below the average.

The period from 1991 to 2006 was a period of strong national personal income growth and was followed by lower rates of growth during the last intercensal period, 2006–13. In the latter period, Taranaki and West Coast were the top-performing regions in terms of growth, undoubtedly influenced by the boom in extractive industries over this period. Canterbury also achieved a growth rate similar to Taranaki. This could be indicative of the Christchurch rebuild after the earthquakes, which has attracted construction activities to the regions and a large inflow of skilled workers.

Karagedikli et al. (2000) had earlier identified a divide between the metropolitan areas of Auckland and Wellington and the rest of the regions. Examining the growth rate in average income between 1981 and 2013 reinforces this picture of a metropolitan–provincial divide. Taking into account the population count of the regions, it can be calculated that the North Island's share of aggregate income increased from 73 per cent in 1981 to 77 per cent in 2001. This is mostly due to the growing demographic and economic importance of Auckland, which increased its share of aggregate personal income in New Zealand from 25.7 per cent in 1981 to 35.2 per cent in 2013.

Consistently poorly performing regions, in terms of relative personal income, are Northland, Gisborne, Hawke's Bay and Manawatu–Wanganui (see also Figure 2.1). The case of Southland is also very interesting as the region had the highest real average income in 1981 (16 per cent above the national average) but experienced decline in the following periods, falling to 10 per cent below average by 2006. Although the boom in the dairy sector subsequently led to increased income growth, real average income in Southland was by 2013 still less than in 1981.

Overall, the period from 1981 to 2013 has been one of 'mixed fortune' across New Zealand (see also Johnson, 2015). Half of the 16 regions experienced a decline (from their 1981 levels) in average real income over this period. Eaqub

(2014) highlights technology changes, ageing, globalisation and urbanisation as some of the main reasons responsible for the decline in regions like Southland.

Although there is considerable persistence in relative positions at the top end, with Wellington and Auckland having respectively the highest and second-highest real incomes since 1986, there has also been a considerable change in the relative standard of living across regions. A much-asked question in the literature has been when and under which circumstances poorer regions have had an opportunity to catch up to the rich regions. Economic theory predicts that, due to factors such as diminishing returns to additional capital per worker, inter-regional trade and diffusion of technology, poor regions will grow faster and catch up to richer regions. This phenomenon, which is referred to as 'absolute convergence' in the literature, is predicated on the restrictive assumption that regions differ only in their initial 'endowment' of capital and labour. They will then converge to the same level of real income per capita, with this real income growing at a rate determined by technological progress. However, the literature suggests that such absolute convergence is unlikely to occur in practice because regions differ in the composition of employment by skill level and in population growth. Studies such as Durlauf et al. (2005) identified around 145 factors that can determine the growth of a region.

It is nonetheless useful to check formally whether New Zealand regions are growing apart or together in terms of income per capita. Karagedikli et al. (2000) previously found evidence of absolute convergence amongst the regions between 1981 and 1996 once Auckland and Wellington were excluded from the data. Regions with high initial real incomes (such as Southland) experienced the greatest decline in income over the 1981–96 period. Using data from the three additional censuses from 2001, 2006 and 2013, we re-examine income convergence across the whole period from 1981 to 2013 by means of regression analysis. Like Karagedikli et al. (2000) we check whether the regression results depend on whether Auckland and Wellington are included or not. Mathematically, the regression equation is

$$\frac{g_{it,t+d}}{d} = \alpha + \beta lnY_{it} + \gamma_t + \varepsilon_{it}$$

in which $g_{it,t+d}/d$ is the annualised growth rate in average real income in region *i* during the intercensal period between years *t* and *t* + *d*, with *d* typically 5 years, except for the 2006–13 period when d = 7; lnY_{it} is a natural logarithm of average real income in region *i* at time *t*; γ_t is a national business cycle effect; and ε_{it} represent random fluctuations. The results can be found in Table 2.2.

Table 2.2: Regressions to test absolute income convergence among New Zealand regions

Model	Panel data		Cross-sectional data	
Dependent variable	Annualised real intercensal growth for all regions	Annualised real intercensal growth for all regions, excl. Auckland and Wellington	Annualised 32-year real growth rate for all regions (1981–2013)	Annualised 32-year real growth for all regions, excl. Auckland and Wellington
log of lagged mean income	–0.009	–0.037**	–0.012	–0.021*
	(–1.115)	(–3.284)	(–1.365)	(–2.766)
Constant[26]	0.059	0.363**	0.128	0.222*
	(0.692)	(2.970)	(1.361)	(2.755)
Number of observations	96	84	16	14
Period effect	Yes	Yes	No	No
t values in parentheses*p<0.10; **p<0.05; ***p<0.01				

The results are very clear. When Auckland and Wellington are included, there is no evidence of convergence in real income among New Zealand regions. This reconfirms the earlier finding by Karagedikli et al. (2000). However, once Auckland and Wellington are excluded, there is evidence of absolute income convergence among the other regions. This is the case when comparing the regions cross-sectionally for the entire period (with the regression coefficient on initial income being –0.021) or as a panel of intercensal periods while allowing for business cycle effects (with the regression coefficient on initial income being

[26] There was a sign error in the T-values for the constant published in the book version for the constant. All t values reported for the constant are positive not negative as previously reported.

-0.037). The long-run annual convergence rate of 0.021 over the 32-year period suggests that the gap in real income between any two New Zealand regions (excluding Auckland and Wellington) has been reduced by 2.1 per cent annually. This is less than the 3.3 per cent rate of convergence Karagedikli et al. (2000) found for the period 1981–96, but very similar to the so-called 2 per cent rule found by Barro and Sala-i-Martin (1992) for regions in the United States. Ganong and Shoag (2015) find that in the United States inter-regional income convergence has been declining. Housing supply regulations have led there to high house prices and rents in growing cities, which has deterred the inward migration that might have contributed to convergence.

It should be noted that the regressions reported in Table 2.2 do not provide an analysis of why some regions grow faster than others. For such an analysis many additional variables would need to be considered, such as the rate of investment in infrastructure, the average skill level of the regional population, the sectoral structure of the regional economy, etc. When such factors are taken into account, the coefficient on the log of mean initial income informs on so-called conditional rather than absolute convergence, and this coefficient may or may not be statistically significant (see Le Gallo & Fingleton, 2014).

In summary we conclude that, in terms of average personal income, Auckland and Wellington have pulled away from the other regions of New Zealand. Among the other 14 regions only six (Taranaki, Canterbury, West Coast, Nelson, Marlborough and Tasman) have experienced an increase in average real income over 32 years since 1981. This is an astonishing finding given that the material standard of living improved for most people in most regions in the post-war period leading up to the post 1980 era of economic liberalisation and globalisation. However, the experience of New Zealand is not unique in this respect. For example, it is the lack of improvement in the average standard of living in the poorer regions of the United Kingdom that triggered the widespread dissatisfaction with greater economic integration of that country in the European Union. Ultimately, these regional differences were a major factor responsible for the rather unexpected outcome of the 2016 Brexit referendum. It is reasonable to expect that similar sentiments prevail in peripheral regions of New Zealand, given that greater international economic integration and economic liberalisation have not been effective in raising the income of the average worker in such regions.

However, the focus on average income hides the growing inequality in personal income within each of the regions. Indeed, it can be shown that the relative position of an individual in the income distribution is to a far greater extent determined by their age, gender, skill level and labour force status than by their location. We turn therefore in the next section to income inequality within regions. We find nonetheless that there are notable differences between regions in inequality measures. Specifically, Auckland and Wellington have had the fastest growth in income inequality across all such measures.

2.3 Income inequality within New Zealand regions

Many measures have been proposed in the literature to quantify the extent to which people in a particular region or country have different incomes. In this section we examine intra-regional income distribution in New Zealand by means of three common types of measures: the Gini coefficient, percentile ratios and the Palma ratio. Table 2.3 presents the Gini coefficients for all regions of New Zealand from 1981 to 2013.

Table 2.3: Gini coefficients of intra-regional income distribution for males, 1981 to 2013

	Gini coefficients							Percent changes				
Regions	1981	1986	1991	1996	2001	2006	2013	81-86	86-01	01-06	06-13	81-2013
Northland	0.4079	0.3642	0.4053	0.4531	0.4568	0.4259	0.4409	-11%	25%	-7%	4%	8%
Auckland	0.3653	0.3621	0.4114	0.4606	0.4678	0.4535	0.4718	-1%	29%	-3%	4%	29%
Waikato	0.3867	0.3566	0.3998	0.4500	0.4497	0.4222	0.4321	-8%	26%	-6%	2%	12%
Bay of Plenty	0.3775	0.3472	0.4006	0.4407	0.4435	0.4224	0.4332	-8%	28%	-5%	3%	15%
Gisborne	0.3911	0.3499	0.4065	0.4473	0.4558	0.4273	0.4355	-11%	30%	-6%	2%	11%
Hawke's Bay	0.3783	0.3397	0.3900	0.4297	0.4361	0.4133	0.4248	-10%	28%	-5%	3%	12%
Taranaki	0.3774	0.3468	0.3985	0.4392	0.4524	0.4290	0.4319	-8%	30%	-5%	1%	14%
Manawatu-Wanganui	0.3834	0.3469	0.3944	0.4302	0.4413	0.4166	0.4215	-10%	27%	-6%	1%	10%
Wellington	0.3463	0.3533	0.4113	0.4570	0.4733	0.4563	0.4650	2%	34%	-4%	2%	34%
West Coast	0.3483	0.3204	0.3800	0.4171	0.4365	0.4045	0.4084	-8%	36%	-7%	1%	17%
Canterbury	0.3728	0.3492	0.3946	0.4315	0.4389	0.4229	0.4244	-6%	26%	-4%	0%	14%
Otago	0.3857	0.3584	0.4051	0.4429	0.4571	0.4342	0.4458	-7%	28%	-5%	3%	16%
Southland	0.3883	0.3299	0.3805	0.4185	0.4325	0.3940	0.3994	-15%	31%	-9%	1%	3%
Tasman	0.3972	0.3481	0.3810	0.4185	0.4350	0.4055	0.4214	-12%	25%	-7%	4%	6%
Nelson	0.3713	0.3513	0.3909	0.4183	0.4411	0.4181	0.4304	-5%	26%	-5%	3%	16%
Marlborough	0.3719	0.3402	0.3749	0.4078	0.4210	0.4027	0.4010	-9%	24%	-4%	0%	8%
New Zealand	0.3744	0.3561	0.4077	0.4511	0.4615	0.4415	0.4511	-5%	30%	-4%	2%	20%

Post 1981, we can distinguish four different phases of changing inequality in personal incomes in New Zealand. This applies both to the regions and to the country as a whole. During the first phase (1981–86) inequality declined everywhere, except in Wellington. Subsequently, inequality rose sharply everywhere between 1986 and 2001. Nationally the Gini coefficient rose by about 30 per cent over this period, with Wellington having the second-highest rate of growth in inequality (34 per cent). The highest rate of inequality growth was experienced in West Coast (36 per cent) and the lowest in Marlborough (24 per cent). In the third phase, between 2001 and 2006, the Gini coefficient decreased in all regions and nationally by about 4 per cent. Hyslop and Yahanpath (2006) found a similar decline in individual earnings inequality of around 4 per cent between 1998 and 2004, using data on earnings in the Household Labour Force Survey. They attributed the decline in inequality in that period to a relatively faster-increasing demand for labour at the lower end of the distribution. Government policies like Working for Families (WFF) also contributed to declining inequality (MSD, 2003).

There is evidence of a resumption of the widening of the distribution between 2006 and 2013, with most regions experiencing a rise in the Gini coefficient (but with no change in Canterbury and Marlborough), although the change is modest (at most 4 per cent). It appears plausible to suggest that the 2008 GFC and its aftermath contributed to this recent widening, but this would require further investigation. Considering the entire 1981–2013 period, personal income inequality peaked in most regions in 2001. One striking exception is Auckland, where inequality in 2013 as measured by the Gini coefficient was greater than ever (at least since 1981, but probably much longer than that).

Being a single summary measure, a weakness of the Gini coefficient is its inability to differentiate between different kinds of inequalities within the income distribution (Atkinson, 1983; De Maio, 2007). Specifically, the Gini coefficient places less emphasis on incomes at the top and bottom ends of the income spectrum (Cobham & Sumner, 2013). To consider what is happening at these extremes, we present two percentile ratios. The 50:10 ratio takes the ratio of median income (i.e. the 50th percentile) over the bottom decile (i.e. the 10th percentile) while the 90:50 ratio compares the income at the 90th percentile to median income. Tables 2.4 and 2.5 present the 90:50 ratio and the 50:10 ratio respectively.

Table 2.4: 90:50 percentile ratios 1981 to 2013

Regions	1981	1986	1991	1996	2001	2006	2013
Northland	2.1	2.2	2.5	2.7	2.7	2.4	2.7
Auckland	1.9	2.0	2.3	2.5	2.7	2.6	2.9
Waikato	2.0	2.0	2.3	2.4	2.5	2.4	2.4
Bay of Plenty	2.0	2.0	2.5	2.5	2.6	2.3	2.5
Gisborne	2.0	2.0	2.4	2.5	2.5	2.4	2.4
Hawke's Bay	1.9	1.9	2.2	2.3	2.4	2.2	2.4
Taranaki	2.0	2.0	2.3	2.5	2.6	2.4	2.5
Manawatu–Wanganui	2.0	2.0	2.2	2.3	2.5	2.3	2.4
Wellington	1.9	2.0	2.4	2.6	2.9	2.7	3.0
West Coast	1.8	1.9	2.3	2.4	2.5	2.2	2.3
Canterbury	1.9	2.0	2.3	2.3	2.4	2.3	2.3
Otago	1.9	2.0	2.3	2.4	2.5	2.3	2.5
Southland	1.9	1.8	2.2	2.2	2.4	2.1	2.2
Tasman	2.0	2.1	2.3	2.3	2.5	2.2	2.4
Nelson	1.9	2.0	2.2	2.2	2.5	2.2	2.5
Marlborough	2.0	1.9	2.1	2.1	2.3	2.2	2.3
New Zealand	**2.0**	**2.0**	**2.3**	**2.5**	**2.6**	**2.5**	**2.5**

Table 2.5: 50–10 percentile ratios 1981 to 2013

Regions	1981	1986	1991	1996	2001	2006	2013
Northland	3.6	2.6	2.6	3.1	3.5	3.5	3.2
Auckland	4.0	2.9	3.4	4.5	4.8	4.9	4.8
Waikato	3.7	2.8	3.1	4.0	4.1	3.9	3.7
Bay of Plenty	3.7	2.6	2.9	3.6	3.8	3.7	3.4
Gisborne	3.5	2.5	2.8	3.6	3.9	3.8	3.8
Hawke's Bay	3.8	2.7	3.0	3.8	4.0	3.7	3.5
Taranaki	3.6	2.7	3.0	3.7	3.9	3.6	3.6
Manawatu–Wanganui	3.9	2.8	3.1	3.9	4.0	3.8	3.5
Wellington	3.8	3.0	3.6	4.5	4.5	4.4	4.3
West Coast	3.6	2.5	2.7	3.3	3.3	3.6	3.5
Canterbury	3.8	2.8	3.0	3.9	4.0	4.0	3.8
Otago	3.9	2.9	3.1	4.0	4.3	4.6	4.5
Southland	3.4	2.8	2.9	3.6	3.8	3.4	3.4
Tasman	3.6	2.5	2.6	3.4	3.6	3.4	3.3
Nelson	4.1	2.7	3.0	3.8	3.9	3.5	3.4
Marlborough	3.5	2.6	2.7	3.5	3.4	3.2	3.2
New Zealand	**3.8**	**2.8**	**3.2**	**4.1**	**4.3**	**4.2**	**3.9**

Table 2.4 demonstrates clearly that incomes of those at the top have grown much faster than median income. Nationally, income at the 90th percentile of the distribution was twice the median in 1981 but increased to 2.6 times the median in 2001. As previously noted by Dixon (1999) and Karagedikli et al. (2000) inequality increased the most during the 1986–96 period of financial and product market deregulation. The 90:50 ratio peaked in many regions in 2001. Only Auckland and Wellington have seen further increases in this ratio subsequently. Of all New Zealand cities, those two are the most globally connected with earnings of highly paid professionals in private and public sector jobs determined by global market forces. The absolute increase in the 90:50 ratio between 1981 and 2013 was greater in Auckland and Wellington than in any other region. Generally, the changes in the 90:50 ratios are closely correlated with the changes in the Gini coefficients discussed previously.

At the bottom end of the distribution, intercensal changes are similar to those of the other measures of inequality, and peak inequality also occurred in 2001 (see Table 2.5). Auckland, West Coast and Otago are notable exceptions (where the 50:10 ratio peaked in 2006). Nationally, median income was 3.8 times income at the lowest decile in 1981 and this ratio increased to 4.3 by 2001. However, the greatest increase in the 50:10 ratio occurred between 1991 and 1996. As this ratio is determined not only by the wages of the lesser paid but also by social welfare provisions, the 1991 benefit cuts are likely to have had a major impact over this period. Easton (1996) identifies benefit cuts and the 1991 Employment Contracts Act as important contributors to the rise in poverty in the early 1990s. An interesting difference between the 90:50 ratio changes and the 50:10 ratio changes is that the data suggest that the top of the distribution pulled away the most from the middle between 1986 and 1991, but the middle pulled away from the bottom the most in the next inter-censal period. Karagedikli et al. (2002) showed that, parallel to this, women experienced an increase in equality during the second half of the reform decade while men experienced the greatest increase during the first half.

Another difference between the changes at the top end of the distribution (Table 2.4) and the bottom end of the distribution (Table 2.5) is that at the top end inequality increased in all regions between 1981 and 2013. In contrast, in the majority of regions inequality at the bottom end was less in 2013 than in 1981.

There are likely to be two dominant causes. One is population ageing, leading to increases in the number of people in receipt of New Zealand Superannuation, which is linked to wages paid (the after-tax NZ Super rate for qualifying couples is about two-thirds of the 'average ordinary time wage' after tax). The other factor is that the median wage has been rather stagnant, predominantly a result of globalization, which is something that New Zealand shares with many other developed countries. Steady increases in the minimum wage may have also contributed to the narrowing of the bottom end of the income distribution in some regions, but Maloney and Pacheco (2012) found only a very minimal effect of the rise in minimum wage between 1999 and 2008 on relative poverty rates. Besides having seen the greatest inequality growth at the top end of the distribution, Auckland and Wellington also stand out as regions in which inequality grew the fastest at the bottom end of the distribution (although Otago saw also a relatively large increase in the 50:10 ratio).

Our final measure of intra-regional income inequality is the Palma ratio, based on the work of Gabriel Palma (2011), which calculates the ratio between the income share of the top 10 per cent of the population and the share of the bottom 40 per cent. The ratio is based on evidence of constant shares for the intermediate 50 per cent in most countries. If the share of income of the middle 50 is fairly constant, then changes in the distribution of income are mainly driven by what is happening at the very top and the bottom. Hence the Palma ratio complements the Gini coefficient by addressing one of the Gini's limitations, which is that it is overly sensitive to the middle of the distribution while ignoring the top and bottom. Additionally, Cobham and Sumner (2013) argue that the Palma ratio is appealing because it is more easily interpretable than changes in Gini. Table 2.6 presents the Palma ratios for all regions from 1981 to 2013.

Table 2.6: Palma ratios 1981–2013

Regions	1981	1986	1991	1996	2001	2006	2013
Northland	2.1	1.6	2.0	2.7	2.9	2.4	2.5
Auckland	1.6	1.6	2.2	3.1	3.4	3.2	3.3
Waikato	1.8	1.5	2.0	2.8	2.8	2.4	2.4
Bay of Plenty	1.7	1.4	1.9	2.6	2.6	2.4	2.4
Gisborne	1.9	1.5	2.0	2.7	2.9	2.4	2.5
Hawke’s Bay	1.8	1.4	1.9	2.4	2.6	2.3	2.3
Taranaki	1.7	1.4	1.9	2.6	2.9	2.6	2.5
Manawatu–Wanganui	1.8	1.4	1.9	2.4	2.6	2.3	2.2
Wellington	1.4	1.5	2.2	3.0	3.5	3.3	3.1
West Coast	1.4	1.2	1.7	2.2	2.6	2.0	2.0
Canterbury	1.7	1.5	1.9	2.5	2.6	2.4	2.4
Otago	1.8	1.5	2.0	2.7	2.9	2.6	2.7
Southland	1.9	1.3	1.7	2.3	2.6	2.0	2.0
Tasman	1.9	1.4	1.7	2.3	2.5	2.1	2.2
Nelson	1.6	1.5	1.9	2.2	2.6	2.4	2.4
Marlborough	1.6	1.4	1.7	2.1	2.4	2.1	2.0
New Zealand	**1.7**	**1.5**	**2.1**	**2.8**	**3.1**	**2.8**	**2.8**

The Palma ratio provides further evidence of growing income inequality in New Zealand. In 1981 the top 10 per cent of earners had a combined income that was 1.7 times as much as the combined income of the bottom 40 per cent. Nationally and in all regions the Palma ratio peaked in 2001. At that time, the top 10 per cent earned together 3.1 times the income of the bottom 40 per cent. Once again, the greatest inequality is observed in Auckland and Wellington, where, despite some decline post 2001, the Palma ratio remained above 3 by 2013. In fact, the Palma ratio more than doubled in Auckland and Wellington over the 1981–2013 period. The smallest increase over this period can be observed in Southland, which had a Palma ratio of 1.9 in 1981 and 2.0 in 2013.

2.4 Conclusion

While money may not automatically buy happiness, a certain level of income is clearly essential for avoiding hardship and deprivation. Several recent studies, such as Eaqub (2014) and Johnson (2015), have pointed out that a person’s income is determined not only by their age, education, occupation, experience, family situation, etc., but also by where they live; i.e., geography matters. In this chapter we have looked at the extent to which incomes vary not only across New

Zealand regions, but also within the same region. Explaining differences in income between individuals is a complex matter and, in this chapter, we simply used census data on personal income from all sources as a tool to look at income inequality both within and between regions. We basically extended to 2013 an earlier 1981–96 analysis of regional changes in the distribution of personal income that was reported in Karagedikli et al. (2000).

We find that no region in New Zealand escaped the sharp growth in income inequality and the decline in the standard of living that was paid as the price of the transition from a highly regulated economy to an internationally competitive economy between the mid-1980s and mid-1990s. The dramatic changes in real incomes and in inequality within and between regions which occurred in that period dominate the changes over the entire period from 1981 to 2013. Subsequent changes have been considerably less dramatic, though still noteworthy. While living standards have improved since the mid-1990s, in half of the 16 regions considered people are likely to have been individually worse off on average in 2013 than in 1981. Additionally, income inequality continued to grow until 2001. Admittedly, precise conclusions on changes in the standard of living and inequality depend on the selected measures, but clear patterns emerge at least qualitatively from the data reported here.

To some extent, each region has some unique features, and for each of the 16 regions considered in this chapter it is possible to tell a tailor-made story of real income growth and income inequality. Space does not permit such an approach. Instead, it is possible to classify the regions in terms of real income growth and ranking in income inequality. The latter has been calculated as the aggregate ranking of the four measures in intra-regional income inequality in 2013 introduced in the previous section: the Gini coefficient, the 90:50 percentile ratio, the 50:10 percentile ratio and the Palma ratio. Table 2.7 splits the regions halfway into those with relatively high income inequality and those with relatively low income inequality. In terms of real income growth, the split is between those with positive real income growth 1981–2013 (which is the case in half the regions) and negative real income growth (the remaining half).

Table 2.7: A classification of New Zealand regions by real income growth and income inequality

	Relatively high inequality 2013	Relatively low inequality 2013
Negative real income growth 1981–2013	Northland Waikato Bay of Plenty Gisborne Otago	Hawke's Bay Manawatu–Wanganui Southland
Positive real income growth 1981–2013	Auckland Taranaki Wellington	Marlborough Nelson Tasman Canterbury West Coast

On all but one criterion Auckland ranks first. The city had the greatest 1981–2013 real income growth. However, no account could be taken of the greater housing cost in Auckland vis-à-vis the other regions. Auckland is also ranked first on all 2013 inequality measures, except for the 90:50 ratio where it is second behind Wellington (with this kind of inequality undoubtedly boosted there by Wellington's highly qualified workforce in both public and private sectors).

The combination of negative real income growth and relatively high income inequality may be interpreted as the worst set of outcomes for people on lower incomes; whereas positive real income growth combined with relatively low inequality in 2013 is the best of both worlds for them. In this respect, an interesting dichotomy emerges: the worst outcomes are predominantly in North Island regions (Northland, Waikato, Bay of Plenty and Gisborne) except for Otago. The 'good' outcomes can be found in South Island regions (Marlborough, Nelson, Tasman, Canterbury and West Coast). Like Auckland, Taranaki and Wellington are doing relatively well in terms of income growth but also experience relatively high inequality. Hawke’s Bay, Manawatu–Wanganui and Southland had relatively low income inequality in 2013 but experienced negative income growth.

Are the regions growing apart, as Eaqub (2014) suggests? Although the answer depends on the focus and also on how we define regions, the findings reported in this chapter reinforce his conclusions and those of Johnson (2015). First of all, Auckland stands out but is of course internationally among a large number of cities where strengthening agglomeration forces have boosted relative economic outcomes.

To a lesser extent Wellington also stands out but mainly due to the impact of being the nation’s capital. It can be shown that during the ‘reform years’ average income in Auckland and Wellington diverged from the average income in other regions, while the regions’ measures of intra-regional inequality converged. The opposite took place post 2001: average incomes converged, but differences between regions in inequality measures became larger. The best general statement that can be made therefore is that there has been growing diversity in experiences of the regions along a range of socio-economic indicators. This, however, is not a new phenomenon: it was already noted in a New Zealand Planning Council report of the 1980s (see Bedford et al., 1989).

In conclusion, where you live does have some impact on your position in the national distribution of personal income — and probably more so, the smaller the geographical area considered. In this respect, the breakdown of the country into 16 regions is quite coarse. Differences between places within regions undoubtedly play an important role in the growing intra-regional income inequality documented in this chapter. Nonetheless, personal characteristics such as age, education and experience continue to play a far greater role than location in an individual’s prospects regarding income and wealth, because the skilled are mobile and move to where their human capital will earn its greatest return. Sorting behaviour — with the young and highly educated moving to, and partnering in, the large cities — does lead to widening income differentials. In that case those in declining regions are best served by policies that enhance outcomes for the least mobile or that ‘nudge’ new economic activities to such regions, e.g. through encouraging migrant settlement or new investment.

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Appendix Chapter 2

The analysis of regional inequality in Chapter 2 was based on income data for males; male incomes are used as a proxy for labour earnings of all full-time workers because total income is a function of hours worked and there is much more regional variation in female than male participation. In this appendix we present results using data for all individuals earning positive income regardless of gender. The results using income for all individuals are in line with the results using male data and reinforce the growing spatial inequality in New Zealand especially the differences between the two large regions of Auckland and Wellington and other New Zealand regions. Using data on personal income for all individuals and the Gini coefficient as the measure of inequality, Auckland and Wellington are the regions that experienced the greatest growth in inequality between 1981 and 2013. This highlights the divide between the changes in the distribution of income in these areas and other New Zealand areas.

This appendix replicates all the tables in Chapter 2 but uses all individual incomes instead of male income only. All main conclusions with respect to the inter-regional and intra-regional distribution of income remain valid when all incomes are considered. Although, we note that when all individuals are considered (male and female), we find the number of regions with positive income growth increased and no region experienced both negative income growth with high inequality. The changes in female incomes dampened the growth in inequality. For most other regions apart from Auckland and Wellington, inequality in personal incomes of all individuals actually fell. In Wellington and Auckland, as measured by the Gini coefficient, inequality for all individual incomes rose by 8 percent in Auckland compared to 29 percent for male incomes only. Wellington which had the highest growth in inequality for male incomes at 34 percent, still had the highest increase in inequality when all incomes are considered but inequality grew by only 11 percent. The changes in female incomes are strongly linked to the increase in the female labour force participation rates. The increase in female participation in the labour force has helped to offset some of the negative effects of the economic reforms and globalisation in some regions.

The following abbreviations are used for regions in Table 2.A.1 below:

Abbreviations: NTHL- Northland; AUCL- Auckland; WAIK- Waikato; BOPL- Bay of Plenty; GISB- Gisborne; HAWK- Hawke's Bay; TARA- Taranaki; MAWA- Manawatu-Whanganui; WLGT- Wellington; TASM- Tasman; NELS- Nelson; MARL- Marlborough; WECO- West Coast; CANT- Canterbury; OTAG- Otago; STHL- Southland; NZ- New Zealand

Table 2.A.1: Relative average personal income of **all individuals** in New Zealand regions 1981-2013

	1981		1986		1991		1996		2001		2006		2013
STHL	1.12	WLGT	1.14	WLGT	1.19	WLGT	1.15	WLGT	1.17	WLGT	1.15	WLGT	1.15
WLGT	1.11	AUCL	1.07	AUCL	1.10	AUCL	1.12	AUCL	1.12	AUCL	1.11	AUCL	1.09
WAIK	1.05	NZ	$32,975	NZ	$31,887	NZ	$34,415	NZ	$37,715	NZ	$41,060	TARA	1.00
AUCL	1.00	TARA	1.00	WAIK	0.97	WAIK	0.99	WAIK	0.97	WAIK	0.96	NZ	$42,944
NZ	$36,542	WAIK	0.98	TARA	0.96	TARA	0.99	TARA	0.96	TARA	0.95	CANT	0.99
TARA	1.00	BOPL	0.96	STHL	0.93	STHL	0.94	STHL	0.94	CANT	0.93	WAIK	0.95
BOPL	0.99	NTHL	0.95	CANT	0.93	BOPL	0.93	CANT	0.92	BOPL	0.91	STHL	0.95
MAWA	0.97	STHL	0.95	BOPL	0.92	CANT	0.92	BoP	0.90	Marl	0.90	WECO	0.91
HAWK	0.96	HAWK	0.94	NELS	0.91	NELS	0.91	NELS	0.88	NELS	0.90	BOPL	0.90
OTAG	0.95	NELS	0.94	MAWA	0.90	HAWK	0.87	HAWK	0.87	STHL	0.90	NELS	0.89
CANT	0.95	CANT	0.93	HAWK	0.89	MAWA	0.87	MARL	0.86	HAWK	0.88	MARL	0.89
GISB	0.93	MAWA	0.92	OTAG	0.89	MARL	0.87	MAWA	0.86	OTAG	0.87	OTAG	0.89
NTHL	0.92	OTAG	0.91	MARL	0.88	TASM	0.86	NTHL	0.86	NTHL	0.86	HAWK	0.87
MARL	0.91	GISB	0.90	GISB	0.85	Otago	0.86	TASM	0.85	MAWA	0.86	TASM	0.86
NELS	0.90	Marl	0.88	NTHL	0.85	NTHL	0.85	OTAG	0.85	TASM	0.85	MAWA	0.84
WECO	0.88	WECO	0.87	WECO	0.83	GISB	0.85	GISB	0.82	GISB	0.83	NTHL	0.83
TASM	0.85	TASM	0.83	TASM	0.83	WECO	0.83	WECO	0.81	WECO	0.83	GISB	0.82

Note: Results are the average income of all individuals relative to the national average. For example, in 1981, average income in STHL (Southland) was 1.12 times the national average of $36,542

Table 2.A.2: Regressions to test absolute income convergence of average incomes of **all individuals** across New Zealand regions

	Panel data		Cross-sectional data	
	Annualised real intercensal growth for all regions	Annualised real intercensal growth for all regions, excl. Auckland and Wellington	Annualised 32-year real growth rate for all regions (1981-2013)	Annualised 32-year real growth for all regions, excl. Auckland and Wellington (1981-2013)
Log of lagged mean income	-0.006	-0.038***	-0.007	-0.018*
	(-0.890)	(-3.458)	(-0.947)	(-2.799)
Constant	0.042	0.370**	0.08	0.196*
	(0.557)	(3.224)	(0.991)	(2.844)
Number of observations	96	84	16	14
Period effect	Yes	Yes	No	No
t values in parentheses *p<0.10; **p<0.05; ***p<0.01				

Note: Results show tests of convergence in average incomes of **all individuals** including and excluding Wellington and Auckland regions.

Table 2.A.3: Gini coefficients of intra-regional incomes of **all individuals** between 1981 and 2013

	Gini cofficients							Percentage changes				
Regions	**1981**	**1986**	**1991**	**1996**	**2001**	**2006**	**2013**	**81-86**	**86-01**	**01-06**	**06-13**	**81-13**
Northland	0.4781	0.4114	0.4066	0.4485	0.4579	0.4326	0.4374	-14%	11%	-6%	1%	-9%
Auckland	0.4357	0.4019	0.4232	0.4637	0.4702	0.4598	0.4708	-8%	17%	-2%	2%	8%
Waikato	0.4682	0.4086	0.4190	0.4641	0.4641	0.4407	0.4421	-13%	14%	-5%	0%	-6%
Bay of Plenty	0.4623	0.4010	0.4125	0.4496	0.4516	0.4343	0.4351	-13%	13%	-4%	0%	-6%
Gisborne	0.4662	0.3985	0.4076	0.4482	0.4543	0.4315	0.4339	-15%	14%	-5%	1%	-7%
Hawke’s Bay	0.4636	0.3978	0.4043	0.4360	0.4425	0.4260	0.4290	-14%	11%	-4%	1%	-7%
Taranaki	0.4606	0.4023	0.4180	0.4578	0.4690	0.4461	0.4480	-13%	17%	-5%	0%	-3%
Manawatu-Whanganui	0.4555	0.3984	0.4086	0.4389	0.4471	0.4290	0.4286	-13%	12%	-4%	0%	-6%
Wellington	0.4209	0.3992	0.4295	0.4611	0.4740	0.4631	0.4673	-5%	19%	-2%	1%	11%
West Coast	0.4365	0.3804	0.3991	0.4363	0.4493	0.4273	0.4330	-13%	18%	-5%	1%	-1%
Canterbury	0.4521	0.3984	0.4127	0.4434	0.4507	0.4386	0.4391	-12%	13%	-3%	0%	-3%
Otago	0.4569	0.4076	0.4195	0.4535	0.4647	0.4480	0.4538	-11%	14%	-4%	1%	-1%
Southland	0.4818	0.4023	0.4139	0.4437	0.4586	0.4223	0.4255	-16%	14%	-8%	1%	-12%
Tasman	0.4761	0.4063	0.4056	0.4369	0.4504	0.4288	0.4338	-15%	11%	-5%	1%	-9%
Nelson	0.4428	0.3989	0.4081	0.4300	0.4420	0.4271	0.4318	-10%	11%	-3%	1%	-2%
Marlborough	0.4593	0.4006	0.3967	0.4274	0.4374	0.4241	0.4168	-13%	9%	-3%	-2%	-9%
New Zealand	0.4506	0.4039	0.4222	0.4586	0.4669	0.4513	0.4561	-10%	16%	-3%	1%	1%

Note: Results show the Gini coefficients of intra-regional incomes of **all individuals** in all regions between 1981 and 2013

Table 2.A.4: 90:50 percentile ratios of **all individual incomes** between 1981 and 2013

Regions	**1981**	**1986**	**1991**	**1996**	**2001**	**2006**	**2013**
Northland	2.6	2.5	2.7	2.8	2.9	2.6	2.7
Auckland	2.3	2.3	2.5	2.5	2.7	2.6	2.7
Waikato	2.4	2.4	2.6	2.8	2.8	2.5	2.7
Bay of Plenty	2.5	2.4	2.7	2.8	2.8	2.6	2.7
Gisborne	2.4	2.4	2.6	2.7	2.8	2.6	2.5
Hawke's Bay	2.4	2.3	2.6	2.7	2.7	2.5	2.5
Taranaki	2.5	2.4	2.7	2.8	2.9	2.6	2.7
Manawatu-Whanganui	2.4	2.3	2.6	2.7	2.7	2.6	2.5
Wellington	2.2	2.2	2.5	2.7	2.8	2.8	2.8
West Coast	2.3	2.3	2.7	2.8	3.0	2.7	2.7
Canterbury	2.4	2.4	2.6	2.7	2.6	2.5	2.6
Otago	2.5	2.4	2.7	2.7	2.8	2.6	2.7
Southland	2.5	2.3	2.6	2.7	2.7	2.5	2.5
Tasman	2.7	2.5	2.5	2.6	2.7	2.6	2.6
Nelson	2.5	2.3	2.6	2.6	2.7	2.5	2.5
Marlborough	2.5	2.4	2.5	2.5	2.6	2.5	2.4
New Zealand	2.4	2.4	2.6	2.7	2.8	2.6	2.7

Note: Results show the 90-50 percentile ratios of income of **all individuals** between 1981 and 2013

Table 2.A.5: 50:10 percentile ratios of **all individual incomes** between 1981 and 2013

Regions	1981	1986	1991	1996	2001	2006	2013
Northland	7.3	4.2	2.5	3.0	3.1	3.5	3.1
Auckland	7.8	3.9	3.2	4.4	4.7	5.2	5.0
Waikato	8.5	4.7	3.0	3.8	3.8	4.1	3.8
Bay of Plenty	8.0	4.2	2.6	3.2	3.4	3.6	3.3
Gisborne	7.4	4.4	2.5	3.5	3.7	3.8	3.7
Hawke's Bay	7.7	4.5	2.8	3.4	3.5	3.8	3.4
Taranaki	7.6	4.1	2.8	3.4	3.5	3.7	3.4
Manawatu-Whanganui	7.4	4.4	3.0	3.6	3.6	3.9	3.5
Wellington	7.4	4.2	3.6	4.3	4.4	4.7	4.5
West Coast	7.3	4.1	2.6	3.0	2.9	3.5	3.2
Canterbury	7.3	4.3	3.0	3.7	3.7	4.1	3.8
Otago	6.8	4.5	3.2	4.0	4.2	4.7	4.6
Southland	8.2	5.1	3.2	3.5	3.6	3.7	3.3
Tasman	6.7	5.0	3.3	3.5	3.5	3.9	3.4
Nelson	7.7	4.8	3.2	3.4	3.5	3.7	3.3
Marlborough	7.6	4.7	2.7	3.4	3.3	3.5	3.0
New Zealand	7.8	4.3	3.0	3.9	4.0	4.4	4.1

Note: Results show the 50-10 percentile ratios of income of **all individuals** between 1981 and 2013

Table 2.A.6: Palma ratios 1981-2013

Regions	1981	1986	1991	1996	2001	2006	2013
Northland	3.2	2.0	1.9	2.5	2.7	2.3	2.4
Auckland	2.4	1.9	2.2	3.0	3.2	3.1	3.1
Waikato	3.1	2.0	2.1	2.9	3.0	2.6	2.5
Bay of Plenty	2.9	1.8	1.9	2.5	2.6	2.4	2.3
Gisborne	3.0	1.8	2.0	2.5	2.6	2.3	2.4
Hawke's Bay	3.0	1.8	1.9	2.3	2.5	2.3	2.3
Taranaki	2.9	1.9	2.0	2.7	3.0	2.7	2.6
Manawatu-Whanganui	2.8	1.8	1.9	2.4	2.5	2.3	2.2
Wellington	2.2	1.9	2.3	2.9	3.3	3.1	3.0
West Coast	2.4	1.6	1.8	2.3	2.5	2.2	2.3
Canterbury	2.7	1.8	2.0	2.4	2.7	2.5	2.5
Otago	2.8	1.9	2.1	2.6	2.9	2.6	2.7
Southland	3.4	1.9	2.0	2.5	2.9	2.2	2.3
Tasman	3.1	1.9	1.9	2.3	2.6	2.3	2.3
Nelson	2.5	1.8	1.9	2.2	2.5	2.3	2.3
Marlborough	2.8	1.9	1.8	2.2	2.4	2.3	2.1
New Zealand	2.7	1.9	2.1	2.7	3.0	2.8	2.7

Note: Results show the Palma ratios of income of **all individuals** between 1981 and 2013

Table 2.A.7: A classification of New Zealand regions by real income growth and inequality

	Relatively high inequality 2013	Relatively low inequality 2013
Negative real income growth 1981-2013		Southland ✓
Positive real income growth 1981-2013	Northland ↓ Waikato ↓ Bay of Plenty ↓ Taranaki✓ Canterbury ← Otago ↓ Auckland ✓ Wellington✓	Gisborne ↘ Hakwe's Bay ↓ Manawatu-Wanganui ↓ West Coast✓ Tasman✓ Nelson✓ Marlborough✓

Note: Arrow indicates how regions shift in the classification when all individuals (males and females) are considered i.e. comparing Table 2.7 and Table 2.A.7

Chapter Three: Article 2 - More pensioners, less income inequality? The impact of changing age composition on inequality in big cities and elsewhere[27]

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[27] Alimi, Maré and Poot (2018) - This work co-authored with Emeritus Prof. Jacques Poot and Dr. Dave Maré is published in U. Blien, K. Kourtit, P. Nijkamp & R. Stough (Eds.), *Modelling aging and migration effects on spatial labor markets*. Springer. A revised version of this paper is also forthcoming in the New Zealand Population Review and was awarded the 2017 Statistics New Zealand Jacoby Prize for best research on a population related topic by a current or recent student

Abstract

As is the case in most developed countries, the population of New Zealand is ageing numerically and structurally. Population ageing can have important effects on the distribution of personal income within and between urban areas. The age structure of the population may affect the distribution of income through the life-cycle profile of earnings but also through the spatial-temporal distribution of income within the various age groups. By decomposing New Zealand census data from 1986 to 2013 by age and urban area, this chapter examines the effects of population ageing on spatial-temporal changes in the distribution of personal income to better understand urban area-level income inequality (measured by the Mean Log Deviation index). We focus explicitly on differences between metropolitan and non-metropolitan urban areas. New Zealand has experienced a significant increase in income inequality over the last few decades, but population ageing has slightly dampened this trend. Because metropolitan areas are ageing slower, the inequality-reducing effect of ageing has been less in these areas. However, this urban-size differential-ageing effect on inequality growth has been relatively small compared with the faster growth in intra-age group inequality in the metropolitan areas.

Disclaimer

Access to the data used in this study was provided by Statistics New Zealand (SNZ) under conditions designed to give effect to the security and confidentiality provisions of the Statistics Act 1975. All frequency counts using Census data were subject to base three rounding in accordance with SNZ's release policy for census data.

Acknowledgements

We are grateful to Statistics New Zealand for providing access to the Census datasets and to NIDEA, University of Waikato for providing the facilities to access the data. Work on this chapter was supported by a New Zealand Royal Society Marsden-Funded programme of research: Tai Timu Tangata: Taihoa e? (The subnational mechanisms of the ending of population growth: Towards a theory of depopulation) [Contract MAU1308]. This work will appear as a chapter in: U. Blien, K. Kourtit, P. Nijkamp & R. Stough (eds.) Modelling Aging and Migration Effects on Spatial Labor Markets. New York & Berlin: Springer. It is also available as a Motu Working Paper: Alimi, O., Maré, D., & Poot, J. (2017). More pensioners, less income inequality? (No. 17-02). Motu Economic and Public Policy Research.

3.1 Introduction

This chapter examines the role of changes in age structure of the population on income inequality in New Zealand over the 27-year period from 1986 to 2013. The spatial unit of analysis is the urban area, which captures about 85 percent of the population. More specifically, we contrast metropolitan with non-metropolitan areas. We compare results from two popular approaches – the population decomposition by sub-group approach used in Mookherjee & Shorrocks (1982) and the density decomposition approach of DiNardo et al. (1996).

Much previous research on income inequality in New Zealand has been using survey data.[28] A disadvantage of using survey data in New Zealand is that the number of observations in a survey is often small, leading to relatively large sampling errors at sub-national levels. This limits the extent to which survey data can be used to study sub-national income inequality. This limitation of survey data is avoided in the present study by using micro-level data on individuals in urban areas from the previous six Censuses of Population and Dwellings in New Zealand between 1986 and 2013. We focus specifically on the role of changes in age structure and age-specific incomes within and between urban areas on the personal distribution of income. This is an important topic because the ageing of the population is expected to accelerate in the decades to come.

Our main finding is that, contrary to studies in some other countries, the ageing of the population in New Zealand has *slowed down* overall inequality growth.[29] We find that this effect is smaller in magnitude in metropolitan areas because these areas remain relatively more youthful. The slower ageing of the population in these large cities has made a small contribution to the faster growing inequality in metropolitan areas vis-à-vis non-metropolitan areas. However, most of the difference in inequality growth between the big cities and other urban areas is due to relatively faster growing inequality *within* specific age groups in metropolitan areas.

Inequality has risen in most of the developed world, especially over the last three decades. The literature suggests that growing inequality is *inter alia* due to: changing patterns of household formation; growing international economic

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[28] See, for example, Hyslop & Maré (2005) and Ball & Creedy (2015).
[29] For example, studies like Deaton & Paxson (1994) and Cameron (2000) found that population ageing increases inequality.

integration through migration, trade and capital mobility; growing unemployment; skill-biased technical change; as well as institutional factors such as decreasing levels of unionisation and minimum wages. Most studies have found that economic factors are the biggest drivers of growing income inequality,[30] but demographic factors have played a role as well.[31]

New Zealand stands out among the developed countries as having seen the relatively fastest growth in inequality, particularly during the structural and economic reforms of the late 1980s and early 1990s.[32] Changes in income inequality in New Zealand have been well documented.[33] At the subnational level, rapid inequality growth in the two largest metropolitan areas of Auckland and Wellington stands out (Alimi et al., 2016). This is largely in line with the rest of the developed world where large metropolitan areas are often areas with high – and fast growing – dispersion of income.[34] We examine here whether ageing of the population has played a role in rising income inequality and what role spatial differences in age composition have had in this context.

In New Zealand, only few studies have examined the distributional impact of changes in the age composition of the population and these studies did so at the national level.[35] The relationship between population ageing and inequality is not clear a priori. The impact of population ageing on the income distribution is uncertain due to the possibility of opposing within-age and between-age effects (von Weizsäcker, 1996). Spatially, the age structure will have effects on both intra-area and inter-area inequality, as areas often have different age profiles. Bigger areas tend to have a greater share of young people. This may mean a higher intra-area inequality, particularly when accounting for post-compulsory education and family formation. At the same time, 'prime aged' workers in the large cities have higher average incomes due to agglomeration and productivity effects. Generally, population size is positive correlated with inequality.[36] In contrast, areas that possess amenities that attract retirees may have lower intra-

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[30] See for example Castells-Quintana et al. (2015) for a review of the literature of the trends and determinants of income inequality in Europe.
[31] See e.g. Cameron (2000), Zhong (2011) and Peichl et al. (2012).
[32] See Evans et al. (1996) for a description of these reforms.
[33] See Perry (2014; 2015), Karagedikli et al. (2000; 2003), and Alimi et al. (2016).
[34] See OECD (2016).
[35] See Hyslop & Maré (2005) and Ball & Creedy (2015).
[36] A 2016 OECD report, which examines 153 metropolitan areas in 11 countries, finds that inequality in metropolitan areas is higher than the national average in all countries apart from Canada (OECD, 2016 p.33).

area inequality due to the relatively narrow dispersion of incomes among retirees. New Zealand offers a relatively generous universal pension to all citizens and most other residents aged 65 and over. Hence retirement migration from big cities to lower average income areas lowers intra-area inequality in the retirement areas and increases intra-area inequality in the big cities. Retirement migration also contributes to higher inter-area inequality. However, the nature of the relationship between age structure and income inequality is blurred by the fact that the underlying dynamics of changing age structure can be complex and dependent on the relative impacts of natural increase and migration on age composition. Additionally, the way in which migration impacts on income inequality will be strongly dependent on the type of migration.[37]

The chapter proceeds as follows: Section 2 reviews the literature on ageing and inequality. Section 3 discusses the two decomposition techniques that are used to analyse spatial-temporal changes in income inequality in New Zealand. Section 4 describes the data and reports the results. Section 5 concludes.

3.2 Literature review

The patterns of ageing and income inequality in New Zealand have both been well documented at the national and sub-national levels. Jackson (2011) and Johnson (2015) provide descriptive accounts of changes in age structure at the national and sub-national levels. Perry (2014, 2015) and Easton (2013) provide evidence of the long-run upward trend in inequality at the national level. Karagedikli et al. (2000, 2003) and Alimi et al. (2016) provide a sub-national analysis of income inequality trends at the regional council level. The relationship between population ageing and the distribution of income has long been examined in the literature, alongside other socio-demographic influences on inequality.[38] However, very few studies use formal theoretical foundations to link ageing to the distribution of income. Notable exceptions are Deaton & Paxson (1994, 1995) and von Weizsäcker

[37] Given that migrants are predominantly young, net inward migration contributes to the relative youthfulness of the big cities. However, a study of the effects of migration on the income distribution would need to take into account the differential effects of net permanent & long-term migration (which is on average more skilled than the local labour force and, like student migration, disproportionally towards the metropolitan areas) and temporary migration (which is less skilled and more attracted to non-metropolitan areas). The explicit analysis of the effects of migration on income inequality is beyond the scope of the present paper.

[38] See Lam (1997) for a review of the literature that examines the role of demographic variables (including changes in age structure) on income inequality.

(1996). Deaton & Paxson (1994, 1995) use the implications of the permanent income hypothesis to show that income inequality increases as the population ages while von Weiszäcker (1996) examines the role of the public transfer system. He concludes that the effect of ageing on population is ambiguous and distinguishes several channels with opposing effects through which ageing may affect the distribution of income.

Most of the recent research on this topic has been empirically oriented. Fortin et al. (2011) provide a review of the adopted methodologies and emphasise the decomposition approaches that have become common in the literature.

Just as the theory suggests, empirical evidence on the relationship between changes in the age structure and the distribution of income has been mixed, although most studies find that population ageing increases income inequality.[39] Nonetheless, some studies find a very small effect or no effect at all. Barrett et al. (2000) focussed on 1975-1993 consumption and income inequality in Australia and concluded that the ageing of the population had played only a minor role in growing inequality. Fritzell (1993) examined data from five countries (Canada, Germany, Sweden, UK and US) and concluded that changes in age distribution or changes in family composition cannot explain changes in inequality in these countries. Jantti (1997) came to similar conclusions when examining data from the Luxembourg Income Study on Canada, Netherlands, Sweden, UK and US.

The varied evidence from empirical studies is not surprising. As earlier identified by Lam (1997), any conflicting results on the role of age structure on income distribution can be due to variations between studies in the relative strength of between-group effects and within-group effects. The combined effect of the two depends on which effect is stronger. This may vary across populations.

In New Zealand, few studies to date have examined the effects of age structure on income inequality. Hyslop & Maré (2005) examined the factors contributing to changes in the New Zealand distribution of income between 1983 and 1998. Using the density decomposition approach of DiNardo et al. (1996)[40], they examined the role of household structure, national superannuation (old age pension), socio-demographic attributes (which include number, age, sex, ethnicity and education levels of adults in the household, together with the numbers of

[39] See for example Mookherjee & Shorrocks (1982), Cameron (2000), Zhong (2011), Peichl et al. (2012), Jenkings (1995) and Lin et al. (2015).
[40] See also Jenkings and Van Kerm (2005)

children in various age groups), employment outcomes, and economic returns to such attributes. They found that changes in household structure and socio-demographic attributes were the major factors contributing to changes in the income distribution in New Zealand (each contributing around one-sixth of the overall increase in the Gini coefficient). Changes in household structure tended to raise the top end of the income distribution while lowering the bottom end. Changes in household socio-demographic attributes also widened the distribution of income, particularly at higher incomes.

Ball & Creedy (2015) analysed income and expenditure data from 1983 to 2007 and found that the age and gender composition of the population was important for understanding inequality. However, Aziz et al. (2015) show, using the New Zealand Treasury's microsimulation model to forecast demographic changes that are expected over the next 50 years, that population ageing and expected changes in labour force participation by themselves do not have a significant impact on aggregate income inequality.

Our present study is similar to earlier work by Hyslop & Maré (2005) but instead of taking a national approach and examining the role of several economic and socio-demographic factors using survey data, we take a sub-national approach and focus exclusively on the spatial-temporal role of the age structure on the distribution of income.

3.3 Decomposition methods

We use two popular approaches in the literature – the decomposition by population subgroup approach of Mookherjee & Shorrocks (1982) and the semi-parametric density decomposition method of DiNardo et al. (1996) – to examine different ways in which changes in the age structure could affect the aggregate distribution of income at the urban area level. We use both methods to analyse the inter-temporal effect of changes in the age structure nationally as well as spatially across metropolitan and non-metropolitan areas between 1986 and 2013.[41] There are two ways in which age structure can affect the distribution of income:

The composition effect (or the age shares effect): This reveals how much of a role the population composition of an area plays in observed inequality. It is the effect

[41] Metropolitan areas defined as urban areas that make up the six largest New Zealand cities (in order of size) of Auckland, Wellington, Christchurch, Hamilton, Tauranga and Dunedin. All other urban areas are considered non-metropolitan areas.

on inequality of differences in the shares of different age groups for given mean incomes at various ages.

The age-specific income distribution effect: This examines the effect of differences in the age-specific income distribution on observed inequality for a given age composition of the population.

For both effects, we consider changes over time and across places.

We focus on the class of Generalised Entropy (GE) measures of inequality due to their property of permitting the expression of overall inequality as a weighted sum of sub-level inequalities. Within this class, we use the Mean Log Deviation (MLD) index as our measure of inequality because the MLD weights the inequality measure for a group by the group's population share. Hence MLD provides a direct evaluation of the effect of changes in age composition. One alternative GE measure is the Theil index of inequality which weights groups by income share. In the present context of analysing the impact of changes in demographic composition, the MLD is the more natural and more easily interpretable index.

Without loss of generality, let's assume that a population of size N is grouped in A age groups indexed by $a = 1, 2, \ldots, A$. Within each age group a there are N_a individuals, with individuals indexed by $i = 1, 2, \ldots, N_a$. Hence, $N = \sum_{a=1}^{A} N_a$. Given that we have access to microdata, the income of the individuals is known and defined as y_{ia}, i.e. the income of individual i in age group a. However, in many data collections, such as the census, income is only observed in income brackets. Let there be j income brackets, $j = 1,2,\ldots,J$. We will denote the income of individual i in age group a and in income bracket j by y_{ija}. As is done commonly, we will assume that income of each individual i in income bracket j and age group a is the same for everyone, denoted by y_j, namely the midpoint of the bracket (and a statistically estimated amount for the open-ended top bracket, see section 4). We assume that there are N_{ja} individuals in income bracket j and age group a, who then each earn y_j. Hence, $N = \sum_{a=1}^{A} N_a = \sum_{a=1}^{A} \sum_{j}^{J} N_{ja} = \sum_{j=1}^{J} \sum_{a=1}^{A} N_{ja} = \sum_{j=1}^{J} N_j$. It is convenient to also introduce notation for the population fraction in each age group, $\pi_a = N_a/N$.

We can now also define various income aggregates. The aggregate income of all individuals in income bracket j in age group a is $Y_{ja} = y_j N_{ja}$. The aggregate income of all those in age group a is $Y_a = \sum_{j=1}^{J} Y_{ja} = \sum_{j=1}^{J} y_j N_{ja}$ while the aggregate income of those in income bracket j is $Y_j = \sum_{a=1}^{A} Y_{ja} = \sum_{a=1}^{A} y_j N_{ja} = y_j \sum_{a=1}^{A} N_{ja} = y_j\, N_j$. Total income in the economy is $Y = \sum_{a=1}^{A} Y_a = \sum_{a=1}^{A} \sum_{j=1}^{J} y_j N_{ja} = \sum_{j=1}^{J} \sum_{a=1}^{A} y_j N_{ja} = \sum_{j=1}^{J} y_j \sum_{a=1}^{A} N_{ja} = \sum_{j=1}^{J} y_j\, N_j = \sum_{j=1}^{J} Y_j$. Finally, we denote average income in the economy by $\mu = Y/N$, average income of those in age group a by $\mu_a = Y_a/N_a$, and relative income of those in age group a by $r_a = \mu_a/\mu$.

Given this notation, MLD can be expressed as follows (see, e.g., Mookherjee & Shorrocks, 1982):

$$MLD = \sum_{a=1}^{A} \sum_{j=1}^{J} \frac{N_{ja}}{N} \log\left(\frac{Y/N}{Y_{ja}/N_{ja}}\right) = \sum_{a=1}^{A} \sum_{j=1}^{J} \pi_{ja} \log\left(\frac{1}{r_{ja}}\right)$$

(1)

It is useful to note that *MLD* in invariant to population scale *N* and the unit of measurement of income (e.g. nominal or real). It is straightforward to show that overall inequality can be decomposed into the sum of within-age-group inequality and between-age-group inequality:

$$\begin{aligned} MLD &= \sum_{a=1}^{A} \frac{N_a}{N} \left[\sum_{j=1}^{J} \frac{N_{ja}}{N_a} \log\left(\frac{Y_a/N_a}{Y_{ja}/N_{ja}}\right) \right] + \sum_{a=1}^{A} \frac{N_a}{N} \log\left(\frac{Y/N}{Y_a/N_a}\right) \\ &= \sum_{a=1}^{A} \pi_a MLD_a + \sum_{a=1}^{A} \pi_a \log\left(\frac{1}{r_a}\right) \end{aligned}$$

(2)

in which $\sum_{a=1}^{A} \pi_a MLD_a$ is the age-group-weighted sum of within-age-group inequality and $\sum_{a=1}^{A} \pi_a \log\left(\frac{1}{r_a}\right)$ the age-group-weighted sum of the logarithm of the inverse of age-group-relative income (i.e., between-age-group inequality). It should be noted that such decompositions hold also true for any other mutually exclusive and collectively exhaustive classifications, such as gender and location. The decomposition can also be applied hierarchically, for example when overall income inequality is decomposed by age and sex.

When gauging a change in overall inequality over a given period, equation (2) clearly shows that there are three contributing factors: firstly, changes in the age group shares (structural population ageing); secondly, changes in inequality within each age group; and, thirdly, changes in the age-group-relative incomes (for example due to changes in the lifecycle profile of earnings). It is easy to see that a change in the *MLD*, can be expressed exactly as follows:

$$\Delta MLD = \underbrace{\sum_{a=1}^{A} \overline{\pi_a} \Delta MLD_a}_{\substack{aggregate \\ change\ in \\ within-age-group \\ inequality\ for\ given \\ age\ shares \\ C1}} + \underbrace{\sum_{a=1}^{A} \overline{MLD_a} \Delta\pi_a}_{\substack{aggregate \\ change\ in \\ within-age-group \\ inequality\ due\ to \\ changing\ age\ shares \\ C2}} + \underbrace{\sum_{a=1}^{A} \overline{\log\left(\frac{1}{r_a}\right)} \Delta\pi_a}_{\substack{aggregate \\ change\ in \\ between-age-group \\ inequality\ due\ to \\ changing\ age\ shares \\ C3}} + \underbrace{\sum_{j=1}^{J} \overline{\pi_a} \Delta\log\left(\frac{1}{r_a}\right)}_{\substack{aggregate \\ growth\ in \\ age-group\ relative \\ income\ for\ given \\ age\ shares \\ C4}} \qquad (3)$$

in which a bar over an expression represents the simple arithmetic average of the variable over the two periods, i.e. $\bar{x} = \frac{1}{2}(x_{t-1} + x_t)$.

Component *C*4 in Eq. (3) above represents the aggregate impact on inequality of growth (the change in natural logarithmic values) in age-group-specific mean incomes, but *relative* to overall mean income. Mookherjee & Shorrocks (1982) argue that it is more natural to think of growth in the *levels* of age-group-specific mean incomes rather than growth in relative incomes. For this reason, they replace Eq. (3) by a decomposition that holds only approximately, but which explicitly includes age-specific mean income growth:[42]

[42] Mookherjee & Shorrocks (1982) note that this approximation appears sufficient for computational purposes (p.897). It is clear that C3' – C3 = $\sum_{a=1}^{A} \overline{r_a} \Delta\pi_a$. Experimentation with a range of changing income distributions shows that the sign of *C*3 can be sometimes different from that of *C*3' and, similarly, the sign of *C*4 can be different from that of *C*4*'*. This may lead to slightly different interpretations. In this paper we follow Mookherjee & Shorrocks (1982) and use the approximate decomposition. Results for the exact decomposition are available upon request.

$$\Delta MLD \approx \underbrace{\sum_{a=1}^{A} \overline{\pi_a} \Delta MLD_a}_{\substack{aggregate \\ change\ in \\ within-age-group \\ inequality\ for\ given \\ age\ shares \\ C1}} + \underbrace{\sum_{a=1}^{A} \overline{MLD_a} \Delta \pi_a}_{\substack{aggregate \\ change\ in \\ within-age-group \\ inequality\ due\ to \\ changing\ age\ shares \\ C2}} + \underbrace{\sum_{a=1}^{A} (\overline{r_a} - \overline{logr_a}) \Delta \pi_a}_{\substack{aggregate \\ change\ in \\ between-age-group \\ inequality\ due\ to \\ changing\ age\ shares \\ C3'}} + \underbrace{\sum_{a=1}^{A} (\overline{\pi_a r_a} - \overline{\pi_a}) \Delta \log \mu_a}_{\substack{aggregate \\ growth\ in \\ age-group\ mean \\ income\ for\ given \\ age\ shares \\ C4'}} \tag{4}$$

In the next section we will report result by using this approximate decomposition given in Eq. (4).

The second decomposition method considers the income distribution as a density which may have a different shape for different age groups. Inequality is quantified by a dispersion measure applied to a given distribution of income of individuals or households. Besides the *MLD* measure of inequality described above, common alternative dispersion measures are the Gini coefficient, Theil index, the Coefficient of Variation, etc. We can quantify the effect of any change in the shape of the distribution of income by any of these inequality measures. DiNardo et al. (1996) consider it useful to decompose overall change in inequality into a contribution from *within-group* inequality change, calculated for a counterfactual income distribution in which population composition is assumed to have stayed the same, and a contribution from *between-group* change calculated for a counterfactual income distribution at which inequality within groups is assumed to remain the same.

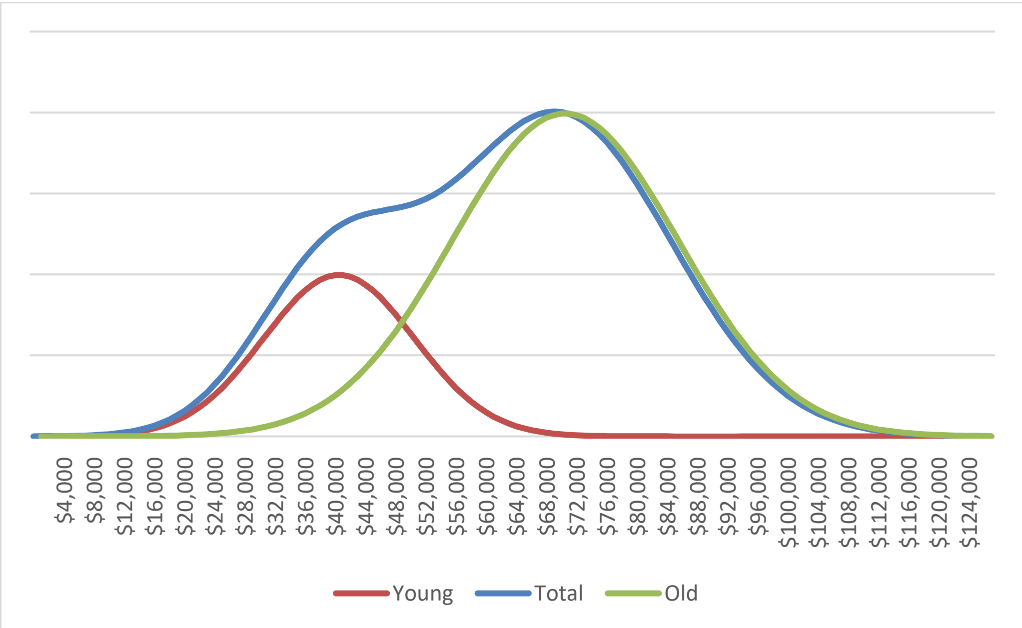
One advantage of this approach is that it provides in our context a visual representation of the roles of the age composition effect and the age-specific distribution effect respectively. Let $f_Y(y; x) = \int f_{Y|X}\, dF_X$ represent the general distribution of income with respect to personal characteristic *X*. The integral sign is used to depict aggregate income with respect to attributes *X* that can be quantified by continuous variables. When *X* is a discrete variable, such as an age group, the corresponding expression is $f_Y(y; x) = \sum f_{Y|X}\, \varphi_X$ where $\varphi = Prob(X = x)$.

In this chapter we focus exclusively on the age distribution (denoted by *A* as before). This distribution may be specific to a certain location, say urban area *U*, and at a particular point in time. Hence the overall income distribution in urban area U is then given by

$$f_Y^U(y;a) = \underbrace{\sum f_{Y|A}^U}_{\substack{age-specific\\ conditional\\ distibution}} \underbrace{Prob(A=a)}_{\substack{Compositional\ or\\ shares\ effect}} \tag{5}$$

To illustrate this, consider Figure 3.1 which presents a hypothetical distribution with two broad age categories in U: younger people and older people. In this Figure, older people do not only have higher incomes than younger people have but they are also more numerous.

Figure 3.1. Hypothetical income distribution in an urban area U, showing total and age-specific distributions for young and old people



The impact of age structure on change in the overall distribution of income in U could be through a composition effect, i.e. through changes in $Prob(A = a)$ or through changes in the age-specific conditional distribution of income $f_{Y|A}^U$. To calculate both effects, we employ a benchmarking approach. To proceed we will need to introduce some notation and keep in mind the application to New Zealand Census data from 1986 until 2013. The beginning census year of the study (1986) will be compared to the last census year (2013).

We now define:

- $f_Y^{N86|N86} = \sum f_{Y|A}^{N86}\ \pi_a^{N86}$ represents the actual 1986 national distribution of incomes based on the 1986 conditional age-specific distributions $f_{Y|A}^{N86}$

and the 1986 shares of people in each age group π_a^{N86}. Similarly, $f_Y^{N13|N13} = \sum f_{Y|A}^{N13}\ \pi_a^{N13}$ represents the corresponding 2013 distribution of income;

- $\check{f}_Y^{N13|N86} = \sum f_{Y|A}^{N13}\ \pi_a^{N86}$ represents a 2013 counterfactual distribution, based on the 2013 age-specific conditional distribution of incomes but 1986 shares of people in each age group i.e. $\check{f}_Y^{N13|N86} = \sum f_{Y|A}^{N13}\ \pi_a^{N86} = \sum f_{Y|A}^{N13}\ \pi_a^{N13}.\frac{\pi_a^{N86}}{\pi_a^{N13}}$

Changes in inequality over time can either be attributed to changes in the age composition effect or due to changes in the age-specific distribution of income. The role of changes in age composition between 1986 and 2013 can be calculated by comparing the 2013 original distribution f_Y^{N13} to the counterfactual distribution $\check{f}_Y^{N13|N86}$which is based on 2013 age-specific conditional distribution of incomes but 1986 shares of people in each age group. i.e. the difference is $f_Y^{N13} - \check{f}_Y^{N13|N86}$. The $\check{f}_Y^{N13|N86}$ holds changes in the age-specific distribution over the period constant so any differences between the actual 2013 distribution and this counterfactual distribution are due to the changes in age composition. Since the population aged between 1986 and 2013, this will estimate the effect of the ageing of the population on the income distribution.

The effect of changes in the age-specific distribution between 1986 and 2013 will be calculated by comparing the counter factual distribution $\check{f}_Y^{N13|N86}$ to the 1986 original distribution i.e. by calculating $\check{f}_Y^{N13|N86} - f_Y^{N86}$. Since $\check{f}_Y^{N13|N86}$ is based on the 1986 age structure, any difference between this distribution and the 1986 distribution is due to the changes in the age-specific conditional distribution.

This benchmarking approach provides an alternative way of decomposing the change in inequality measured by the *MLD* index. Here we can write changes in income inequality between 1986 and 2013 as:

$$\begin{aligned}\Delta MLD_{13-86} &= MLD(f_Y^{N13}) - MLD(f_Y^{N86}) \\ &= \underbrace{\left[MLD(f_Y^{N13}) - MLD\left(\check{f}_Y^{N13|N86}\right)\right]}_{Age\ composition\ effect} \\ &\quad + \left[\underbrace{MLD\left(\check{f}_Y^{N13|N86}\right) - MLD(f_Y^{N86})}_{Age-specific\ distribution\ effect}\right]\end{aligned}$$

(6)

This is a very simple way of decomposing the change in the *MLD* index into two parts: the first part shows the contribution of the changing age composition for given age-specific inequality while the second component shows how much, for a given age distribution, the change in age-specific inequality contributed to the overall change.

Finally, it should be noted that the calculation of the effect of the changing age composition on inequality can be done separately for every urban area. Of particular interest is then the extent to which the age composition effects play a greater or lesser role in explaining inequality change in certain areas and whether the sign of the age composition effect (positive or negative) is the same in all areas. Here we simply consider the distinction between metropolitan and non-metropolitan areas.

There are certain limitations to the density decomposition approach. Firstly, it follows a partial equilibrium analysis: we calculate the effect on inequality if the population composition changes but age-specific distributions remain the same, or vice versa. Hence this approach ignores the *interaction* between these two effects: changes in population composition can in general equilibrium also affect the age-specific distribution of income, and vice-versa, through migration and labour market adjustments.

Another limitation, which is a characteristic of all decomposition methods, is that such methods do not contribute to understanding the various economic mechanisms through which ageing affects inequality. Instead, decomposition provides simply an accounting framework that allows us to quantify the relative magnitude of the impact of compositional change.

3.4 Data and results

3.4.1 Data on personal income

All data used are from the six New Zealand Censuses of Population and Dwelling from 1986 to 2013. The population is limited to people aged 15 and above who are earning positive incomes. Age data are available by single year of age. However, because we are interested in the broad trend of structural population ageing, we collapse all ages into four age groups: 15-24, 25-44, 45-64 and those 65 and over.

The income data represent total personal income before tax of people earning positive income in the 12 months before the census night.[43] It consists of income from all sources such as wages and salaries, self-employment income, investment income, and superannuation. It excludes social transfers in kind, such as public education or government-subsidised health care services. Instead of recording actual incomes, total personal incomes are captured in income bands in each census with the top and bottom income bands open ended. For example, the top band in the 2013 census data captures everybody earning $150,000 and over. An important issue with the open-ended upper band is the calculation of mean income in the open-ended band. At the national level this is not a problem as Statistics New Zealand publishes an estimate of the midpoint of the top band for the country based on Household Economic Survey (HES) estimates. However, HES top-band mean incomes for sub-national areas are not reliable due to sampling errors. To resolve this problem, Pareto distributions have been fitted to the upper tail of the urban-area specific distributions. We use the Stata RPME command developed by von Hippel et al. (2016).

3.4.2 Changes in the age distribution of the population

Population ageing is a key feature of the changes in the New Zealand age structure between 1986 and 2013. Jackson (2011) identified increasing longevity and declining birth rates as the main drivers of this trend. The patterns of ageing have been well described nationally and sub-nationally. Plenty of studies have examined the implications of an ageing population on the labour force, government revenues and economic growth (see Jackson, 2011; Stephenson & Scobie, 2002; McCulloch & Frances, 2001). Spatially, attention has been given to examining the impact of accelerated aging of the rural areas and the role of rural-urban migration in driving this decline. Here we focus on differences between metropolitan and non-metropolitan areas in ageing. Table 3.1 shows the trends in population composition by age groups for metropolitan and non-metropolitan areas, and for all urban areas combined, from 1986 to 2013.

[43] Hence people not in paid employment and business owners reporting a loss have been excluded.

Table 3.1: Structural population ageing in New Zealand from 1986 to 2013

	Metropolitan Areas					
Age group	1986	1991	1996	2001	2006	2013
15-24	22%	20%	19%	17%	17%	15%
25-44	39%	41%	41%	41%	39%	36%
45-64	24%	24%	25%	28%	30%	32%
65+	14%	15%	15%	14%	14%	16%
All	100%	100%	100%	100%	100%	100%
	Non-Metropolitan Areas					
15-24	21%	18%	17%	14%	14%	12%
25-44	37%	38%	38%	36%	33%	30%
45-64	25%	25%	26%	30%	32%	34%
65+	17%	18%	19%	20%	20%	23%
All	100%	100%	100%	100%	100%	100%
	All Urban Areas Combined					
15-24	22%	19%	18%	16%	16%	14%
25-44	39%	40%	40%	40%	38%	35%
45-64	24%	24%	26%	29%	30%	33%
65+	15%	16%	16%	16%	16%	18%
All	100%	100%	100%	100%	100%	100%

Note: Metropolitan areas are the six largest New Zealand cities (in order of size): Auckland, Wellington, Christchurch, Hamilton, Tauranga and Dunedin. All other urban areas are considered non-metropolitan areas

The ageing of the population between 1986 and 2013 is very clear. Nationally (all urban areas combined), the proportion of the population in the youngest age group 15-24 declined from 22 percent in 1986 to 14 percent in 2013 while for the oldest age group, 65+, the proportion increased from 15 percent to 18 percent. By 2013, the proportion of the population in the oldest age group exceeded that in the youngest age group.

Spatially, there is disparity across urban areas in the patterns of ageing. Non-metropolitan areas age more rapidly. In 1986, metro and non-metro had almost the same proportion of people in the youngest age group, 15-24, (around 22 percent) but by 2013 the proportion in non-metropolitan areas had fallen by about 9 percentage points while in metropolitan areas it fell by only 7 percentage points. The disparity is even starker when comparing the changes in the oldest age group 65+: the proportion in this group increased by about 2-percentage points in metropolitan areas compared to a 6-percentage point increase in non-metropolitan areas. It is evident that non-metropolitan areas have undergone more rapid ageing and were older on average than metropolitan areas by 2013.

3.4.3 Changes in the Mean Log Deviation measure of income inequality

As noted in the introduction, New Zealand stands out among the developed countries as having seen the relatively fastest growth in inequality in recent decades, particularly during the 1980s and early 1990s. Across all urban areas, inequality grew by about 18 percent between 1986 and 2013 (see Table 3.2). It increased in all intercensal periods apart from between 1986 and 1991, and between 2001 and 2006 (see Figure 3.2). Like the changes in age structure, the changes in income inequality are not the same everywhere. Much like what has been found in other countries, inequality increased more rapidly in metropolitan areas.[44] The metropolitan and non-metropolitan divide had been highlighted in previous New Zealand studies by Karagedikli et al. (2000, 2003) and Alimi et al. (2016). They found the highest rates of income and inequality growth in the metropolitan areas of Auckland and Wellington. Table 3.2 shows that metropolitan areas saw a 25 percent increase in the MLD, as compared with only 2 percent growth in non-metropolitan areas. It is clear that most of the growth in inequality that happened in New Zealand between 1986 and 2013 was driven by the changes in the metropolitan areas.

Table 3.2: Metropolitan versus non-metropolitan growth rates in income inequality

	1986 (MLD)	2013 (MLD)	Growth 1986-2013 (percentages)
Metro	0.3607	0.4500	25%
Non Metro	0.3563	0.3623	2%
All urban areas combined	0.3509	0.4153	18%

Note: Metropolitan areas are the six largest New Zealand cities (in order of size): Auckland, Wellington, Christchurch, Hamilton, Tauranga and Dunedin. All other urban areas are considered non-metropolitan areas. Income inequality is measured by the Mean Log Deviation (MLD) index. To calculate the MLD for all urban areas combined, the Statistics New Zealand Household Economic Survey estimates of national-level mean income in the open-ended top bracket were used, not the estimates of mean income derived from fitting Pareto distributions to the top end of the distribution. This implies that the MLD for all urban areas combined does not perfectly decompose into within-group and between-group contributions equivalent to Eq. (2).

The 1986-2013 change in *MLD* displayed in Figure 3.2 is disaggregated in tabular form into changes in the inequality index for each age group in Table 3.3. Focusing on the aggregate patterns, but with the same conclusions also true for metro and non-metro areas, within-age-group inequality increased the most between 1986 and 2013 in the 65+ group, closely followed by the 15-24 age

[44] See OECD (2016).

group. The within-group measure of inequality for these two groups rose across all urban areas by around 68 percent and 35 percent respectively. The 25-44 group was the only age group to experience a decline in within-group inequality, at around 10 percent.

Figure 3.2: Mean Log Deviation index of income inequality, New Zealand 1986-2013

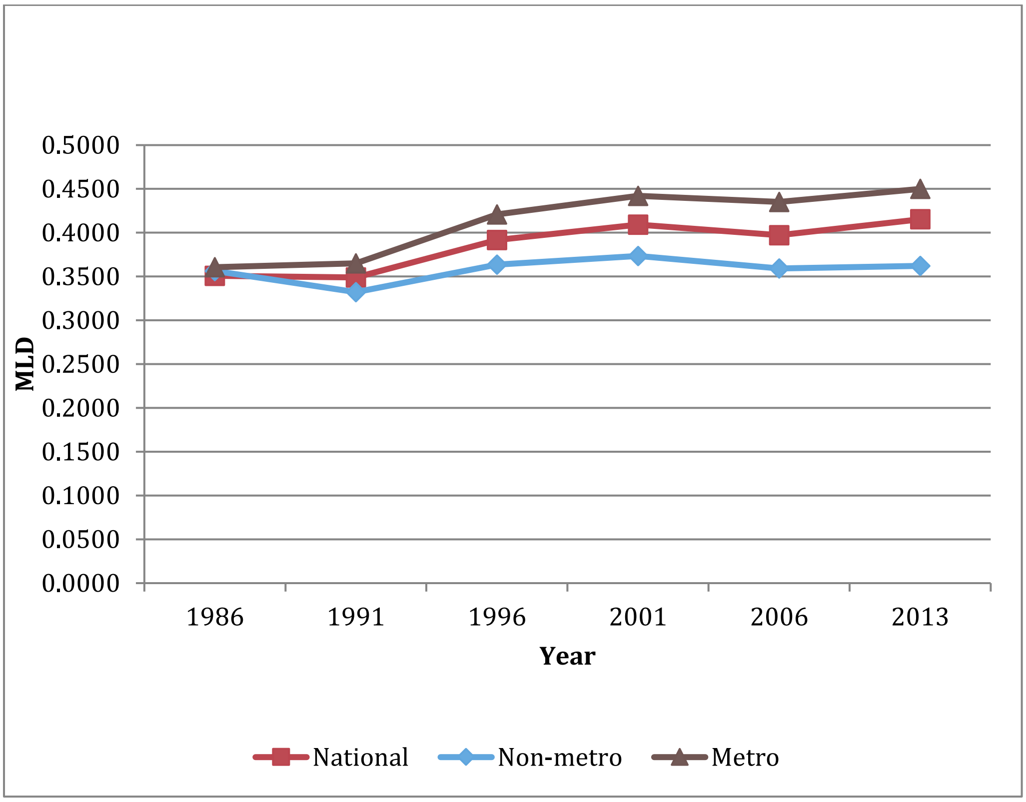


Table 3.3: New Zealand income inequality by type of area and age group, 1986-2013

	Age group	1986	1991	1996	2001	2006	2013	Change (86-13)	Mean
	Metropolitan								
15-24	*MLD*	0.3708	0.3667	0.4305	0.4672	0.4879	0.5100	38%	0.4389
	r	69%	60%	50%	45%	43%	39%	-30%	51%
	π	22%	20%	19%	17%	17%	15%	-7%	18%
25-44	*MLD*	0.3697	0.3472	0.3463	0.3528	0.3267	0.3414	-8%	0.3473
	r	119%	121%	121%	120%	117%	113%	-5%	119%
	π	39%	41%	41%	41%	39%	36%	-3%	40%
45-64	*MLD*	0.3197	0.3328	0.3958	0.4030	0.3749	0.3972	24%	0.3706
	r	117%	117%	126%	124%	127%	129%	12%	123%
	π	24%	24%	25%	28%	30%	32%	8%	27%
65+	*MLD*	0.1638	0.1725	0.2024	0.2352	0.2743	0.2929	79%	0.2235
	R	68%	67%	60%	60%	63%	70%	2%	64%
	π	14%	15%	15%	14%	14%	16%	2%	15%
	Non-metropolitan								
15-24	*MLD*	0.3805	0.3500	0.4032	0.4322	0.4560	0.4881	28%	0.4183
	r	73%	64%	55%	50%	52%	49%	-24%	57%
	π	21%	18%	17%	14%	14%	12%	-9%	16%
25-44	*MLD*	0.3908	0.3397	0.3191	0.3158	0.2896	0.3083	-21%	0.3272
	r	118%	121%	121%	118%	116%	112%	-6%	118%
	π	37%	38%	38%	36%	33%	30%	-7%	36%
45-64	*MLD*	0.3166	0.3090	0.3559	0.3612	0.3278	0.3274	3%	0.3330
	r	115%	115%	123%	125%	126%	126%	11%	122%
	π	25%	25%	26%	30%	32%	34%	10%	29%
65+	*MLD*	0.1498	0.1442	0.1626	0.1797	0.2044	0.2152	44%	0.1760
	r	71%	73%	67%	67%	67%	73%	2%	70%
	π	17%	18%	19%	20%	20%	23%	7%	20%
	All urban areas combined								
15-24	*MLD*	0.3733	0.3627	0.4206	0.4554	0.4779	0.5022	35%	0.4320
	r	71%	62%	52%	47%	46%	42%	-29%	53%
	π	22%	19%	18%	16%	16%	14%	-7%	18%
25-44	*MLD*	0.3678	0.3398	0.3303	0.3349	0.3088	0.3309	-10%	0.3354
	r	119%	121%	122%	120%	119%	115%	-4%	119%
	π	39%	40%	40%	40%	38%	35%	-4%	39%
45-64	*MLD*	0.3057	0.3146	0.3617	0.3683	0.3328	0.3559	16%	0.3399
	r	116%	116%	123%	123%	124%	126%	10%	121%
	π	24%	24%	26%	29%	30%	33%	8%	28%
65+	*MLD*	0.1522	0.1560	0.1805	0.2069	0.2374	0.2562	68%	0.1982
	r	69%	68%	62%	62%	64%	70%	2%	66%
	π	15%	16%	16%	16%	16%	18%	3%	16%

Note: *r* is relative income and π is age-group share of population for given year and area

One factor explaining these trends in within-group income inequality is labour force participation. Among the 15-24 group, the proportion of those attending tertiary education, and therefore only working part-time and at low wages, has been increasing. Among those aged 65+, labour force participation has been increasing, thus leading to a larger number receiving income over and above New Zealand superannuation. Both trends increase inequality. The proportion of the 65+ age group participating in the labour force fulltime in urban areas rose from 3 percent in 1986 to 11 percent in 2013. This change led to an increase in the dispersion of income between those mostly relying on superannuation (plus perhaps some income from investments or private pensions) and those still in paid work. The opposite effect happened at the other end of the scale where those in the 15-24 age group experienced a reduction in labour force participation. This is due to an increasing proportion of this group spending more time in education and formal training. The reduction in labour force participation in this group, especially the reduction in those working full time, contributed to an increase the dispersion of income within the 15-24 age group.[45]

In terms of the life course, inequality is higher within the 15-24 age group than at other ages. Apart from the high inequality in the first age group, and excluding 1986 and 1991, inequality does follow the usual life course pattern suggested in the literature, with increases in income inequality as a specific age cohort ages, until the public pension (New Zealand superannuation) becomes available at age 65. [46]

With respect to relative mean income, the 15-24 group have seen the biggest drop, irrespective of urban location. Across all urban areas, the relative income of this age group dropped by 29 percentage points, falling from 71 percent of average income in 1986 to around 42 percent of 2013 average income. In contrast, the 45-64 and 65+ groups increased their relative incomes by 10 and 2 percentage points respectively.

Using Eq. (2), Table 3.4 shows how each age group contributes to income inequality measured by the MLD index: within-group inequality makes the largest contribution to total inequality (varying between 83.7 percent in 2006 and 91.5 percent in 1986). However, between-age-group inequality is becoming a bigger share of total inequality: its contribution increased from around 8.5 percent in 1986 to 15.7 per cent in 2013. This is primarily due to the increased divergence in relative mean incomes across age groups.

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[45] The labour force participation rate for those aged 15 to 24 declined from 76 percent in 1986 to 61 percent in 2013, with full-time employment falling by even more at 40 percentage points.

[46] New Zealand Superannuation is the public pension paid to all residents over the age of 65 (immigrants must have resided in the country for 10 years or longer). Any eligible New Zealander receives NZ Super regardless of how much they earn through paid work, savings and investments, what other assets they own or what taxes they have paid. NZ Super is indexed to the average wage. The after-tax NZ Super rate for couples (who both qualify) is based on 66% of the 'average ordinary time wage' after tax. For single people, the after-tax NZ superannuation rate is around 40% of that average wage. See https://www.workandincome.govt.nz/eligibility/seniors/superannuation/payment-rates.html

Table 3.4: Decomposition of *MLD* into between-age-group and within-age-group components: all urban areas combined

	Within-group contribution to *MLD* ($\pi_j MLD_j$)					
Age group	1986	1991	1996	2001	2006	2013
15-24	0.0816	0.0705	0.0758	0.0729	0.0775	0.0724
25-44	0.1421	0.1372	0.1328	0.1330	0.1162	0.1147
45-64	0.0744	0.0761	0.0932	0.1051	0.1010	0.1167
65+	0.0231	0.0250	0.0289	0.0326	0.0375	0.0464
Sum of within age group inequality	0.3212	0.3088	0.3307	0.3436	0.3322	0.3502
	Between-group contribution to *MLD* ($\pi_j \log(\frac{1}{r_j})$)					
Age group	1986	1991	1996	2001	2006	2013
15-24	0.0749	0.0929	0.1180	0.1208	0.1244	0.1258
25-44	-0.0662	-0.0785	-0.0788	-0.0739	-0.0653	-0.0485
45-64	-0.0358	-0.0352	-0.0536	-0.0579	-0.0652	-0.0761
65+	0.0568	0.0610	0.0752	0.0765	0.0709	0.0638
Sum of between-age-group inequality	0.0297	0.0402	0.0609	0.0655	0.0649	0.0651
All urban areas combined *MLD*						
Between as a percent of total	8.5%	11.5%	15.5%	16.0%	16.3%	15.7%
Within as a percent of total	91.5%	88.5%	84.5%	84.0%	83.7%	84.3%
Total	0.3509	0.3490	0.3916	0.4091	0.3971	0.4153

From 1986 to 2006, the 25-44 age group made the biggest contribution to within-group inequality. The large population share of this group was responsible for this effect (see Table 3.3). By 2013 however, within-inequality of the 45-64 age group made the greatest contribution to total inequality, reflecting the combined effect of population ageing and growing inequality within this group. The trends for those aged 15-24 and those aged 65+ provide an interesting contrast. In the 15-24 age group, within-inequality rose very fast but the diminishing population share of this group reduced their contribution to aggregate within-inequality over time. For the 65+ group, both within-inequality as well as population share increased, thereby increasing this group's impact on overall inequality.

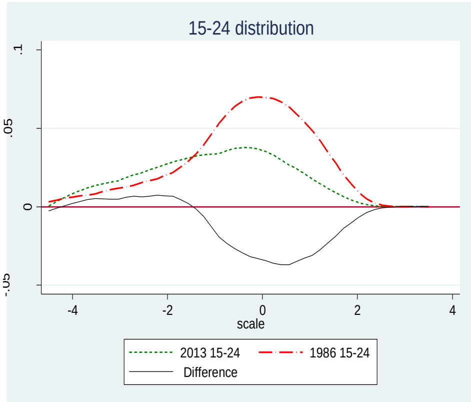
The combined effect of changing age-specific relative incomes and changed age-group shares of population can be clearly seen in the middle panel of Table 3.4. Incomes in the 25-44 and 45-64 age groups are above average, thereby yielding negative between-group contributions to *MLD*. The most striking trend is the contribution of declining relative incomes of the young (see also Table 3.3) to growing overall inequality measured by the *MLD*.

3.4.4 Changes in the density of the income distribution

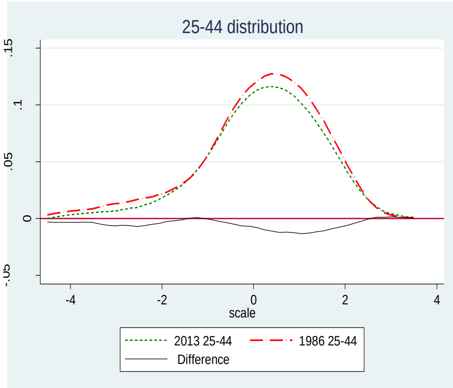
We will now proceed with a visual approach to present the contribution of each age group to the overall change in the distribution of income across all urban areas between 1986 and 2013.

Figure 3.3: A comparison of the 1986 and 2013 income distributions by age group: all urban areas combined

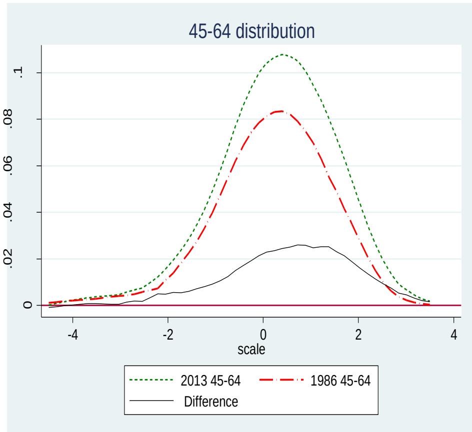
A. 15-24



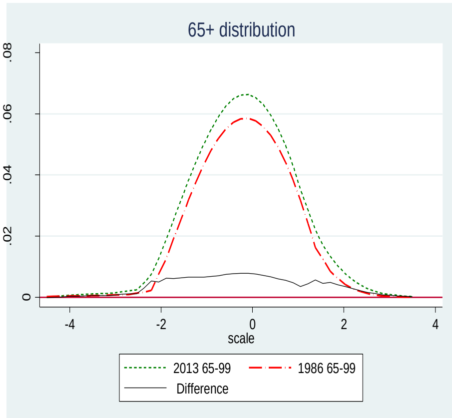
B. 25-44



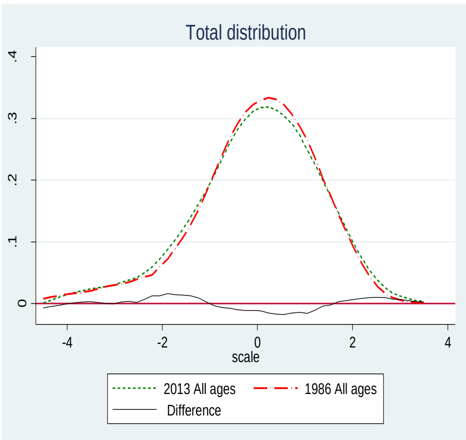
C. 45-64



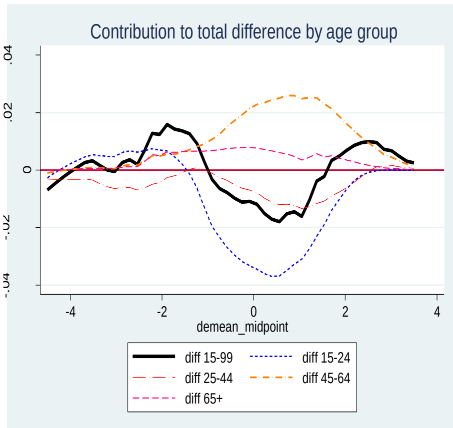
D. 65+



E. Total



F. Age contributions to change



Note: Difference = 2013 distribution – 1986 distribution

Figure 3.3 presents the standardized 1986 and 2013 log income distribution for each age group and all urban areas combined. The densities diagrams are standardized by de-meaning all income data by overall average income. The areas under the curves represent the population shares of the age groups. Hence, the overall income distribution in panel E is the sum of the densities A to D and has thetotal area under the density function equal to one (as in the stylised example of Figure 3.1). Overlaying the density diagrams for 1986 and 2013 provides a visual appreciation of the changes in the distribution over time.

Focusing on age groups, the 2013 distribution of the 15-24 age group is wider than the 1986 distribution (see Figure 3.3, panel A) and this is due to an increase in the number and/or share of people in the bottom of the distribution and a reduction in the middle and top. Panel B shows that changes in the income distribution of those aged 25-44 group have been relatively minor (although they have, given the size of this group, still a major impact on the overall distribution). Panels C and D show the changes in the 45-64 and 65+ age groups respectively. The distributions for these groups are wider in 2013 than in 1986. The increase in inequality for these groups is predominantly due to an increase in the number of people in the middle and top of the distributions. Panel E pools all age groups together and shows that the overall distribution is wider in 2013 compared with 1986. This change is driven by a 'hollowing out' of the middle of the income distribution, due to more people at both the bottom and top ends of the distribution. Panel F graphs the difference between the 2013 and 1986 distributions by age group.[47] This figure shows clearly how the younger age groups (15-24 and 25-44) have been predominantly responsible for the 'hollowing out at the middle of the distribution.[48]'

Similar to disaggregating inequality changes by the *MLD* index, changes in the aggregate income distribution density are due to the combined effect of changes in the number of people at the various age groups and changes in the age-group-specific densities. We will therefore now proceed with calculating the

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[47] The graphs in panel F are scaled. To calculate the scaled age group contribution to total difference, the density of each age group in each year is scaled by their respective income share.

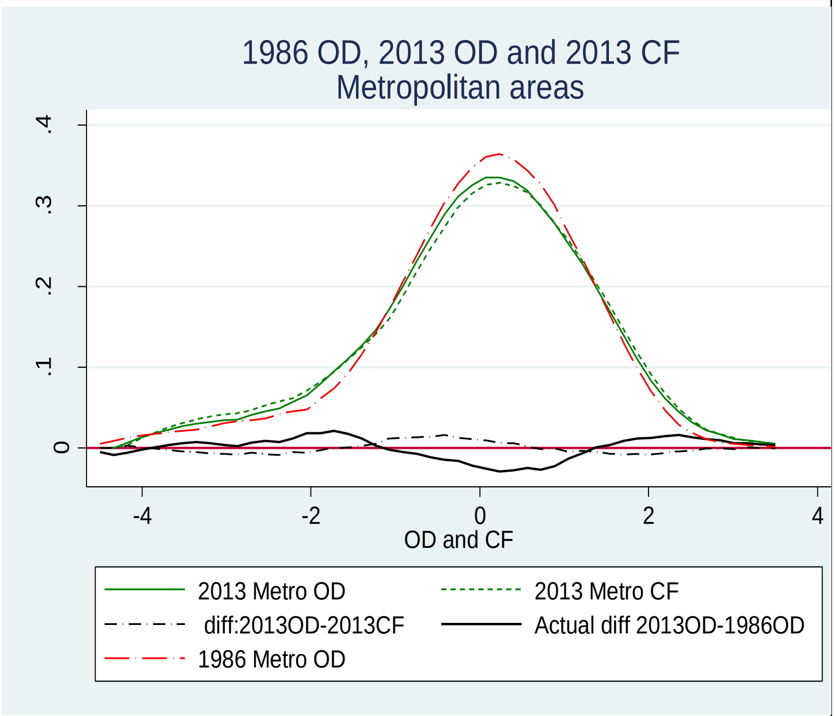
[48] This hollowing out of the income distribution is not necessarily evidence of a 'vanishing middle class' phenomenon that has been reported for the USA and other developed countries (e.g., Foster & Wolfson, 2010). To investigate a 'vanishing middle class' phenomenon would require a comparison of lifetime income across population groups rather than a comparison of age-specific income. This is beyond the scope of the present paper.

counterfactual densities as outlined in the previous section. Given the counterfactual densities, the change in inequality between 1986 and 2013 can be decomposed by means of the *MLD* index as given in Eq. (6).

Figure 3.4 presents the 2013 and 1986 original distributions, the counterfactual distribution (with age distribution fixed at the 1986 shares and within-age-group inequality as in 2013), as well as the differences between them for metropolitan, non-metropolitan and the combined areas[49].

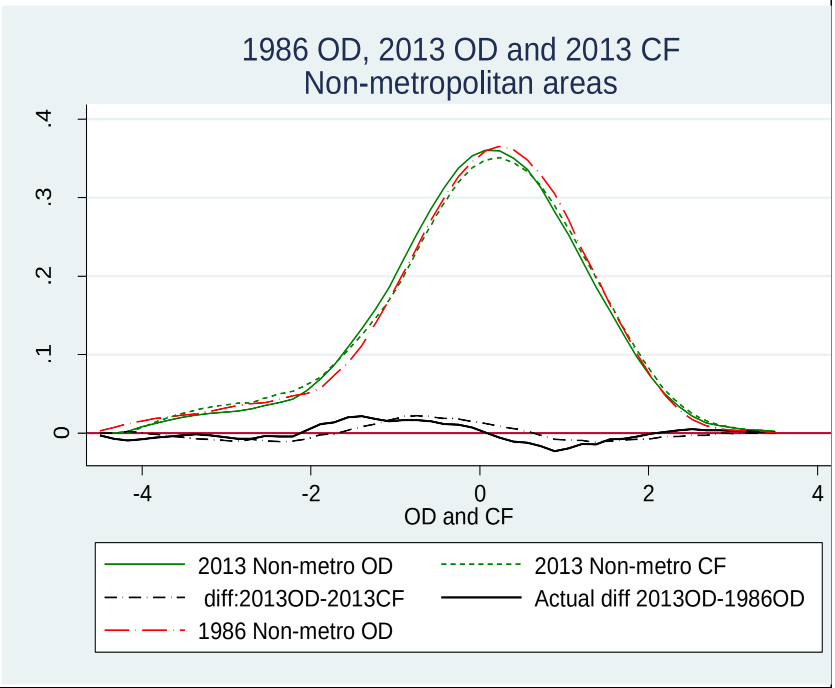
Figure 3.4: Original and counterfactual income distributions and their differences

Metro

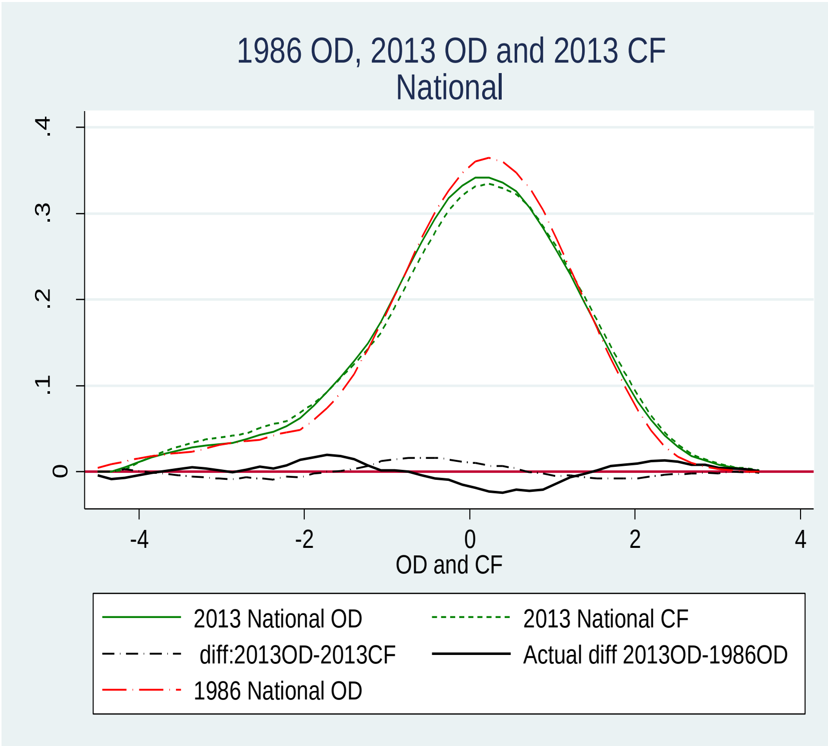


[49] The focus of the decompositions is to explain the role of spatial differences in age structure on the differences between inequality between metropolitan and non-metropolitan areas. Thus the decompositions does not explore the interactions between age group and location.

Non-Metro



All urban areas combined



Note: Difference =2013 distribution-1986 distribution

Figure 3.4 shows that the age-composition effects are a very small component of the overall difference between 1986 and 2013. There are only small differences in the shape of the original distribution and the counterfactual distribution. Visually, it is difficult to tell these distributions apart although the age composition effect in metropolitan areas appears larger and is driven by more people at the top of the distribution in comparison to non-metropolitan areas. In other words, the difference between the original distribution and the counterfactual distribution in metropolitan areas shows a bigger bump at the top of the distribution than for non-metropolitan areas. To quantify the effect of age composition, we report the *MLD* of the original and counterfactual distribution and the differences between them. Table 3.5 presents these results.

The actual *MLD*s are of course identical to those in Table 3.2. In line with the graphical evidence, Table 3.5 shows that the age-share effect has been relatively small but negative. Hence, had age-specific distributions been the same in 1986 as in 2013, the changes in the age structure from 1986 to 2013 would have led to lower income inequality. Across all urban areas, the changes in the age structure (ageing of the population) reduced the *MLD* by about 0.0295. In contrast, the age-specific distribution effect was positive and much larger, leading to an overall 1986-2013 increase in the *MLD* of 0.0939 for all urban areas combined.

Table 3.5: Estimates of age-share and age-specific distributional effects, measured by *MLD*, using the density decomposition approach

Area	2013 Distribution (OD)	2013 Counterfactual distribution (CF)	1986 Distribution (OD)	Total change= 2013OD - 1986OD	Age share effect = 2013OD - 2013CF	Age specific distribution effect= 2013CF-1986OD
Metro	0.4500	0.4765	0.3607	0.0893	-0.0265	0.1158
Non-metro	0.3623	0.3937	0.3563	0.0060	-0.0314	0.0374
All urban areas combined	0.4153	0.4448	0.3509	0.0644	-0.0295	0.0939

While ageing has had an inequality-reducing effect overall, the magnitude of this effect varies spatially. This is not surprising giving the spatial variation in the rates of ageing. The faster ageing of the non-metropolitan areas contributed to a larger inequality-reducing age composition effect (–0.0314, compared with –0.0265 in metropolitan areas).

We see from Table 3.5 that the difference in inequality growth between metropolitan areas and non-metropolitan areas is not fully accounted for by the difference in age composition. The results show that most of the difference in the inequality trends of metropolitan and non-metropolitan areas is due to the much greater age-group-specific inequality growth in the former.

It is easy to reconcile the results based on the *MLD* decomposition approach with those based on the density decomposition approach. This can be seen from Table 3.6, which compares the *MLD* decomposition of Eq. (4) with the density decomposition of Eq. (6). Both methods show that population ageing has had income inequality-reducing effect. The effects are similar, but somewhat smaller in absolute value with the *MLD* decomposition approach. Had the age-specific income distributions remained the same, the *MLD* would have decreased by –0.0223 for all urban areas combined (the sum of effects *C*2 and *C*3' in Table 3.6). The corresponding quantity from the density decomposition approach is –0.0295. Examination by age group shows that this inequality-reducing effect is driven by the negative contributions of the two younger age groups. The youngest age group (15-24) has seen rapidly rising within-group inequality but a reduction in the share of this group has contributed negatively to the change in within-group inequality.

Table 3.6: Contribution to changes in Mean Log Deviation between 1986 and 2013 by age group

	Components of change (see Eq. 4)				Total change	Age-specific distribution effect (C1+C4’)	Age share effect (C2+C3’)	Density (DFL) age share effect	Contribution to within-inequality changes (C1+C2)	Contribution to between-inequality changes (C3’+C4’)
Metropolitan areas										
Age group	C1	C2	C3’	C4’						
15-24	0.026	-0.0309	-0.084	0.0248	-0.0641	0.0508	-0.1149		-0.0049	-0.0592
25-44	-0.0107	-0.0101	-0.0286	0.0137	-0.0357	0.0030	-0.0387		-0.0208	-0.0149
45-64	0.0219	0.0289	0.0826	0.0248	0.1583	0.0467	0.1115		0.0508	0.1074
65+	0.0198	0.0041	0.0189	-0.0146	0.0282	0.0052	0.0230		0.0239	0.0043
Sum	0.0569	-0.008	-0.0111	0.0488	0.0866	0.1057	-0.0191	-0.0265	0.0489	0.0377
Non-metropolitan areas										
Age group	C1	C2	C3’	C4’						
15-24	0.0181	-0.0381	-0.0985	0.0123	-0.1063	0.0304	-0.1366		-0.0200	-0.0862
25-44	-0.0279	-0.0255	-0.0737	0.007	-0.1200	-0.0209	-0.0992		-0.0534	-0.0667
45-64	0.0032	0.0307	0.0973	0.0178	0.1490	0.0210	0.1280		0.0339	0.1151
65+	0.0131	0.0119	0.0684	-0.0119	0.0816	0.0012	0.0803		0.0250	0.0565
Sum	0.0065	-0.021	-0.0065	0.0252	0.0042	0.0317	-0.0275	-0.0314	-0.0145	0.0187
All urban areas combined										
Age group	C1	C2	C3’	C4’						
15-24	0.0234	-0.0326	-0.0873	0.0209	-0.0756	0.0443	-0.1199		-0.0092	-0.0664
25-44	-0.0135	-0.0138	-0.0401	0.0134	-0.0541	-0.0001	-0.0539		-0.0273	-0.0267
45-64	0.0143	0.0279	0.0862	0.0206	0.1491	0.0349	0.1141		0.0422	0.1068
65+	0.0173	0.006	0.0313	-0.0136	0.0411	0.0037	0.0374		0.0233	0.0177
Sum	0.0415	-0.0124	-0.0098	0.0413	0.0604	0.0828	-0.0223	-0.0295	0.0291	0.0315

The 25-44 age group experienced a narrowing of their within-group distribution as well as a reduction in their population share. Both have a negative effect on overall within-group inequality. Table 3.6 shows that the age-specific distribution effect ($C1$+$C4$' in Eq. (4) and the age share effect ($C2$+$C3$') are indeed mostly negative for the 25-44 age group. Interestingly, the metropolitan areas form the exception. In these areas, growth in the mean income of this group relative to growth in overall mean income ($C4$') more than offsets the reduction in within-age group inequality ($C1$).

The contributions of the 45-64 and 65+ groups are in the opposite direction: changes in both groups contribute to growing inequality. This is because within-group inequality, relative income, as well as population share increased for both groups between 1986 and 2013. Thus, for both age groups most components of inequality change are positive. The only exception is the negative component $C4$' for those aged 65+, despite the growth in this group's mean income.[50]

Taking a spatial view by comparing metropolitan areas to non-metropolitan areas, Table 3.6 confirms the smaller inequality-reducing age-composition effect in metropolitan areas. This is as expected due to the less rapid rates of population ageing in the metropolitan areas. The population decomposition by subgroup approach shows that the 1986-2013 changes in the age structure in metropolitan areas reduced *MLD* by about 0.0191, compared to 0.0275 in non-metropolitan areas. As with the national results, we find that most of the growth in inequality is due to changes in the age-specific distribution effect.

Age composition only explains a negligible part of the difference between the changes in inequality between metropolitan areas and non-metropolitan areas. The increase in the age-specific distribution effect on *MLD* has been greater in metropolitan areas (0.1057, about three times the corresponding effect in non-metropolitan areas). The almost equal counteracting age-specific and age-composition effects in non-metropolitan areas explains the very small inequality growth in these areas. If the changes in the age-specific income distribution remain relatively small in non-metropolitan areas in the years to come and ageing there accelerates due to continuing net migration to metropolitan areas, then we may expect inequality to decrease or remain constant in non-metropolitan areas in the foreseeable future.

[50] This is due to the approximation method. For this age group, $(\overline{\pi_a r_a} - \overline{\pi_a}) < 0$. See Eq. (4).

3.5 Conclusion

In this chapter, we examined the relationship between age structure and income inequality in New Zealand using two approaches that have proven popular in the literature. We focussed on differences between metropolitan and non-metropolitan areas in the two ways in which age structure can affect inequality: an age-composition effect and an age-specific distribution effect. We found that the 1986 to 2013 increase in inequality has been mostly due to the changes in the age-specific income distributions. In fact, the age-composition effect has been negative. Population ageing has served to reduce inequality. However, at the same time, age-specific mean incomes diverged, at least until 2001, leading to an increasing share of between-group inequality to overall inequality.

In line with previous analyses on inequality and age structure in New Zealand, we found a notable disparity between metropolitan and non-metropolitan areas in the trends in inequality and age structure. Metropolitan areas have experienced rapid growth in inequality but slower rates of ageing (mostly due to net inward migration rather than greater fertility), while non-metropolitan areas have had slow growth in inequality and faster ageing. We also found that the inequality-reducing effect of population ageing (resulting from the declining shares of younger people) varies across areas and is smaller in metropolitan areas. Notwithstanding this differential age-composition effect, our results show that most of the difference between metropolitan and non-metropolitan areas in inequality growth is due to the much larger age-specific income distribution widening in metropolitan areas.

We complemented the decomposition of changes in the *MLD* index of inequality with a visualisation of changes in density along the income distribution. This revealed a thinning of the density in the middle of the overall distribution, for which the 15-24 and 25-44 age groups were mostly responsible. At the same time, the age group 45-64 added more density to the upper end (right tail) of the distribution, while those aged 15-24 contributed to an increase in density at the lower tail. Together, these changes led to a hollowing out of the distribution.

In this research we have simplified the analysis of spatial differences in income inequality by adopting a metropolitan versus non-metropolitan dichotomy. In future work we intend to use a more refined spatial disaggregation of areas, as well as examine the role of other population composition effects on inequality, such as effects due to country of birth and migrant status, household type and education. Jointly, this may provide further in-depth insights into how population ageing impacts on mean incomes and income inequality across regions and cities.

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Chapter Four: Article 3 - International migration and the distribution of income in New Zealand metropolitan and non-metropolitan areas[51]

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[51] Alimi, Maré and Poot (2018) - This chapter co-authored with Emeritus Prof. Jacques Poot and Adj. Prof Dave Maré is available as an IZA discussion paper: Alimi, O., Maré, D. C., & Poot, J. (2018b). *International migration and the distribution of income in New Zealand metropolitan and non-metropolitan areas*. IZA Discussion Paper. Bonn: IZA Institute of Labour Economics. A version of this chapter was awarded the 2017 Australia and New Zealand Regional Science Association International conference prize for best paper by a current or recent student

Abstract

Since the 1980s, income inequality in New Zealand has been a growing concern - particularly in metropolitan areas. At the same, the encouragement of permanent and temporary immigration has led to the foreign-born accounting for a growing share of the population; this is disproportionally so in metropolitan areas. This paper investigates the impact of immigration, by skill level and length of stay, on the distribution of income in metropolitan and non-metropolitan areas. We apply decomposition methodologies to data obtained from the 1986, 1991, 1996, 2001, 2006 and 2013 Censuses of Population and Dwellings. We find that increases in the immigrant share of population in an area have an inequality-increasing and area-specific effect. Changes in immigrant-group specific distributions of income are inequality-reducing in non-metropolitan areas but inequality-increasing in metropolitan areas. Inequality increased in metropolitan areas because the overall inequality-increasing effect of immigration is larger than the inequality-reducing changes for the New Zealand-born, but the opposite is the case in non-metropolitan areas - the overall inequality-reducing change in the income distribution of the New Zealand-born there was larger than the inequality-increasing effect of immigration.

The methodologies adopted here can also benefit the study of income distribution changes in countries with similar immigration policies, such as Australia and Canada.

Disclaimer

Access to the data used in this study was provided by Statistics New Zealand (SNZ) under conditions designed to give effect to the security and confidentiality provisions of the Statistics Act 1975. All frequency counts using Census data were subject to base three rounding in accordance with SNZ's release policy for census data.

4.1 Introduction

Immigration has a major impact on population size, composition and distribution in New Zealand. Data from the 2013 Census of Population and Dwellings show that nationally, around 1 in 4 persons in New Zealand is foreign-born (Statistics New Zealand, 2014). Sub-nationally, international migration is even more significant in metropolitan areas, like the Auckland region where almost 4 out of 10 people are foreign-born. Accompanying the rising rate of immigration is a growing public debate on the appropriate levels of immigration and the perceived or actual societal impacts of immigrants. In addition to social concerns, there are also concerns about the effect of immigrants on the labour market[52] through their impact on wages and employment. These concerns are voiced both in the popular media (see Fyers, 2017) and among professional economists (Fry & Wilson, 2017).

There is already considerable New Zealand evidence on the impact of immigration on economic variables like wages and house prices (see Stillman & Maré, 2008; Maré & Stillman, 2009; and the review by Hodgson & Poot, 2011). However, the impact of immigration on the distribution of labour income has not previously been investigated explicitly at national or sub-national levels in New Zealand. To do so is the objective of the present paper. Additionally, the methodologies applied here may be useful in the context of countries like Australia and Canada, which have similar immigration policies.

International migration may affect the overall distribution of income in a destination area through three specific channels: 1) the compositional channel – due to differences between the aggregate income distributions of migrants and locals, and the changing relative proportions of these groups in the population; 2) the immigrant-specific income distribution channel whereby income distributions of migrants change differentially from those of locals; and 3) the general equilibrium effect of immigration on the income distribution of locals.

We focus on six different groups of international migrants and compare them with two groups of New Zealand-born using the sub-group decomposition

[52] New Zealand has the fifth highest proportion of immigrants in the population among OECD countries (after Luxembourg, Switzerland, Australia and Israel), see e.g. https://data.oecd.org/migration/foreign-born-population.htm

methodology of Mookherjee and Shorrocks (1982). We calculate how each of these groups contributes to changes in the overall distribution of income between 1986 and 2013 in metropolitan and non-metropolitan areas. Because immigrants are self-selected on certain characteristics like age and sex, we use a regression decomposition approach to calculate the conditional-contributions of migrant groups accounting for age, sex and employment status. By calculating the by-group between and within-group contribution using the regression framework and comparing it to the sub-group decomposition method, we aim to reconcile two different strands of decomposition literature which has evolved separately in the literature but have had few attempts to reconcile them.

The 1986 to 2013 period represents a period of rising immigration as well as diversification in the type of immigrants coming to New Zealand. Phillips (2005) notes that "for over 130 years, from 1840 to the 1970s, New Zealand sought to people itself with 'kith and kin' from the United Kingdom. In the years since then, immigration from new countries has transformed the nation's culture and values". As well as examining the overall effect of these changes, we account for the fact that migrants are disproportionally attracted to metropolitan areas. Recent events like the Brexit vote in the UK have shown that space matters when considering changes in the income distribution. Focusing on national effects may be misleading or hide significant differences.

The analysis examines the composition effect (or the migrant-share effect) and changes in the distribution of income of migrant and non-migrant groups (migrant-specific income distribution effect). For both effects, we consider changes over time and differences across areas. We focus our analysis on the urban population of New Zealand aged 25 to 64 and earning positive income.[53] This way, we aim to capture labour market effects.[54]

We find evidence of an income inequality-reducing effect of increasing duration of stay in New Zealand among international migrants. Inequality is higher among

[53] The population aged 25 to 64 earning positive income living in urban areas (both non-metropolitan and metropolitan) accounted for more than three quarters of all people aged 25 to 64 in New Zealand in each census period.

[54] Strictly speaking, income captured for the 25-64 age group in Censuses includes other non-labour income, like investment income, but Statistics New Zealand estimates that wages and salaries contribute more than two-thirds of overall income in general and even more so for those aged 25-64 (Statistics New Zealand, 1999). Other data sources like the Household Economic Surveys may provide better information on labour market incomes; but the Census remains the most comprehensive dataset for analysis at the sub-national level where surveys typically suffer from relatively large sampling errors and bias.

newly arrived immigrant groups than among earlier immigrant groups regardless of skill level.

With respect to changes in the distribution of income between 1986 and 2013 across areas, we find that inequality rose slightly by about 1% in all urban areas combined but this masks the spatial difference. Inequality fell in non-metropolitan areas by 11% and rose in metropolitan areas by 4%.

We find that the proportion of immigrants in metropolitan areas is almost double that in non-metropolitan areas in all periods. This has a major impact on overall change in inequality. For the New Zealand-born (excluding New Zealand-born who have returned from living abroad), we find that changes in their population share and in their within-group income distribution are inequality-reducing across all areas. For all immigrant groups, increases in their population share have a universal inequality-increasing effect in both metropolitan and non-metropolitan areas but the effect of changes in the immigrant-specific distribution of income differs by area: it is inequality-reducing in non-metropolitan areas but inequality-increasing in metropolitan areas.

How do immigrants affect the distribution of personal incomes in destination areas? International migrants typically have a different income distribution when compared to locals. For example, immigrants may have a skill distribution that differs from the one for locals. Also, immigrants' skills may be rewarded differently in the labour market compared with those of locals. Furthermore, an increase in the number of immigrants effectively serves as an increase in labour supply and, depending on whether immigrants serve as substitutes or complements to locals, immigration may increase or decrease the labour market income of locals. All these effects imply that an increase in immigration may widen or narrow the distribution of income (or leave it unchanged). The impact of immigration on the earnings of locals is one of the most actively researched areas in the labour economics literature (see, e.g., Card, 1990, Borjas, 2003, Borjas et al., 1997, D'Amuri et al., 2010). In addition, international migrants are not a homogenous group. They may represent different age groups, skills, languages, and ethnicities. International migration may then impact on the overall distribution of income through changes in the distribution of income among migrants themselves, i.e. a "within the migrant group" effect. For example, certain classes of migrants may have skills that are relatively scarce and therefore rewarded highly. An increasing proportion of such migrants among the immigrants may widen the migrant and overall distributions of income.

Empirically, the evidence suggests that immigration has small effects on the individual earnings of locals (see Maré & Stillman, 2009 for New Zealand evidence; Card, 2009, for US evidence; Productivity Commission, 2006, for Australian evidence; and Longhi et al., 2005 for a meta-analysis of the international evidence). This extensive evidence justifies why we choose to focus on the other two channels through which migration can affect the overall income distribution: the population composition effect and migrant-specific distribution effect. Both effects can be quite important. For example, Card (2009) finds that immigration in the US has very small impacts on wage inequality among locals, but when immigrants themselves are counted in the overall population; their presence can explain around 5% of the increase in overall wage inequality in the US between 1980 and 2000.

There are two important considerations when evaluating the role of international migration on the distribution of income in New Zealand: firstly, it is expected that the impact of international migration on the distribution of income will depend on the type of migrant (including New Zealand-born returning from abroad). Secondly, the length of stay of migrants in New Zealand is another important factor to account for when analysing the effect of international migration on inequality. There is existing evidence of convergence in incomes of migrants and locals the longer migrants stay in host countries (see Stillman & Maré, 2009 for New Zealand evidence). Hence, we expect the impact of international migration on the distribution of income to be dependent on the type of migrant as well as on their length of stay. We therefore classify migrants by skill level (into two groups: *High* and *Medium/Low Skilled*) and by their length of stay (also into two groups: *Newly Arrived* and *Earlier* migrants). Apart from these groups, there is also a stock of returning New Zealand-born people who were previously residing overseas. It is expected that these groups may have a different impact on the distribution of income than other immigrants and we therefore include them separately.[55]

[55] Selective emigration by the New Zealand born may influence the distribution of income in New Zealand too. However, there are no data on the incomes of emigrants before they left New Zealand. Some research suggests that the propensity to emigrate is similar across all skill groups, at least in trans-Tasman migration (e.g., Bushnell and Choy, 2001). Other research shows that the

The rest of the study proceeds as follows: Section 2 provides a brief review of the literature on the relationship between migration and the distribution of income. Section 3 introduces the decomposition methodologies. Section 4 describes the data and provides a description of the changes in immigration as well as of the distribution of income in New Zealand between 1986 and 2013. Section 5 presents the results and section 6 concludes.

4.2 Literature Review

Blau and Kahn (2012) and Card (2009) have provided an extensive review of the theoretical and empirical evidence on the relationship between immigration and the distribution of income. Here we will therefore remain brief and focus only on three channels through which international migration affects the distribution of income in destination countries:

- The composition, or shares, effect;
- The effect on incomes of locals;
- The migrant-specific distribution effect.

4.2.1 The composition/shares effect

Immigrants typically possess characteristics that differ from the locally-born and these differences may influence local inequality. Immigrants typically have a different skill composition as well as different returns for skills. Both factors can influence inequality. Card (2009) found that immigrants are clustered at the high and low ends of the educational distribution and tend to have higher residual inequality than natives (p.19). Immigrants are typically self-selected, and the compositional difference could have implications for the overall distribution of income in their destination countries. Lumpe and Weigert (2010) present a theoretical framework that shows that the effect of immigration on between-skill group inequality is ambiguous and depends on the educational attainment level of the host country. In New Zealand's case, the compositional effect may be important as a key objective of past and present migration policy is to attract migrants to address skill shortages.[56] The impact of this selectivity on local

New Zealand-born have the highest rate, among the OECD countries, of highly skilled living abroad (Dumont and Lemaitre, 2005).

[56] There is also a considerable flow of temporary migrants which consists predominantly of people taking up unskilled or semiskilled work in agriculture and tourism.

inequality will depend on where most immigrants fall in the distribution of income in the destination areas – which is dependent on the skill distribution of this area and how migrants are rewarded. There is existing empirical evidence that New Zealand migrants are different from the locally-born and are rewarded differently in the labour market (Stillman &Maré, 2009; Poot & Stillman, 2016; Poot & Roskruge, 2013). Although there is evidence of some convergence over time, some persistent differences remain. For example, using data from 1997 to 2007, Stillman and Maré (2009) provide evidence that around 15 years after arrival, the income difference between immigrants and native-born New Zealanders has halved for men and disappears entirely for women. Thus, given the pattern of difference between migrants and locals in skill distribution as well as in returns for skills, it is expected that the compositional effect might be particularly relevant for New Zealand. The compositional effect may vary spatially, given the selectivity in terms of places immigrants choose to locate in. Most immigrants prefer the bigger metropolitan areas. Moore and Pacey (2003) examined the differences between metropolitan and non-metropolitan areas in the role of immigration with respect to the level of income inequality in Canada between 1980 and 1995.They found that the effects of immigrants on inequality were greater in the metropolitan cities, with the impact in the two cities of Toronto and Vancouver almost twice the rate of impact in any other city in the early 1990s.

4.2.2 Migration and distribution of income of locals

This is perhaps one of the most actively researched areas in the labour migration literature. There has been a lot of effort put into understanding the effect of immigration on labour market outcomes of locals in destination countries. This area of research is very important because migrants are typically an addition to the labour supply and a big part of the debate on the impact of immigration on locals is typically framed around the effect of immigration on wages and employment. Two main methodological approaches have dominated the literature measuring the effect of migrants on the income of locals[57]: the first approach (the area-variation approach) compares the distribution of income in places with high immigration to those with low immigration, it regresses the wages or incomes of locals on the relative number of immigrants in that area while controlling for other factors, the coefficient on the number of immigrant variable is then taken as the

[57] See Blau and Kahn (2012) for a review of the empirical and methodological literature.

impact of immigration on the income of locals. The second approach (factors proportions approach) estimates the parameters of an assumed aggregate production function and uses these parameters to simulate the impact of any type of migration change. Another key distinction in the literature is the way to define the labour market in which to analyse the effect of immigration on wages. Borjas (2003) advocated that the level of analysis should be at the national level because the local labour market can adjust in response to immigration. For example, locals may respond through internal migration which may equilibrate the market but studies like Card (2001) finds that inter-city mobility rates of locals and earlier immigrants are insensitive to immigrant inflows.

Some studies have also used natural experiments in the form of exogenous large shocks to migration, such as the Mariel Boatlift (see Card, 1990), to explore the impact of migration on the earnings of locals. LaLonde and Topel (1991), Altonji and Card (1991), Card (2001), and Borjas (2003, 2005) reported that immigrants lower the wages of natives.[58] In contrast, Dustmann, Fabbri and Preston (2005), Cortés (2008), Manacorda, Manning and Wadsworth (2012), and Card (2005) found that immigrants do not have statistically significant effects on the wages of locals, and Card (2009), Winter-Ebmer and Zweimüller (1996), and Foged and Peri (2016) showed that immigrants increased the wages of locals.

New Zealand evidence from Maré and Stillman (2009), Tse and Maani (2017), and Maani, and Chen (2012) find little evidence that immigrants negatively affect wages of local-born. Maré and Stillman (2009), find some evidence that increases in the number of high-skilled recent migrants have small negative impacts on the wages of high-skilled New Zealand-born workers, which are offset by small positive impacts on the wages of medium-skilled New Zealanders. Tse and Maani (2017) incorporated immigrant effective work experience and spatial regional impacts and finds immigration has little impact on earnings and employment hours. Maani and Chen (2012) focused on skilled immigrants and find no adverse wage impact from skilled immigration on native workers of similar skill but find highly skilled immigration has a small negative wage effect for low-skilled native workers.

Overall, the literature appears inconclusive regarding the wage impact of immigration, given the abundance of positive, negative and insignificant results in

[58] In some studies, immigrants' lower wages of certain types of locals. For example, Card (2001) finds that immigrants lower wages of skilled locals.

the literature, but the evidence points towards the effects being quantitatively small in most cases. A meta-analysis of the literature on the labour market impacts of immigration on native workers in terms of wages and employment reveals small effects (Longhi et al. 2008).[59] We conclude that we expect the effect of immigration on the overall distribution of income through its impact on the income of locals to be quantitatively small[60]. This study therefore excludes this channel and focuses on the composition and migrant-specific distribution channels.

4.2.3 Migrant-specific distribution effect

Immigrants are not a homogenous group and any income differences between migrants themselves may affect the overall distribution of income in destination areas. In New Zealand, besides the targeted "Skilled Migrant" category, there is a whole range of other migrant streams. Many of these are not selective on skills (e.g. family reunification and refugee admission schemes). Indeed, it is highly likely that the distribution of income within the migrant community is wider than among locals (see Card, 2009 for US evidence). Furthermore, there is evidence that the effect of recent immigration on the labour market is mostly felt by earlier migrants, with recent and earlier migrants acting as substitutes in the labour market. For example, Cortés (2008) shows that the negative impact of low skill immigration is felt mostly by earlier immigrants, with immigration lowering their wages (also confirmed by the meta-analysis by Longhi et al. (2005). Thus, depending on the size of the migrant group, immigration may affect the overall distribution of income through the distribution of income among migrants being different from that among the local-born. Consequently, this study examines the role of changes in the migrant-specific distribution of income on the overall distribution of income.

Apart from the mechanisms described above, international migration has also been linked to the distribution of income through other mechanisms. For example, Blau and Kahn (2012) note that immigration may change relative factor supplies, affect returns to capital investment, or influence the child care availability and female labour force participation of higher-earning women. All these factors may

[59] Evidence from studies like LaLonde and Topel (1991). Altonji and Card (1991) and Card (2001, 2005, 2009) also find small effect of immigration on the distribution of income of locals.
[60] Evidence from New Zealand studies find quantitatively small effects

also have implications for the distribution of overall income but are they are beyond the scope of the present study.

The next section presents the decomposition methodologies used in this study.

4.3 Methodology

The study decomposes both levels and changes in inequality. The levels decomposition is the between- and within-group decomposition of the MLD and a regression based on between- and within-group decomposition[61]. Changes in inequality are decomposed using the population decomposition by sub-group approach of Mookherjee and Shorrocks (1982), and the regression-based decomposition approach. The method of Mookherjee and Shorrocks (1982) is described in Alimi, Maré and Poot (2017) but we provide a brief recap here.
Our measure of inequality is the Mean Log Deviation (MLD). The MLD is part of the family of generalised entropy indices (Bourguignon, 1979). These measures have the advantage of being additively decomposable (i.e. inequality among people in a group can be expressed as the weighted sum of inequalities between and within the sub-groups).We use the MLD instead of the slightly more popular Theil measure because our focus is on how changes in the demographic shares of migration in population have affected the distribution of income and, unlike the Theil measure (which weights by income share), the MLD weights by population share. Since we are concerned about the effect of changes in population shares, this makes the MLD a natural choice and fit for purpose. Additionally, it has been shown that MLD is less sensitive to uncertainty about incomes at the upper end of the distribution (Cowell and Flachaire, 2007).
Introducing some notation, let the aggregate income of all those in a migration-status group *m* be Y_m. For simplicity we will refer to the population group representing those who have never migrated as one of the groups. N_m is the population of migrant group *m*. N is the overall population, i.e. $N = \sum_{m=1}^{M} N_m$. Total income in the economy is $Y = \sum_{m=1}^{M} Y_m$. Finally, we denote average income in the economy by $\mu = Y/N$, average income of migrant group *m* by $\mu_m = Y_m/N_m$, relative income of migrant group *m* by $r_m = \mu_m/\mu$ and the fraction of the population that belongs to migrant group *m* as $\pi_m = \frac{N_m}{N}$. If everyone in group *m*

[61] We provide an extension to the regression decomposition methodology that allows us to express the contributions of each migrant group in terms of between and within-group contributions

has the same income (i.e. each person's income is μ_m), we need not be concerned about intra-group inequality and overall inequality can then simply be expressed as the weighted average of the (natural) logarithms of group-relative incomes, i.e.

$$MLD = \sum_{\mathrm{m=1}}^{M} \frac{N_m}{N} \ln\left(\frac{Y/_N}{Y_m/_{N_m}}\right) = \sum_{\mathrm{m=1}}^{M} \pi_m \ln\left(\frac{1}{r_m}\right) \quad (1)$$

More generally, the individuals within group *m* will have different incomes and the overall MLD level can then be decomposed into the weighted sum of within-migrant-group inequalities and the value of between-migrant-group inequality (which is the weighted sum of logged between-group inverse relative incomes):

$$MLD = \sum_{m=1}^{M} \pi_m MLD_m + \sum_{m=1}^{M} \pi_m \ln\left(\frac{1}{r_m}\right) \qquad (2)$$

in which $MLD_m = \sum_{\mathrm{i=1}}^{N_m} \frac{1}{N_m} \ln\left(\frac{\mu_m}{y_i}\right)$ is a measure of within-migrant-group inequality, y_i is the income of individual i,
$\sum_{m=1}^{M} \pi_m MLD_m$ is the migrant-share-weighted sum of within-migrant-group inequality and $\sum_{m=1}^{M} \pi_m \ln\left(\frac{1}{r_m}\right)$ the migrant-share-weighted sum of the logarithm of the inverse of migrant-group relative income (i.e., between-migrant-group inequality).

4.3.1 Population sub-group decomposition of inequality change of Mookherjee and Shorrocks (1982)

With some simple algebra, it can be shown that the change in the MLD between two periods can be expressed exactly as follows:

$$\Delta MLD = \underbrace{\sum_{m=1}^{M} \overline{\pi_m} \Delta MLD_m}_{\substack{aggregate \\ change\ in \\ within-migrant\ group \\ inequality\ for\ given \\ migrant\ shares \\ C1}} + \underbrace{\sum_{m=1}^{M} \overline{MLD_m} \Delta\pi_m}_{\substack{aggregate \\ change\ in \\ within-migrant\ group \\ inequality\ due\ to \\ changing\ migrant\ shares \\ C2}} + \underbrace{\sum_{\mathrm{m=1}}^{M} \overline{\ln\left(\frac{1}{r_m}\right)} \Delta\pi_m}_{\substack{aggregate \\ change\ in \\ between-migrant\ group \\ inequality\ due\ to \\ changing\ migrant\ shares \\ C3}} + \underbrace{\sum_{m=1}^{M} \overline{\pi_m} \Delta \ln\left(\frac{1}{r_m}\right)}_{\substack{aggregate \\ growth\ in \\ migrant\ group\ relative \\ income\ for\ given \\ migrant\ shares \\ C4}} \qquad (3)$$

where a bar over an expression represents the simple arithmetic average of the variable over the two periods, i.e. $\bar{x} = \frac{1}{2}(x_{t-1} + x_t)$. Mookherjee and Shorrocks' (1982) methodological contribution was to suggest an approximate decomposition of ΔMLD, which will explicitly include group-specific mean income growth.[62] We use this approximate change decomposition, such that the change in overall inequality can be expressed as:

$$\Delta MLD \approx \underbrace{\sum_{m=1}^{M} \overline{\pi_m} \Delta MLD_m}_{C1} + \underbrace{\sum_{m=1}^{M} \overline{MLD_m} \Delta \pi_m}_{C2} + \underbrace{\sum_{m=1}^{M} (\overline{r_m} - \overline{\ln r_m}) \Delta \pi_m}_{C3'} + \underbrace{\sum_{m=1}^{M} (\overline{\pi_m r_m} - \overline{\pi_m}) \Delta \ln \mu_m}_{C4'} \quad (4)$$

Where:

- $C1$ is the aggregate change in within-migrant group inequality for given migrant-shares
- $C2$ is the aggregate change in within-migrant group inequality due to changing migrant-shares
- $C3'$ is the aggregate change in between-migrant group inequality due to changing migrant-shares
- $C4'$ is the aggregate growth in migrant-group mean income for given migrant-shares

The sum of $C2$ and $C3'$ thus represents the migrant-shares or composition effect and the sum of $C1$ and $C4'$ represents the migrant group-specific distribution effect.

4.3.2 Regression Decomposition Method

The regression decomposition method is an extension of Shorrocks' (1982) work on decomposition of income by additive factor components. Fields and Yoo (2000) extended this analysis and showed that Shorrocks' (1982) theorem is applicable when using an additive income generating function. An income generating function has the same additive form as any equation expressing total income as the sum of income from various components.

Using the income-generating function of the form:

$$lnY_{it} = \alpha_t + \sum_{k=1}^{K} \beta_{kt} X_{ikt} + \varepsilon_{it} \quad (6)$$

X_{ikt} is the value of the k^{th} covariate that determines the income of an individual *i* at time *t* and lnY_{it} is the logarithm of individual income *i* at time *t*. Fields and Yoo

[62] Mookherjee & Shorrocks (1982) note that this approximation appears sufficient for computational purposes (p.897). It is clear that C3' – C3 = $\sum_{m=1}^{M} \overline{r_m} \Delta \pi_m$. Experimentation with a range of changing income distributions shows that the sign of *C*3 can be sometimes different from that of *C*3' and, similarly, the sign of *C*4 can be different from that of *C*4'. This may lead to slightly different interpretations. In this paper, we follow Mookherjee & Shorrocks (1982) and use the approximate decomposition. Results for the exact decomposition are available upon request.

(2000) showed that the proportion of level of earnings inequality accounted for by factor *k* (relative factor inequality weight) S_{kt} is:

$$S_{kt=}\frac{\widehat{\beta_{kt}}*Cov(X_{kt},lnY_t)}{Var(lnY_t)}\ or\ \frac{\widehat{\beta_{kt}}*SD(X_{kt})*corr(X_{kt},lnY_t)}{SD(lnY_t)} \quad (7)$$

Where:

- $Cov(X_{kt}, lnY_t)$ is the covariance between factor X_k and lnY at time *t*
- $Var(lnY_t)$ is the variance of the logarithm of income
- $SD(lnY_t)$ and $SD(X_{kt})$ are the standard deviations of lnY and X_k at time *t* respectively
- $Corr(X_{kt}, lnY_t)$ is the correlation between factor X_k and lnY

S_{kt} represents the marginal contribution of the explanatory variable to the variance of the dependent variable and can be interpreted as the group-mean contribution of each factor at time *t*. If the regression has one explanatory variable then, in the terminology of sub-group decomposition methodology, S_{kt} represents the between-group contribution of that variable (X_k) to overall inequality[63].

Just as in Shorrocks (1982), with respect to additive contributions to overall income, the relative contribution of a factor to overall inequality S_{kt} is invariant to the choice of inequality measure I_t (if the measure satisfies Shorrock's six axioms). The contribution of an individual factor to earnings inequality is therefore simply:

$$S_{kt} * I_t \quad (8)$$

The estimated contributions of each factor to the level of inequality can then be used to estimate the contributions to inequality change. The contribution of each factor to change[64] in inequality between time *t* and *t*+1 is simply calculated as:

$$\delta_k = S_{k,t+1} * I_{t+1} - S_{k,t} * I_t \quad (9)$$

One of the advantages of the regression decomposition framework is the possibility of accounting for multiple explanatory variables. The sub-group decomposition approach quickly becomes unwieldy if we account for multiple explanatory factors[65]. Fields and Yoo (2000) demonstrate the strength of the

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[63] X_k is either a continuous variable or a set of dummy variables for a classification of factors such as ethnicity, education, etc.

[64] Unlike the contribution of each factor to level S_{kt}, the contribution of each factor to change δ_k in equation (9) is dependent on the choice of inequality measure (Fields and Yoo, 2000)

[65] For example, in our research accounting for sex and migrant status alone means there would be 16 groups (8 migration status categories * 2 sex categories).

regression decomposition approach to account for multiple explanatory variables in their examination of earnings inequality in Korea.

However, there are several limitations of the Fields and Yoo approach[66]. Most notably, with multiple explanatory variables, the standard Fields and Yoo approach relies on the assumption of mutually orthogonal explanatory variables. This assumption is very restrictive since income-determining explanatory variables are often correlated. In the regression framework, the marginal effect of a particular variable is then not unique and is dependent on the order in which the factor is included in the regression. The standard Fields and Yoo approach capture the contribution of each variable as if it was added last. Basically, the contribution of a variable (continuous or set of dummies for a classification) is the increment to R^2 from including the variable in the regression divided by the overall R^2.

Subsequent studies have adopted a Shapley value regression decomposition approach[67]. With its origin in game theory research, this approach uses a regression framework and calculates the average marginal effects of each explanatory variable (e.g. age, sex, migration status) from all possible orderings of the variance in the dependent variable (income). The marginal effects are calculated by introducing the variable into a regression model and measuring the contribution of that variable to the variance of the dependent variable. Since the marginal effect of a particular variable is not unique and is dependent on the order in which the factor is included in the regression, the average of all marginal effects of each variable in all possible orderings is treated as the contribution of that explanatory variable to inequality in the dependent variable. With K number of explanatory variables, the total possible numbers of orderings are K!. Israeli (2007) show that the basic Fields and Yoo approach is a stylised version/approximation of the Shapley value decomposition that assumes no correlation between the explanatory variables.

In this study, we use the Shapley value regression decomposition approach in a framework with age, sex and employment status as other explanatory variables alongside migration status (which already differentiates between skills[68]). We

[66] See Wan (2002,2004) for a discussion of the limitations of the Fields and Yoo approach.
[67] This approach has its origins in Shorrocks (1999), later published in Shorrocks (2013) and has been used in empirical studies such as those of Wan (2004) and Gunatilaka and Chotikapanich (2009).
[68] The definition of variables used in the regression decomposition method are given in Table 4.A.9

examine the contribution of each migrant group to the level of inequality accounting for age, sex and migration status by comparing the group-mean contributions of migrant groups in a regression on only migration dummies with another regression where we include age, sex and employment status.

Migrant categories are represented by a group of eight dummy variables representing each migrant group, as described in Section 4.4.1. For our Shapley regression, we treat them as a block and they are introduced into the regression together. Our full adjusted regression model is:

$$Y_{it} = \sum_{k=1}^{8} \beta_{kt} X_{ikt} + \beta_{at} Age_{it} + \beta_{st} Sex_{it} + \beta_{et} Empstatus_{it} + \varepsilon_{it} \quad (10)$$

X_k are the migration category dummies

To ensure that we had results for the conditional-contribution of each migrant group, we ran our regressions without an intercept because dummy variables were included for all migrant groups. Our marginal contributions are not affected by the exclusion of the intercept, given the way in which the average or marginal effects are calculated:

$$S_{kt=} \frac{\beta_{kt} * Cov(X_{kt}, Y_t)}{Var(Y_t)} \quad (11)$$

S_{kt} does not depend on the addition or removal of a constant i.e. the intercept is incorporated in the set of migration dummies.

Besides calculating the contribution of each migrant-group to between-group inequality using the regression framework, we provide an extension to the regression decomposition method that calculates the within-group contributions by migrant group to the level of inequality as well. To illustrate our extension, we assume an income-generating function with migration status as the only independent variable and three migrant categories represented by dummy variables D_{Hm} for High Skilled migrants, D_{Om} for Other Skilled migrants, and D_{Lm} for Low skilled migrants

$$Y_i = \beta_{Hm} D_{iHm} + \beta_{Om} D_{iOm} + \beta_{Lm} D_{iLm} + e_i \quad (12)$$[69]

In factor component terminology, $\beta_{Hm} D_{iHm}$ can be interpreted as mean income from source - High Skilled migrant, $\beta_{Om} D_{iOm}$ is mean income from source -

[69] There is no constant term in Equation 12 in order to allow us to calculate the contribution of each group.

Other Skilled migrant, and $\beta_{Lm}D_{iLm}$ is mean income from source - Low Skilled migrant. Using Fields' initial approach, the contribution of High Skilled migrants (S_{Hm}), Other Skilled migrants (S_{Om})and Low Skilled migrants (S_{Lm}) are[70]:

$$S_{Hm} = \frac{\widehat{\beta_{Hm}}Cov(D_{Hm,}Y)}{Var(Y)} ; S_{Om} = \frac{\widehat{\beta_{Om}}Cov(D_{Om,}Y)}{Var(Y)} ; S_{Lm} = \frac{\widehat{\beta_{Lm}}Cov(D_{Lm,}Y)}{Var(Y)}$$

S_{Hm} , S_{Om} and S_{Lm} are the mean-group contributions of High Skilled migrants, Other Skilled migrants, and Low skilled migrants respectively to overall inequality in Y such that:

$$S_{Hm} + S_{Om} + S_{Lm} = R^2 \ (13)$$ [71]

Alternatively, we can arrive at $S_{Hm}, S_{Om}\ and\ S_{Lm}$ by regressing each of the estimated income sources ($\widehat{\beta_{Hm}}D_{Hm}$, $\widehat{\beta_{Om}}D_{Om} and\ \widehat{\beta_{Lm}}D_{Lm}$) on Y[72]:

$$\widehat{\beta_{Hm}}D_{Hm} = \alpha + \rho_{Hm}Y_i + u_i \qquad (14)$$

where $\widehat{\beta_{Hm}}$ is the estimated mean for group Hm etc.

S_{Hm} is calculated by:

$$\hat{\rho}_{Hm} = \frac{Cov(\widehat{\beta_{Hm}}D_{Hm}, Y_i)}{Var(Y_i)} = S_{Hm} \quad (15)$$

For S_{Om}, we regress:

$$\widehat{\beta_{Om}}D_{Om} = \alpha + \rho_{Om}Y_i + u_i \quad (16)$$

Such that $S_{Om}$is calculated by:

$$\hat{\rho}_{Om} = S_{Om} = \frac{Cov(\widehat{\beta_{Om}}D_{Om}, Y_i)}{Var(Y_i)} = S_{Om} \quad (17)$$

For S_{Lm}, we regress:

$$\widehat{\beta_{Lm}}D_{Lm} = \alpha + \rho_{Lm}Y_i + u_i \quad (18)$$

Such that $S_{Lm}$is calculated by:

$$\hat{\rho}_{Lm} = \frac{Cov(\widehat{\beta_{Lm}}D_{Lm}, Y_i)}{Var(Y_i)} = S_{Lm} \quad (19)$$

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[70] The βs are estimated by OLS regression of equation (12)

[71] The R^2 in equation (13) is the R^2 of regression estimation of equation (12) with a constant in which one of the dummies is omitted.

[72] This follows from how regressions are calculated. For an equation: $Y = \alpha + \beta X + \in$, $\hat{\beta} = \frac{Cov(X,Y)}{Var(X)}$ and Cov(cX,Y) = cCov(X,Y)

The residual e_i in Equation (12) represents the unexplained variation in inequality not accounted for by the differences in the by-group mean for the migrant categories. This represents the sum of within-group contributions from all migration categories. We now estimate the within-group contributions of each migration category to the level of inequality by assigning this residual to each migrant category. We do this by multiplying the estimated residual ($\widehat{e_i}$) by the migration dummies(D_{Hm}, D_{Om} and D_{Lm}). By allocating the residuals, it is possible to calculate the contribution to inequality levels from each factor arising from differences in group-mean incomes (between-group) as well as within-group inequality.

In this illustration, by allocating the residual, we can write income as the sum of six components:

$$Y_i = \beta_{Hm}D_{Hm} + \beta_{Om}D_{Om} + \beta_{Lm}D_{Lm} + e_iD_{Hm} + e_iD_{Om} + e_iD_{Lm} \quad (20)$$

The between-migrant group contributions are:

$$S_{Hm} = \frac{\hat{\beta}_{Hm}Cov(D_{Hm,}Y)}{Var(Y)} \quad (21)$$

$$S_{Om} = \frac{\hat{\beta}_{Om}Cov(D_{Om,}Y)}{Var(Y)} \quad (22)$$

$$S_{Lm} = \frac{\hat{\beta}_{Lm}Cov(D_{Lm,}Y)}{Var(Y)} \quad (23)$$

Within-migrant group contributions are:

$$W_{Hm} = \frac{Cov(\widehat{e_i}D_{Hm,}Y)}{Var(Y)} \quad (24)$$

$$W_{Om} = \frac{Cov(\widehat{e_i}D_{Om,}Y)}{Var(Y)} \quad (25)$$

$$W_{Lm} = \frac{Cov(\widehat{e_i}D_{Lm,}Y)}{Var(Y)} \quad (26)$$

The overall level of inequality is now the sum of contributions from within and between-group inequality

$$\underbrace{S_{Hm} + S_{Om} + S_{Lm}}_{\substack{Overall\ between-\ group\ inequality \\ or \\ Overall\ between-\ group\ inequality \\ or \\ R^2}} + \underbrace{W_{Hm} + W_{Om} + W_{Lm}}_{\substack{Allocated\ unexplained\ variation \\ or \\ Overall\ within-group\ inequality \\ 1-R^2}} = 1 \quad (27)$$

This method can be extended to a regression with multiple co-variates and will yield estimates of the conditional-contributions of each group to the level of inequality. In the multiple covariates case, unlike the mean-group contributions, the within-group contributions do not depend on the order in which they are introduced into the regression, so we used the method described above in Equations (24)-(26) to calculate the within-group contributions of each group while the mean-group contributions were calculated using the Shapley value decomposition approach (as the average of the marginal contributions from all possible orderings).

Similarities and differences between the regression and sub-group decomposition approaches.

The regression decomposition and sub-group decomposition techniques try to answer similar questions, such as what proportion of the inequality level is explained by some factor/characteristics (e.g. age, sex, etc.). In this paper, we provide an extension to the regression decomposition methodology that allows us to express the contribution to the level of inequality in terms of within and between-group inequality as in the sub-group decomposition. We compare the results from our extension of the regression method by decomposing overall inequality into the between and within contributions of each migrant group and compare it with the results of sub-group decomposition of the MLD into within- and between-group inequality. While the methods are similar, there is a major difference between the subgroup decomposition of the MLD and the regression decomposition approach:

- The regression decomposition approach can be interpreted as the decomposition of the variance. While Shorrocks' (1982) work has shown that the magnitude of the contributions calculated is invariant to the inequality measure (as long as the measure satisfies six axioms), this property does not apply to the signs or direction of change of the contributions from each group. To illustrate this, consider the mean-group contribution to overall inequality of a migrant group with high relative mean incomes. Using the sub-group decomposition approach with MLD as a measure of inequality, this group will make a negative mean-group contribution i.e.

- $Overall\ MLD = \underbrace{\sum_{m=1}^{M} \pi_m MLD_m}_{Within-group\ inequality} +$

  $\underbrace{\sum_{m=1}^{M} \pi_m \ln\left(\frac{1}{r_m}\right)}_{\substack{Between-group\ inequality \\ or \\ Mean-group\ contribution}}$ (28)

- If $r_m > 1$ for a group with high relative mean incomes, the contribution of that group to overall mean-group contributions (between-group inequality) will be negative i.e. $r_m = \mu_m/\mu$. If $\mu_m > \mu$ then $\ln\left(\frac{1}{r_m}\right) < 0$

However, the opposite will be the case in the regression decomposition approach. Groups with higher relative mean incomes will have a positive signed contribution in the regression decomposition approach. The regression decomposition approach is based on the variance as the measure of inequality:

- $Y = \beta_{Hm} D_{Hm} + \beta_{Om} D_{Om} + \beta_{Lm} D_{Lm} + e_i D_{Hm} + e_i D_{Om} + e_i D_{Lm}$ (29)

- $Var(Y) = Cov(Y, Y) = Cov\big(Y, \beta_{Hm} D_{Hm} + \beta_{Om} D_{Om} + \beta_{Lm} D_{Lm} + e_i D_{Hm} + e_i D_{Om} + e_i D_{Lm}\big)$ (30)

- $Var(Y) = \beta_{Hm} Cov(Y, D_{Hm}) + \beta_{Om} Cov(Y, D_{Om}) + \beta_{Lm} Cov(Y, D_{Lm}) + Cov(Y, e_i D_{Hm}) + Cov(Y, e_i D_{Om}) + Cov(Y, e_i D_{Lm})$ (31)

By the definition of variance, groups with higher mean income will make a positive signed contribution while groups with lower mean incomes will have a negative signed contribution. Notwithstanding the difference in this pattern for both decomposition approaches, Shorrocks' (1982) theorem implies that the magnitude of the contributions from both approaches should be similar. Understanding this key difference is important in interpreting and comparing the results from the regression approach and the sub-group decomposition of the MLD which we discuss in the next section.

By calculating the by-group between and within-group contribution using the regression framework, we aim to reconcile two different strands of the regression decomposition literature. Both techniques evolved separately in the literature and there have been few attempts to reconcile them (i.e. Cowell and Fiorio, 2011).

Our work is different from Cowell and Fiorio (2011). While Cowell and Fiorio (2011) noted some the limitations in reconciling the regression decomposition approach with the sub-group approach, (for example, the regression approach becomes cumbersome when controlling for additional characteristics and requires discretisation of variables which might reasonably be considered as continuous) they suggested that additional information can be gained by estimating separate regressions for any subgroup/partition (pgs.522-525). We propose a new approach that allocates the residual in a multivariate framework to arrive at the conditional group contributions of each migrant group which can be compared to the group contributions derived from the sub-group decomposition approach.

It is important to note that our analysis here is at the individual level but our income data from censuses are in income bands. We assign an individual the midpoint of the income band he or she belongs to. The availability of income data in bands poses no problem for neither the sub-group decomposition nor the regression method.[73]

Before presenting the results from our various methodologies, the next section provides descriptive information on the changes in inequality and immigration in New Zealand between 1986 and 2013.

4.4 Data and Descriptive Analysis

4.4.1 Data

The data used are from the unit records of the usually resident New Zealand population from each Census of Population and Dwelling from 1986 to 2013.[74] Our target population consists of the residents of the 40 Main and Secondary urban areas.[75] New Zealand Census data capture information on current area of residence, place of residence at last Census, place of birth and qualifications. We use this information to classify the population by country of birth: New Zealand

[73] We note that the availability of income in bands may have implications for our measure of inequality. Not accounting for within-band variation may lead to under-estimation of actual inequality. Future work will investigate accounting for within-band variation using techniques like interval-regression (see Hansen and Kneale, 2013).

[74] New Zealand Censuses were held in 1986, 1991, 1996, 2001, 2006, 2013 and 2018. The data from the 2018 census were not yet available at the time this study was conducted.

[75] The 40 urban areas were grouped into metropolitan and non-metropolitan areas. Metropolitan areas are the urban areas in the six largest cities of Auckland, Christchurch, Wellington, Hamilton, Tauranga and Dunedin. We use the 2013 Statistics New Zealand definition of urban areas for all periods. The metropolitan areas account for about three quarters of all urban population. The rural population, which is excluded from the data, accounts for only about 14 percent of New Zealand's population.

and abroad. We identify international migrants in each Census as people who are usually resident in New Zealand but whose country of birth is outside of New Zealand (i.e., the foreign-born). We divide the latter group, by their length of stay, into newly arrived and earlier migrants. Newly Arrived are migrants who arrived during the last inter-censal period. Given the information on place of residence five years ago, we can also identify a group of "Returning New Zealand-born"- these are New Zealand-born people who had been overseas five years before the census date and were resident in New Zealand at the time of the census. We consider this group separately as we expect that their effect on the distribution of income might be different from that of New Zealanders who lived in New Zealand continuously between two censuses. As well as classifying migrants by length of stay, we also divide each migrant category into high skilled and medium/low skilled based on qualifications. High Skilled are those who have at minimum a Bachelor's degree qualification while all other qualifications below Bachelor's degrees are in the Medium/Low Skilled category. Thus, the total population is divided into eight categories:

- New Zealand-born – High Skilled and Medium/Low Skilled
- Returning New Zealand-born – High Skilled and Medium/Low Skilled
- Earlier Migrants – High Skilled and Medium/Low Skilled
- Newly Arrived – High Skilled and Medium/Low Skilled

We restrict our analysis to the population aged 25-64 years and focus on those who reported positive incomes to make our analysis reflect labour market incomes. Although Census data are available for the population 15+, we restrict our analysis to those aged 25-64 earning positive incomes because many of the population aged 15-24 and 65+ are likely to earn most of their income from non-labour market sources[76], while negative incomes are likely to be reported by those who are self-employed and those incomes are therefore not an outcome of the labour market. While there are other data sources, such as Household Economic Surveys, that may provide better information on labour incomes, the Census remains the most comprehensive dataset for analysis at the sub-national level – in contrast, surveys typically suffer from sampling errors and biases. The income data represent total personal income before tax of people earning positive income in the 12 months before census night. It consists of income from all sources such

[76] Superannuation for 65+ and student allowances, loans and parental support for those aged 15 to 24 years.

as wages and salaries, self-employment, investments, and superannuation. It excludes social transfers in kind, such as public education or government-subsidised health care services. Instead of recording actual incomes, total personal incomes are captured in income bands in each census with the top and bottom income bands open-ended. For example, the top band in the 2013 census data captures everybody earning $150,000 and over. An important issue with the open-ended upper band is the calculation of mean income in the open-ended band. At the national level, this is not a problem, as Statistics New Zealand publishes an estimate of the midpoint of the top band for the country based on Household Economic Survey (HES) estimates. However, HES top-band mean incomes for sub-national areas are not reliable due to sampling errors. To resolve this problem, Pareto distributions have been fitted to the upper tail of the area-specific distributions.[77] The midpoints of these distributions have been calculated by means of the Stata RPME command developed by von Hippel et al. (2016).

[77] The proportion of the population in the top open-ended band is between 1 and 3% in non-metropolitan areas and between 2 and 7% in metropolitan areas in all census periods.

4.4.2 Descriptive Analysis

This sub-section provides a descriptive summary of the changes in immigration and income distribution between 1986 and 2013. We start the analysis by comparing all immigrant groups against the New Zealand-born. Table 4.1 presents the MLD, relative mean income and population share of New Zealand-born and immigrants by area.

Table 4.1: Comparison of New Zealand-born and International migrants on relative incomes, population share and inequality by area

		1986	1991	1996	2001	2006	2013
Non-metropolitan areas							
NZ-born	MLD	0.3579	0.3235	0.3258	0.3254	0.2961	0.3047
	Rel. mean	0.99	0.99	0.99	0.99	0.99	0.99
	Mean (real)	32,697	34,762	37,245	40,044	44,071	45,797
	Pop share	83.1%	84.5%	84.1%	84.6%	81.5%	79.3%
Immigrants	MLD	0.3607	0.3482	0.3768	0.3891	0.3516	0.3671
	Rel. mean	1.07	1.05	1.04	1.04	1.02	1.02
	Mean (real)	35,518	36,923	38,906	42,183	45,421	47,168
	Pop share	16.9%	15.5%	15.9%	15.4%	18.5%	20.7%
Combined	MLD	0.3589	0.3275	0.334	0.3354	0.3065	0.3177
	Rel. mean	1.00	1.00	1.00	1.00	1.00	1.00
	Mean (real)	33,173	35,096	37,510	40,374	44,321	46,080
	Pop share	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
Metropolitan areas							
NZ-born	MLD	0.3561	0.3389	0.3465	0.3474	0.3220	0.3427
	Rel. mean	1.00	1.01	1.03	1.03	1.04	1.05
	Mean (real)	36,940	42,011	46,421	51,750	56,353	58,539
	Pop share	71.7%	71.7%	69.8%	69.0%	63.5%	59.7%
Immigrants	MLD	0.3346	0.3475	0.4049	0.4227	0.3851	0.3943
	Rel. mean	1.00	0.97	0.94	0.93	0.92	0.92
	Mean (real)	36,775	40,531	42,256	46,533	49,876	51,244
	Pop share	28.3%	28.3%	30.2%	31.0%	36.5%	40.3%
Combined	MLD	0.3500	0.3415	0.3651	0.3719	0.3468	0.3656
	Rel. mean	1.00	1.00	1.00	1.00	1.00	1.00
	Mean (real)	36,893	41,592	45,165	50,133	53,987	55,602
	Pop share	100%	100%	100%	100%	100%	100%

Note: 1) The Returning New Zealand-born categories are excluded from the New Zealand-born category and counted with the international migrant category.
2) Rel. Mean is relative mean income calculated as group-mean income divided by overall mean income for that area
3) Real mean is in 2013 dollars

Table 4.1 continued: Comparison of New Zealand-born and International migrants on relative incomes, population share and inequality by area

		1986	1991	1996	2001	2006	2013
All urban areas							
NZ-born	MLD	0.3583	0.3376	0.3450	0.3473	0.3200	0.3370
	Rel. mean	0.99	1.00	1.01	1.01	1.02	1.03
	Mean (real)	35,533	39,609	43,460	48,115	52,516	54,579
	Pop share	75.1%	75.5%	73.9%	73.2%	68.2%	64.7%
Immigrants	MLD	0.3400	0.3481	0.4004	0.4177	0.3798	0.3904
	Rel. mean	1.02	1.00	0.97	0.96	0.96	0.95
	Mean (real)	36,518	39,847	41,669	45,836	49,156	50,622
	Pop share	24.9%	24.5%	26.1%	26.8%	31.8%	35.3%
Combined	MLD	0.3538	0.3402	0.3596	0.3664	0.3395	0.3565
	Rel. mean	1.00	1.00	1.00	1.00	1.00	1.00
	Mean (real)	35,778	39,668	42,992	47,504	51,446	53,182
	Pop share	100%	100%	100%	100%	100%	100%
Total population 25-64		1,029,201	1,121,880	1,209,630	1,212,711	1,372,773	1,415,343
Proportion of all urban population in metropolitan areas		70.0%	70.4%	71.6%	73.2%	74.0%	74.7%
MLD - Total urban population 15+ [78]		0.3509	0.3490	0.3916	0.4091	0.3971	0.4153
Note: 1) The Returning New Zealand-born categories are excluded from the New Zealand-born category and counted with the international migrant category. 2) Rel. Mean is relative mean income calculated as group-mean income divided by overall mean income for that area 3) Real mean is in 2013 dollars 4) All counts have been rounded to base 3 as per Statistics New Zealand policy for unit record data							

Notes: Results are the by-group MLD, by-group real (2013 $) mean income, relative mean income and population share of New Zealand-born and immigrant groups in metropolitan, non-metropolitan, and all urban areas combined

It is important to reiterate that the target population in this analysis is the population aged 25 to 64 years earning positive income in each Census period between 1986 and 2013. Nonetheless, Table 4.1 shows that the overall intercensal changes in inequality are in the same direction as those for the total urban population 15+ reported in Alimi et al. (2017), which have been reproduced in the bottom row. However, in level terms, inequality growth between 1986 and 2013 is relatively small (from 0.3538 to 0.3565) for those aged 25-64 and much larger (from 0.3509 to 0.4153) for all people aged 15+.

From Table 4.1, we can see that immigrants have become an increasingly important component of the total population. In all areas combined, in 1986 immigrants represented about 25% of the total population under consideration but

[78] MLD calculations for the whole urban population aged 15+ earning positive incomes are reported in Alimi et al. (2017) – see for example Table 2 in Alimi et al. (2017).

by 2013 this had increased to about 35%. Spatially, immigrants are a bigger proportion of the population in metropolitan areas: the proportion of immigrants in metropolitan areas is almost double that in non-metropolitan areas in each census period.

In all periods, immigrants have higher average incomes than New Zealand-born in non-metropolitan areas but the downward trend in the relative mean for immigrants indicates an increase in immigrants with lower incomes – reflecting the growth in temporary worker migration in agriculture and tourism. Although starting with parity with the New Zealand-born in 1986, the relative income of immigrants also exhibits a downward trend in metropolitan areas, reflecting for example the growth in foreign students who are also working part-time. This implies that the New Zealand-born in the studied population have higher average incomes in all periods but 1986. Besides the growth of temporary migration, particularly affecting the tourism, construction and caring sectors[79], this is also the result of differences in employment rates. Compared to the New Zealand-born, immigrants generally have lower employment rates in metropolitan areas[80] .

With respect to the distribution of income, apart from metropolitan areas in 1986, inequality is higher among immigrants than locals in both metropolitan and non-metropolitan areas in all other periods. This is as expected as immigrants typically have a wider distribution of income because of selectivity in migration. Immigrants are disproportionally recruited from the upper end of the distribution (professionals and other high skilled workers) and from the lower end of the distribution (dependent relatives and unskilled temporary workers). A similar finding has been reported for the US (see Reed, 2001).

Our earlier work (Alimi et al., 2016, 2017) signalled a strong increase in income inequality between 1986 and 2013, which is consistent with much of the earlier literature. However, we see in Table 4.1 that the trends differ across locations (metropolitan versus non-metropolitan) and migration status. While for everyone in all areas combined, inequality rose by only about 1% between 1986 and 2013,

[79] See McLeod and Maré (2013)

[80] In metropolitan areas immigrants had lower total employment rates (Full time + Part time) compared to the New Zealand-born in all years considered except in 1986. See Appendix 4.A.1. Besides foreign students working part-time, another contributing factor is the presence of spouses and partners of labour migrants, who are not in the labour force.

inequality rose in metropolitan areas by 4% while it fell in non-metropolitan areas by 11%. Similarly, inequality increased more for immigrants in metropolitan areas (18%) than in non-metropolitan areas (2%). For the New Zealand-born, inequality fell more in non-metropolitan areas (-15%) than in metropolitan areas (-4%). Thus, the 1986-2013 rise (fall) in inequality in metropolitan (non-metropolitan) areas is due to the large (small) increase in inequality for immigrants and the smaller (larger) fall in inequality for New Zealand-born.

One of the channels through which immigration affects the destination distribution of income is through the skill composition effect. One way to present descriptive evidence on the size of the composition effect of immigration is to examine the skill distribution of immigrants and New Zealand-born. If immigrants have a different skill distribution to New Zealand-born, we expect that the difference in composition will influence the overall distribution of income depending on the relative size of the immigrant group. For example, if immigrants represent a large group who are mostly low-skilled; i.e. have mostly low earnings, then an increase in immigration is simply adding a lot of people to the bottom of the income distribution. This may then lead to an increase in inequality. Table 4.2 compares the skills composition of the New Zealand-born and the immigrants across metropolitan and non-metropolitan areas.

Table 4.2 : Skill Composition of New Zealand-born and immigrants by area

	1986	1991	1996	2001	2006	2013
Non-metropolitan						
	New Zealand-born					
High Skilled NZ-born	4.6%	4.9%	6.1%	8.4%	11.7%	15.8%
Medium/Low Skilled NZ-born	95.4%	95.1%	93.9%	91.6%	88.3%	84.2%
Total pop NZ-born	256,251	280,359	288,270	275,073	291,261	283,929
	Immigrants					
High Skilled Immigrants	9.9%	11.5%	15.4%	19.9%	26.0%	32.6%
Medium/Low Skilled Immigrants	90.1%	88.5%	84.6%	80.1%	74.0%	67.4%
Total pop Immigrants	52,071	51,300	54,639	50,187	66,249	73,953
	Combined					
High skilled in area	5.5%	5.9%	7.6%	10.2%	14.3%	19.3%
Medium/Low Skilled in area	94.5%	94.1%	92.4%	89.8%	85.7%	80.7%
Total pop (area)	308,322	31,659	342,909	325,260	357,510	357,882
Metropolitan areas						
	New Zealand-born					
High Skilled NZ-born	8.8%	10.2%	12.6%	16.6%	21.3%	27.2%
Medium/Low Skilled NZ-born	91.2%	89.8%	87.4%	83.4%	78.7%	72.8%
Total pop NZ-born	516,786	566,541	605,334	612,264	644,346	631,746
	Immigrants					
High Skilled Immigrants	11.0%	13.9%	19.2%	25.2%	33.6%	39.6%
Medium/Low Skilled Immigrants	89.0%	86.1%	80.8%	74.8%	66.4%	60.4%
Total pop Immigrants	204,102	223,683	261,354	275,199	370,908	425,724
	Combined					
High Skilled in area	9.5%	11.3%	14.6%	19.2%	25.8%	32.2%
Medium/Low Skilled in area	90.5%	88.7%	85.4%	80.8%	74.2%	67.8%
Total pop (area)	720,888	790,224	866,688	887,463	1,015,254	1,057,470
All urban areas						
	New Zealand-born					
High Skilled NZ-born	7.4%	8.4%	10.5%	14.0%	18.3%	23.7%
Medium/Low Skilled NZ-born	92.6%	91.6%	89.5%	86.0%	81.7%	76.3%
Total pop NZ-born	773,037	846,900	893,604	887,337	935,607	915,675
	Immigrants					
High Skilled Immigrants	10.8%	13.5%	18.5%	24.4%	32.5%	38.5%
Medium/Low Skilled Immigrants	89.2%	86.5%	81.5%	75.6%	67.5%	61.5%
Total pop Immigrants	256,173	274,983	315,993	325,386	437,157	499,677
	Combined					
High Skilled in area	8.3%	9.7%	12.6%	16.8%	22.8%	28.9%
Medium/Low Skilled in area	91.7%	90.3%	87.4%	83.2%	77.2%	71.1%
Total pop (area)	1,029,210	1,121,883	1,209,597	1,212,723	1,372,764	1,415,352
Note: as in Table 4.1, NZ-born return migrants are included in the immigrant group						

Notes: Results are the skill composition of New Zealand-born and immigrants in each census period for each area. High skilled are defined as those with a Bachelor's degree or higher and Medium/Low skilled are those with other qualifications below a Bachelor's degree or no qualifications. The population consists of those aged 25-64 years in receipt of positive income.

Table 4.2 shows that, for all groups considered, the high-skilled are a sharply growing proportion of the population. Combining this with the high-skilled being a larger proportion of immigrants than of New Zealand-born, immigration being a growing share of the workforce, and the highly skilled having the highest incomes, these trends contribute to increases in inequality.[81]

Between 1986 and 2013, the proportion of New Zealand-born who were high skilled increased from about 7.4% to 23.7% while the corresponding proportion for immigrants increased from 10.8% to 38.5%. This is not surprising given that New Zealand has a migration policy that aims to attract highly skilled migrants. Reflecting this skill-biased recruitment and the preference of migrants to stay in metropolitan areas, the proportion of high-skilled immigrants increased by about 29 percentage points in metropolitan areas between 1986 and 2013, compared to a 23 percentage points increase for the same group in non-metropolitan areas and an 18 percentage points increase for the New Zealand-born in metropolitan areas.

In all urban areas combined, the total proportion of highly skilled people was around 8.3% in 1986, compared with 7.4% for the New Zealand-born and 10.8% of immigrants. By 2013, the growing share of immigrants in the population and their more rapid increase in the share of high-skilled individuals led to an increase in the total proportion of high-skilled individuals in urban areas to 28.9%.

We compared New Zealand-born with international migrants and treated international migrants as a homogenous group, but immigrants to New Zealand are heterogeneous and apart from skill level, differences also exist within this group by length of stay in New Zealand. As discussed in Section 4.1, we categorise international migrants by skill level and length of stay and compare them to the New Zealand-born (classified by skill level) in terms of within-group inequality, relative mean incomes and population share. Table 4.3 presents, for all urban areas combined, relative mean income and population share for the six international migrant groups (Returning New Zealand-born – High Skilled and Medium/Low Skilled, Earlier migrants - High Skilled and Medium/Low Skilled,

[81] Or during a period in which inequality declines, the growing presence of high-skilled immigrant may slow down the decline of inequality.

and Newly Arrived migrants – High skilled and Medium/Low Skilled) and two categories of New Zealand-born (High skilled and Medium/Low Skilled)[82].

[82] Appendix 4.A.2 and Appendix 4.A.3 presents the same information for metropolitan and non-metropolitan areas respectively.

Table 4.3: Comparison of MLD, relative mean income, and population share for all international migrant groups and New Zealand-born by area

		NZ-born		Immigrants						
		HS NZ-born	M/LS NZ-born	HS Returning NZ-born	M/LS Returning NZ-born	HS Earlier	HS Newly Arrived	M/LS Earlier	M/LS Newly Arrived	Total
		All urban areas								
1986	MLD	0.3094	0.3466	0.3454	0.3353	0.3191	0.4286	0.3075	0.4164	0.3538
	Rel.inc	1.70	0.94	1.54	0.96	1.66	1.56	0.95	0.91	1.00
	Pop share	5.6%	69.5%	0.5%	2.5%	1.6%	0.6%	17.6%	2.2%	100.0%
1991	MLD	0.3127	0.319	0.3543	0.313	0.3223	0.3843	0.3098	0.3767	0.3402
	Rel.inc	1.77	0.93	1.67	0.95	1.72	1.53	0.90	0.86	1.00
	Pop share	6.4%	69.1%	0.5%	2.1%	1.9%	1.0%	16.2%	2.9%	100.0%
1996	MLD	0.3354	0.3195	0.3499	0.2997	0.3632	0.6172	0.3333	0.499	0.3596
	Rel.inc	1.77	0.92	1.65	0.92	1.66	1.09	0.87	0.75	1.00
	Pop share	7.7%	66.1%	0.6%	2.4%	2.5%	1.8%	15.7%	3.1%	100.0%
2001	MLD	0.3251	0.3215	0.3574	0.3308	0.3797	0.5085	0.3544	0.4798	0.3664
	Rel.inc	1.66	0.91	1.59	0.92	1.51	1.14	0.84	0.72	1.00
	Pop share	10.3%	62.9%	0.7%	1.7%	3.7%	2.2%	14.9%	3.6%	100.0%
2006	MLD	0.2997	0.2983	0.3261	0.3008	0.3509	0.4144	0.338	0.3926	0.3395
	Rel.inc	1.51	0.91	1.50	0.95	1.33	1.06	0.81	0.75	1.00
	Pop share	12.5%	55.7%	1.2%	2.0%	5.7%	3.5%	14.9%	4.6%	100.0%
2013	MLD	0.3248	0.3093	0.3701	0.3504	0.3465	0.4393	0.3462	0.4299	0.3565
	Rel.inc	1.46	0.89	1.44	0.91	1.26	1.05	0.78	0.71	1.00
	Pop share	15.3%	49.4%	1.1%	1.4%	9.4%	3.0%	17.0%	3.3%	100.0%
Abs pop share change (%pts)		9.7%	-20.1%	0.7%	-1.1%	7.8%	2.5%	-0.6%	1.2%	0.0%
Act pop change		276.8%	-2.3%	218.5%	-23.5%	694.2%	641.3%	33.1%	111.5%	37.5%

Note: Absolute and Actual pop (population) changes reported are changes between 1986 and 2013. Absolute change is the percentage point difference in the proportion of each group between 1986 and 2013 (prop2013-prop1986). Actual pop change is the percentage change in the population of each group between 1986 and 2013 calculated as: (Population 2013-population 1986)/population 1986 for each group. HS NZ-born and M/LS NZ-born represent High Skilled and Medium/Low Skilled New Zealand-born respectively; HS Ret. NZ-born and M/LS Ret. NZ-born represent High Skilled and Medium/Low Skilled Returning New Zealand-born; HS Earlier and LS Earlier represent High Skilled and Medium/Low Skilled Earlier migrants;

Notes: Results are the by-group MLD, relative mean income and population share of the different categories of migrant groups in all urban areas combined. HS (High skilled) are defined as those with a Bachelor's degree or higher and M/LS (Medium/Low skilled) are those with other qualifications below a Bachelor's degree or no qualifications. Newly Arrived are those who arrived in the last inter-censal period and earlier migrant are arrivals prior to the last inter-censal period.

Medium/Low Skilled earlier immigrants are the largest migrant group, representing between 15% and 17% of the total population in all census periods. Apart from Medium/Low Skilled Returning New Zealand-born and Medium/Low Skilled Earlier migrants, all international migrant groups increased as a proportion of the population between 1986 and 2013. The trend in the Medium/Low Skilled Returning New Zealand-born group was mostly driven by events in Australia. More than half of the Returning New Zealand-born groups were returnees from Australia, thus the size of this group is very sensitive to economic changes in Australia. The 2006 to 2013 period coincided with buoyant economic conditions in Australia, particularly the growth in the mining sector, and higher real wages in Australia meant lower inflows of Medium/Low Skilled New Zealand-born individuals from Australia.[83]

To show the scale of immigration changes in New Zealand, we examine the relative population increase of immigrant groups (relative to their 1986 population) in all areas combined. We find that High Skilled Returning New Zealand-born increased by almost 219%, High Skilled Earlier migrants increased by around 694%, High Skilled Newly Arrived migrants increased by 641% while Medium/Low Skilled Earlier and Medium/Low Skilled Newly Arrived increased by around 33% and 112% respectively. Only Low Skilled Returning New Zealand-born declined by about 24% relative to the 1986 population. The relative changes are important as research from the US has shown that the impact of immigration is most likely felt by earlier migrants who are close substitutes for recent arrivals in the labour market (see LaLonde & Topel, 1991; Cortés, 2008). The changes may have implications for the between-group distribution of income and by extension the overall distribution of income.

We find that inequality is, in each year, highest among newly arrived immigrants, regardless of skill level. This provides some evidence of a narrowing of the income distribution by duration of stay of immigrants. With respect to by-group inequality changes between 1986 and 2013, inequality rose for all immigrant groups between 1986 and 2013. Out of all groups (New Zealand-born and Immigrants), only the Medium/Low Skilled New Zealand-born group saw a decline in inequality over this period. Another interesting observation is that

[83] Return migration from Australia increased sharply after the end of our observation period, March 2013. See Statistics New Zealand (2015).

inequality is higher among High Skilled New Zealand-born returning migrants than High Skilled New Zealand-born who were in the country 5 years earlier. This suggests that return migration is selective of both the most highly successful (in terms of the achieved earnings level) and those who were the least successful in the foreign labour market.

Finally, given the differences between immigrants and New Zealand-born and the likely diversity between and within immigrant groups, we decompose the MLD level into within and between components using Equation (2) and examine the contribution of each migrant category to overall inequality in each period by area. Table 4.4 presents the results for all urban areas combined.

Table 4.4: Between-group and within-group contributions to MLD level by area from 1986 to 2013

Between and Within-group contributions to the level of inequality for all urban areas						
Between-group contributions						
	1986	1991	1996	2001	2006	2013
HS NZ-born	-0.0296	-0.0363	-0.0443	-0.0519	-0.0518	-0.0582
M/LS NZ-born	0.0456	0.0518	0.0538	0.0611	0.0524	0.0570
HS Ret. NZ-born	-0.0022	-0.0024	-0.0031	-0.0031	-0.0049	-0.0042
M/LS Ret. NZ-born	0.0010	0.0011	0.0020	0.0014	0.0010	0.0014
HS Earlier Migrants	-0.0083	-0.0101	-0.0124	-0.0153	-0.0162	-0.0215
HS Newly Arrived Migrant	-0.0025	-0.0041	-0.0016	-0.0029	-0.0020	-0.0015
M/LS Earlier Migrant	0.0089	0.0162	0.0215	0.0259	0.0315	0.0413
M/LS Newly Arrived Migrant	0.0020	0.0044	0.0091	0.0121	0.0134	0.0115
Sum of Between	0.0149	0.0206	0.0250	0.0273	0.0234	0.0258
Prop-Between	4%	6%	7%	7%	7%	7%
Within-group contributions						
	1986	1991	1996	2001	2006	2013
HS NZ-born	0.0173	0.0199	0.0260	0.0334	0.0374	0.0497
M/LS NZ-born	0.2410	0.2205	0.2113	0.2022	0.1661	0.1527
HS Ret. NZ-born	0.0017	0.0017	0.0022	0.0024	0.0039	0.0042
M/LS Ret. NZ-born	0.0083	0.0065	0.0073	0.0058	0.0060	0.0048
HS Earlier Migrants	0.0052	0.0060	0.0089	0.0140	0.0199	0.0327
HS Newly Arrived Migrant	0.0024	0.0037	0.0109	0.0111	0.0143	0.0133
M/LS Earlier Migrant	0.0540	0.0502	0.0523	0.0528	0.0503	0.0588
M/LS Newly Arrived Migrant	0.0090	0.0110	0.0157	0.0175	0.0181	0.0143
Sum of Within	0.3389	0.3195	0.3346	0.3392	0.3160	0.3305
Prop-Within	96%	94%	93%	93%	93%	93%
Total inequality	0.3538	0.3401	0.3596	0.3665	0.3394	0.3563
Total inequality here is slightly different from the last column in Table 4.3 in some years due to base 3 rounding						

Note: Results are the between- and within-group contributions to overall inequality (as measured by the MLD) for the migrant group categories in all urban areas combined in each census period from 1986 to 2013

Table 4.4 shows that, in all urban areas combined, between-group inequality accounted for around only 4% of MLD inequality in 1986. This share then increases to 7% by 1996 and remains constant thereafter until 2013. Between-migration group inequality calculated here is higher than the between-age group inequality reported by Alimi et al. (2017), indicating bigger differences (at least in average income) across migrant groups than age groups. Spatially, between-group inequality is lower in non-metropolitan areas than in metropolitan areas.[84] This suggests that migrant groups are "closer" in non-metropolitan areas (at least in terms of average incomes). Examining the contribution of each migrant category indicates that Medium/Low Skilled New Zealand-born and Medium/Low Skilled Earlier migrants have the biggest and second biggest contribution respectively to aggregate within-group inequality. This is not surprising as these groups are the biggest and second biggest in terms of population share.

Decomposing the level of MLD into the sum of between- and within-group contributions shows that most of the change in inequality is driven by what is happening within each migrant group, with big differences in the trends in the within-group contributions across the migrant groups. In the next section, we focus on changes between 1986 and 2013 and employ change-decomposition strategies to decompose overall inequality change between years and to understand the role of changes within each migrant group.

4.5 Decomposition of Inequality Change Results

Up to this point, we have considered how the overall level of income inequality is the result of inequality within migrant groups, the relative importance of these groups, and their average incomes. Income inequality has been quantified by just a single index, the MLD. In this section, we quantify how changes in each of the migrant groups have contributed to overall change in inequality between 1986 and 2013. We focus on the between- and within-group inequality contributions of each group using the two different change decomposition of inequality change approaches (Mookherjee and Shorrocks' sub-group decomposition and regression-based approach).

[84] See the Appendix 4.A.4 of Chapter 4.

4.5.1 Mookherjee and Shorrocks decomposition of inequality change by sub-groups

Table 4.5: Contribution to changes in Mean Log Deviation (MLD) index of inequality between 1986 and 2013 by migrant group when using the Mookherjee and Shorrocks approach

	Components of change (see Eq. 4)				Total change (approx) 1986-2013	Composition effect C2+C3’	Group specific distribution effect C1+C4’	Contribution to within-group inequality C1+C2	Contribution to between-group inequality C3’+C4’
Non-metropolitan									
Migrant Status	C1	C2	C3’	C4’					
HS NZ-born	-0.0005	0.0264	0.0997	0.0050	0.1306	0.1261	0.0045	0.0259	0.1046
M/LS NZ-born	-0.0454	-0.0398	-0.1255	-0.0148	-0.2254	-0.1653	-0.0602	-0.0852	-0.1402
HS Ret. NZ-born	0.0002	0.0016	0.0050	0.0002	0.0069	0.0066	0.0004	0.0018	0.0051
M/LS Ret. NZ-born	-0.0005	-0.0022	-0.0067	-0.0003	-0.0097	-0.0089	-0.0008	-0.0027	-0.0070
HS Earlier	0.0006	0.0109	0.0374	0.0012	0.0501	0.0483	0.0018	0.0115	0.0387
HS Newly Arrived	-0.0002	0.0064	0.0149	-0.0004	0.0206	0.0212	-0.0006	0.0061	0.0145
M/LS Earlier	-0.0015	-0.0050	-0.0160	-0.0012	-0.0237	-0.0210	-0.0027	-0.0065	-0.0172
M/LS Newly Arrived	-0.0014	0.0042	0.0099	-0.0002	0.0125	0.0141	-0.0016	0.0028	0.0096
Sum	**-0.0487**	**0.0024**	**0.0187**	**-0.0104**	**-0.0381**	**0.0211**	**-0.0592**	**-0.0463**	**0.0082**
Metropolitan									
Migrant Status	C1	C2	C3’	C4’					
HS NZ-born	0.0020	0.0316	0.1105	0.0161	0.1602	0.1421	0.0181	0.0336	0.1265
M/LS NZ-born	-0.0155	-0.0720	-0.2192	-0.0155	-0.3221	-0.2912	-0.0310	-0.0875	-0.2347
HS Ret. NZ-born	0.0002	0.0025	0.0076	0.0016	0.0118	0.0101	0.0017	0.0026	0.0092
M/LS Ret.NZ-born	0.0004	-0.0043	-0.0127	-0.0004	-0.0169	-0.0170	0.0000	-0.0039	-0.0131
HS Earlier	0.0019	0.0309	0.0998	0.0020	0.1346	0.1307	0.0039	0.0328	0.1019
HS Newly Arrived	0.0005	0.0120	0.0295	0.0001	0.0420	0.0415	0.0005	0.0124	0.0296
M/LS Earlier	0.0097	-0.0025	-0.0077	-0.0062	-0.0066	-0.0101	0.0035	0.0073	-0.0139
M/LS Newly Arrived	0.0011	0.0049	0.0121	-0.0012	0.0169	0.0170	-0.0001	0.0059	0.0109
Sum	**0.0002**	**0.0031**	**0.0199**	**-0.0035**	**0.0197**	**0.0230**	**-0.0032**	**0.0033**	**0.0164**

Table 4.5 continued: Contribution to changes in Mean Log Deviation (MLD) between 1986 and 2013 by migrant group when using the Mookherjee and Shorrocks approach

	Components of change (see Eq. 4)				Total change (approx)	Composition effect C2+C3’	Group specific distribution effect C1+C4’	Contribution to within-group inequality C1+C2	Contribution to between-group inequality C3’+C4’
All urban areas									
Migrant Status	C1	C2	C3’	C4’					
HS NZ-born	0.0016	0.0308	0.1094	0.0136	0.1554	0.1402	0.0152	0.0324	0.1230
M/LS NZ-born	-0.0222	-0.0660	-0.2022	-0.0170	-0.3074	-0.2682	-0.0392	-0.0882	-0.2192
HS Ret NZ-born	0.0002	0.0023	0.0071	0.0013	0.0109	0.0095	0.0015	0.0025	0.0084
M/LS Ret NZ-born	0.0003	-0.0038	-0.0110	-0.0004	-0.0148	-0.0148	-0.0001	-0.0035	-0.0114
HS Earlier	0.0015	0.0259	0.0851	0.0020	0.1146	0.1111	0.0035	0.0275	0.0871
HS Newly Arrived	0.0002	0.0107	0.0260	0.0000	0.0369	0.0367	0.0002	0.0109	0.0260
M/LS Earlier	0.0067	-0.0018	-0.0057	-0.0046	-0.0055	-0.0076	0.0021	0.0049	-0.0104
M/LS Newly Arrived	0.0004	0.0049	0.0120	-0.0008	0.0165	0.0169	-0.0005	0.0053	0.0112
Sum	**-0.0113**	**0.0031**	**0.0207**	**-0.0060**	**0.0066**	**0.0238**	**-0.0173**	**-0.0082**	**0.0148**

Notes: Results are the contributions to change in overall inequality (as measured by the MLD) between 1986 and 2013 in all urban areas combined. C1 is the aggregate change in within-migrant group inequality for given migrant-shares; C2 is the aggregate change in within-migrant group inequality due to changing migrant-shares; C3' is aggregate change in between-migrant group inequality due to changing migrant-shares; C4' is aggregate growth in migrant-group mean income for given migrant-shares

Table 4.5 presents the by-migrant group contributions to the changes in MLD between 1986 and 2013. This is further split into the composition and within-migrant-group specific distribution effects. Section 3.1 showed that the calculated components of change C3’ and C4’ are approximations. The calculated total change is therefore not exactly equal to the total 1986-2013 change in the MLD that can be obtained from Table 4.1. However, the approximation is very good. Table 4.5 reports an approximate change in the MLD in non-metropolitan areas of -0.0381, whereas the actual change was -0.0412 (see Table 4.1). For metropolitan areas the approximate 1986-2013 increase in MLD is 0.0197 and the actual increase is 0.0156. Finally, for all areas combined the approximate increase is 0.0066 and the actual increase is 0.0027.

Spatially, there are some distinctions in the changes between metropolitan and non-metropolitan areas. Inequality fell in non-metropolitan areas while it rose in metropolitan areas. The advantage of the Mookherjee and Shorrocks approach is that we can split the total change into the overall contribution of each group to within-group contributions (C1+C2) and between-group contributions (C3 and C4), or into a composition effect (C2+C3’) and a group-specific distribution effect (C1+C4’). Before we discuss the by-migrant group contributions, we describe below what determines the type of contribution each migrant group will make (i.e. whether these will be inequality-increasing or inequality-decreasing contributions).

The changes in each of C1 to C4’ will determine whether a group will make an inequality-increasing or inequality-decreasing contribution. What determines the direction of each term? Considering each of C1 to C4’ below:

- $C1 = \sum_{m=1}^{M} \overline{\pi_m} \Delta MLD_m$. This is the aggregate change in within-migrant group inequality for given migrant shares.

Given that migrant shares π_m will always be positive, changes from this component are dependent on the changes in within-group inequality (ΔMLD_m). If within-group inequality increases (decreases) for a group, then the contribution from C1 for that group will be inequality-increasing (inequality-decreasing).

- $C2 = \sum_{m=1}^{M} \overline{MLD_m} \Delta \pi_m$. It is the aggregate change in within-migrant group due to changing migrant shares.

Given that MLD_m is always positive, the changes from this component are dependent on the changes in the population share ($\Delta\pi_m$). If the share of a group increases (decreases) then C2 will make an inequality-increasing (inequality-decreasing) contribution.

- $C3' = \sum_{m=1}^{M}(\overline{r_m} - \overline{\ln r_m})\Delta\pi_m$. It is the aggregate change in between-migrant group due to changing migrant shares.

As for C2, the direction of change (whether inequality-increasing or inequality decreasing) from this component is dependent on the changes in the population share ($\Delta\pi_m$). r_m is a positive number and lnr_m will always be smaller than r_m, thus the direction of change from $C3'$ will be dependent on whether the population share (π_m) of a group increases or decreases. The contribution from $C3'$ for groups that increase (decrease) in share will be inequality-increasing (inequality-reducing).

- $C4' = \sum_{m=1}^{M}(\overline{\pi_m r_m} - \overline{\pi_m})\Delta\ln\mu_m$. It is the aggregate growth in migrant-group mean income for given migrant-shares

In terms of the direction of change, $C4'$ is slightly more complex and the direction of change is dependent on changes in group-mean income (μ_m) as well as the relative mean income(r_m). If for a group:

  - $\overline{r_m} > 1$ and group-mean income increases i.e. $\Delta\ln\mu_m > 0$, the direction of change of $C4'$ will be inequality-increasing. Intuitively for this group, this change represents an increase in average income for a group that is above the overall average(μ). This change will be inequality-increasing as it widens the overall distribution i.e. the top moves further away;
  - $\overline{r_m} < 1$ and group-mean income increases i.e. $\Delta\ln\mu_m > 0$, the direction of change of $C4'$ will be inequality-decreasing. Intuitively for this group, this change represents an increase in average income for a group that is below the overall average(μ). This change will be inequality-decreasing as it narrows the overall distribution of income;
  - $\overline{r_m} > 1$ and group-mean income decreases i.e. $\Delta\ln\mu_m < 0$, the direction of change of $C4'$ will be inequality-decreasing. Intuitively for this group, this change represents a decrease in average income

for a group that is above the overall average(μ). This change will be inequality-decreasing;

- $\overline{r_m} < 1$ and group-mean income decreases i.e. $\Delta \ln \mu_m < 0$, the direction of change of $C4'$ will be inequality-increasing. Intuitively for this group, this change represents a decrease in average income for a group that is below the overall average(μ). This change will be inequality-increasing as it widens the overall distribution; i.e. the bottom becomes further apart

By knowing what determines the direction of each of C1-C4, we now examine the overall contribution, along with the between-group inequality contribution (C3'+C4') and the within-group inequality contributions (C1+C2) of each group. We begin the analysis with all urban areas combined. The direction of change of within-group contributions will be determined by within-group inequality changes (ΔMLD_m) and change in group population share($\Delta \pi_m$) and between-group contributions will be determined by relative mean income ($\overline{r_m}$) and changes in mean income ($\Delta \ln \mu_m$).

The total contribution to inequality from all high skilled groups i.e. High Skilled New Zealand-born, High Skilled Returning New Zealand-born, High Skilled Earlier Migrants and High Skilled Newly Arrived Migrants was inequality-increasing while Medium/Low skilled groups made inequality-reducing total contributions except for Medium/Low Newly Arrived. The inequality-increasing contributions of high skilled groups occurred because in these groups, relative mean income was high (greater than 1) and within-group inequality, population share, and mean incomes increased. Thus, groups at the top of the distribution experienced greater within-group inequality and an increase in average income; this can be described as a widening of the income distribution at the top.

For medium/low skilled groups, there was more variation in the patterns but apart from Medium/Low Newly Arrived, all other low skilled groups had inequality-reducing total contributions. For these groups even though group-mean income increased, their relative income was low (relative mean less than 1) and their population share also fell. This led to inequality-reducing between-group contributions for these groups, except for Medium/Low Newly Arrived, which had an inequality-increasing between-group contribution. The Medium/Low Newly Arrived group was different because it was the only low skilled group to experience an increase in population share; thus, their inequality-increasing contribution was driven by the composition effect. Within-group inequality contributions also varied in the low skilled groups. Except for Medium/Low New Zealand-born and Medium/Low Returning New Zealand-born, all low skilled groups had inequality-increasing within-inequality contributions. The Medium/Low New Zealand-born group was an exception because both within-group inequality and population share fell for this group while Medium/Low Returning New Zealand-born had a fall in population share.

Spatially, the trends in metro and non-metro areas mirrored each other - changes in population share for each migrant group across both areas were in the same direction although the magnitude differed[85]. In both areas, all high skilled groups had in increase in population share while low skilled groups had a decrease in population share (except for M/LS Newly arrived). This implies that the composition effect (C2+C3') is inequality-increasing for high skilled groups but inequality-reducing for low skilled groups. Overall, the composition effect is inequality-increasing, with a slightly larger magnitude in metropolitan areas. Notwithstanding these similarities, across areas, there are some differences due to the differences in the within-group specific distribution changes (C1+C4'). For example, in non-metropolitan areas, within-group inequality fell for the High Skilled New Zealand-born, High Skilled New Zealand Newly Arrived, Medium/Low Skilled Earlier and Medium/Low Skilled Newly Arrived, in contrast to metropolitan areas. Hence, aggregate change in within-migrant group inequality for given migrant-shares (C1) made an inequality-reducing contribution for these groups in non-metropolitan areas compared to metropolitan areas[86]. Also, the High Skilled Newly Arrived group had an inequality-reducing contribution from the aggregate growth in migrant-group mean income for given migrant-shares (C4') in non-metropolitan areas in contrast to metropolitan areas. The reason for this difference is that the average income for this group fell slightly

[85] This implies that the direction of change of C2 and C3' is the same for each migrant group in both non-metropolitan and metropolitan areas.
[86] Except for M/LS Earlier, although within-group inequality fell for these groups in non-metropolitan areas, the within-group contributions to inequality for these groups were inequality-increasing because of the stronger inequality-increasing aggregate change in within-migrant group inequality due to changing migrant-shares (i.e. although C1 was negative, C4' was positive and larger than C1).

in metropolitan areas. This group was the only group to experience a fall in average incomes.

Focusing on the role of immigrant groups (foreign-born and Returning New Zealand-born groups)[87], we can now answer the questions: what role have specific immigrant groups played in the changes in the distribution of income between 1986 and 2013, and what role has the skill-biased immigration policy had on the distribution of income? Our results show that in all urban areas combined, high skilled immigrant groups (High Skilled Returning. New Zealand-born, High Skilled Earlier migrants and High Skilled Newly Arrived) display inequality-increasing between- and within-group contributions. This is because for these groups, their relative group mean was above the overall mean in all periods, and between 1986 and 2013, within-group inequality increased, population share increased, and mean income increased. These changes led to inequality-increasing between- and within-group contributions.

Of all immigrant groups, High Skilled Earlier Migrants and High Skilled Newly Arrived Migrants made the highest and second-highest inequality-increasing total contributions, respectively. In terms of magnitude, the inequality-increasing total contribution was larger for earlier immigrants compared to newly arrived immigrants and this is unsurprising given that earlier high skilled immigrants experienced a larger change in population share, a higher growth in within-group inequality and had a higher relative mean income.

For the Medium and Low skilled immigrants (Medium/Low Skilled Returning New Zealand-born, Medium/Low Skilled Earlier Migrants and Medium/Low Skilled Newly Arrived), except for Medium/Low Skilled Newly Arrived, these groups had an inequality-reducing between-inequality contribution. This is because for these groups, although mean-group income increased between 1986 and 2013, mean-group income was less than overall mean income, and their population share also declined. These changes combined to narrow between-group inequality. Medium/Low Skilled Newly Arrived was an exception to this case because even though it had similar changes and patterns in relative income and mean income and within-group inequality as with other Medium/Low Skilled

[87] We have classified the Returning New Zealand-born group as one of the immigrant groups. Hence immigrant groups are all other groups except the High Skilled New Zealand-born and Medium/Low Skilled New Zealand-born

groups, it differed in one key aspect: its population share increased. This difference ensured that Medium/Low Skilled Newly Arrived had inequality-increasing between-group contributions[88].

Within-group contributions for the low skilled immigrant groups were inequality-increasing except for the Medium/Low Skilled Returning New Zealand-born. For Medium/Low Skilled Earlier migrants, the inequality-increasing within-group contribution was driven by the increase in within-group inequality. Although the population share of this group fell, the inequality-reducing change in within-migrant group inequality due to falling migrant-shares (C2) was not large enough to offset the inequality-increasing contribution from the increase in within-migrant group inequality for given migrant-shares (C1). For Medium/Low Skilled Newly Arrived, both within-group inequality and population share increased, hence this group had an inequality-increasing within-group contribution (C1 and C2 are both positive).

If we combine all immigrant groups, the total change in immigrant groups is inequality-increasing across areas[89]. Unsurprisingly, the effect is larger in metropolitan areas, which have seen greater levels of immigration and larger widening of the income distribution of immigrants. The inequality-increasing change in inequality due to immigration is smaller in non-metropolitan areas and combined with a larger inequality-reducing change from the New Zealand-born group (sum of High Skilled New Zealand-born and Medium/Low Skilled New Zealand-born), has led to a fall in overall inequality in these areas. This is in contrast to metropolitan areas, where overall inequality rose because the inequality-increasing effect of changes in immigration was larger than the inequality-reducing change from the New Zealand-born group (sum of total change for High Skilled New Zealand-born and Medium/Low Skilled New Zealand-born).

Similarly, the inequality-increasing compositional effect of immigration (C2+C3) is slightly higher in metropolitan areas while the inequality-reducing group-specific distributional changes are slightly higher in non-metropolitan areas. This is not surprising as metropolitan areas have had greater increases in the shares of

[88] The inequality-increasing effect from C3' dominated the inequality-reducing effect from C4' and ensured that M/LS Newly Arrived had an inequality-increasing between-group contribution.
[89] Summing the total change of all immigrant groups in each of metropolitan and non-metropolitan areas.

immigrants while non-metropolitan areas have had falls for most immigrant groups in within-group inequality[90]. However, the magnitude of the composition effect is similar across all areas, whereas the migrant-group-specific distribution effect (C1+C4) is almost negligible in metropolitan areas, but strongly inequality-reducing in non-metropolitan areas.

Next, we present the between- and within-group contributions of migration groups to the level of inequality using the regression decomposition approach. We begin by comparing the regression results with the within- and between-group contributions from the sub-group decomposition of the MLD level, then we proceed to present the conditional contribution of migration status accounting for age, sex and employment status[91]. These contributions are then used to estimate the contribution of different migrant groups to the change in income inequality between 1986 and 2013.

4.5.2 Regression decomposition approach

This section presents results from the regression decomposition approach.
We check the performance of our extension to the regression approach by comparing the between- and within-group contributions to the level of inequality from this method to the within- and between-group contributions from the sub-group decomposition of the MLD level (Table 4.4). As usual we focus on our three sets of geographical areas: non-metropolitan areas, metropolitan areas, and all urban areas combined. The results for all urban areas are presented in Table 4.6 and the results for metropolitan and non-metropolitan areas are separately presented in the appendix.

[90] Except High Skilled Returning New Zealand-born and High Skilled Earlier immigrants
[91] Instead of accounting for multiple factors, as most studies that use regression decomposition do, we focus exclusively on "explaining" overall income inequality in terms of the composition of the population across the eight migrant groups.

Table 4.6: Comparison of between- and within-group contributions to the level of inequality (MLD) from the regression and sub-group decomposition approach

All urban areas combined												
	Regression decomposition of inequality level						**Sub-group decomposition of inequality level**					
Migrant status	1986	1991	1996	2001	2006	2013	1986	1991	1996	2001	2006	2013
	Between-group contribution						**Between-group contribution**					
HS NZ-born	12%	14%	13%	14%	14%	14%	-8%	-11%	-12%	-14%	-15%	-16%
M/LS NZ-born	-7%	-7%	-6%	-6%	-7%	-7%	13%	15%	15%	17%	15%	16%
HS Ret. NZ-born	1%	1%	1%	1%	1%	1%	-1%	-1%	-1%	-1%	-1%	-1%
M/LS Ret. NZ-born	0%	0%	0%	0%	0%	0%	0%	0%	1%	0%	0%	0%
HS Earlier Migrants	3%	4%	3%	4%	4%	4%	-2%	-3%	-3%	-4%	-5%	-6%
HS Newly Arrived Migrant	1%	1%	0%	0%	0%	0%	-1%	-1%	0%	-1%	-1%	0%
M/LS Earlier Migrant	-1%	-2%	-2%	-2%	-3%	-4%	3%	5%	6%	7%	9%	12%
M/LS Newly Arrived Migrant	0%	-1%	-1%	-1%	-1%	-1%	1%	1%	3%	3%	4%	3%
Overall between-inequality proportion	**7%**	**9%**	**8%**	**9%**	**8%**	**8%**	**4%**	**6%**	**7%**	**7%**	**7%**	**7%**
	Within-group contribution						**Within-group contribution**					
HS NZ-born	12%	13%	18%	20%	21%	26%	5%	6%	7%	9%	11%	14%
M/LS NZ-born	58%	54%	49%	46%	42%	35%	68%	65%	59%	55%	49%	43%
HS Ret. NZ-born	1%	1%	1%	1%	2%	2%	0%	0%	1%	1%	1%	1%
M/LS Ret. NZ-born	2%	2%	2%	1%	2%	1%	2%	2%	2%	2%	2%	1%
HS Earlier Migrants	3%	4%	5%	7%	9%	13%	1%	2%	2%	4%	6%	9%
HS Newly Arrived Migrant	1%	2%	3%	3%	4%	4%	1%	1%	3%	3%	4%	4%
M/LS Earlier Migrant	13%	12%	11%	10%	10%	10%	15%	15%	15%	14%	15%	17%
M/LS Newly Arrived Migrant	2%	2%	3%	3%	3%	2%	3%	3%	4%	5%	5%	4%
Overall within-inequality proportion	**93%**	**91%**	**92%**	**91%**	**92%**	**92%**	**96%**	**94%**	**93%**	**93%**	**93%**	**93%**

Note: Results are the between- and within-group contributions in all urban areas combined from the regression and sub-group decomposition approaches. The sub-group decomposition contributions are based on converting the contributions in Table 4.4 to percentages$(\frac{by-group\ contribution}{overall\ inequality} * 100)$. The regression approach contributions are based on the formulae presented in Section 4.3.2

The results in Table 4.6 show some similarities, but also some differences between the results from the sub-group decomposition of the MLD level and our extension of the Fields and Yoo approach. The overall between- and within-group contributions from both approaches are similar. From each method, the between-group effects contribute little to the overall level of income inequality in urban areas in New Zealand. The within-group contribution of each migrant-group from the regression approach is also consistent with the sub-group decomposition approach. While the overall between- and within-group inequality contributions (expressed in percentages) from both approaches are directly comparable, the signs of the by-migrant mean group contributions from the sub-group approach are opposite to those obtained in the regression approach. As noted earlier, this is because the two approaches are based on different measures of inequality. The regression approach is a variance decomposition. The mean-group contribution in the regression approach is the proportion of the variance in income explained by a specific migrant group[92]. The MLD sub-group approach is based on the MLD level decomposition. The key difference in the way in which these two measures calculate inequality is that they assign opposing signs to migrant groups above and below the overall mean. With the regression approach, groups with higher mean income than the overall mean will have a positive by-migrant group contribution[93] while with the MLD, these groups will have a negative between-group contribution[94].

Figure 4.1 presents a comparison of the between- and within-group contributions from both approaches. We see that the MLD method shows an upward trend until 2001 in the contribution of between-group inequality to overall inequality. With the regression method, there is also an increase in between-group inequality between 1986 and 1991, but this is followed by a decline between 1991 and 1996 and little variation thereafter.

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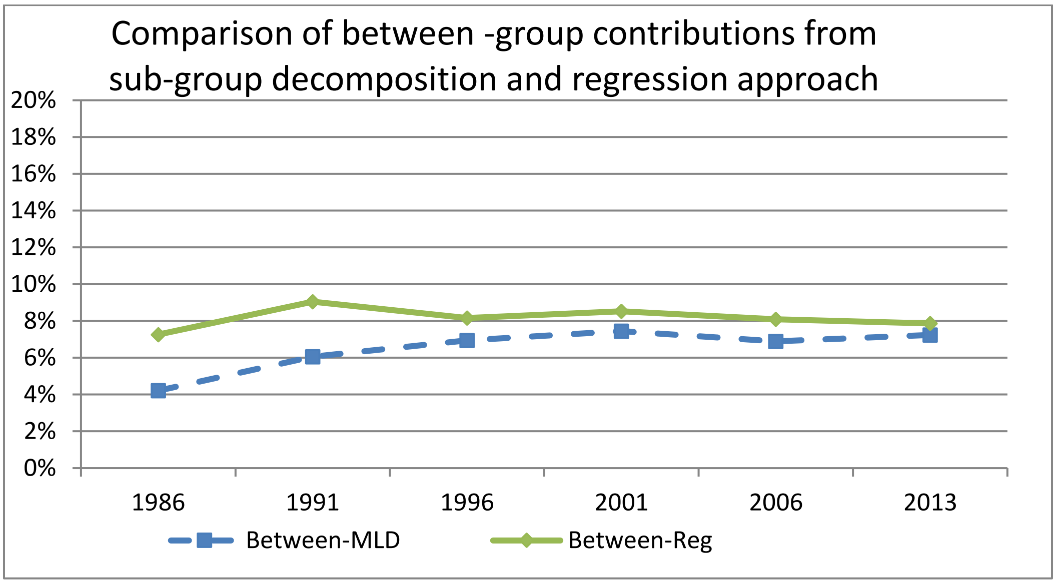
[92] The contribution (S_k) from the regression approach is from a decomposition of variance. Shorrocks showed that the contributions calculated from these are applicable to other measures of inequality such as the MLD, which satisfies a set of six axioms (see Shorrocks, 1982).

[93] In our regression model, the sign of the contribution depends on the covariance of the group income with the overall income. Groups that have high average incomes such as High Skilled NZ-born will have positive co-variances with total income and thus positive contribution.

[94] If $r_m > 1$ for a group with high relative mean incomes, the contributions of that group to overall mean-group contributions (between-group inequality) will be negative i.e. $r_m = \mu_m/\mu$. If $\mu_m > \mu$ then $\ln\left(\frac{1}{r_m}\right) < 0$

Figure 4.1 : Between- and within-group contributions from the regression and sub-group decomposition approaches



Notes: Figure 4.1 compares the between-group MLD contributions from the regression and sub-group decomposition approaches

We have shown that the results from our extension of the regression approach and the sub-group level decomposition approach are similar. Given that one of the advantages of the regression approach is the ease of accounting for multiple factors, we report the contribution of each migrant group to inequality accounting for age, sex and employment status. We compare the results from this adjusted decomposition with the basic approach (with migration indicators as the only covariates). We present the results for all urban areas combined[95] in Table 4.7. It is important to remember that for the multivariate regression, the between-group contributions are calculated using a Shapley value approach and are the average of the marginal contributions of each factor from all possible orderings while the within-group contributions do not depend on the order in which they are included and are calculated using the standard Fields and Yoo approach. In the multivariate regression, we report only the conditional between-group and conditional within-group contributions for migration[96]. The sum of conditional between-group and

[95] Results for Non-metropolitan and Metropolitan areas are available in Appendix 4.A.5 and Appendix 4.A.6.

[96] In the basic regression, the sum of within and between-migrant group contributions add up to total inequality. However, in the extended regressions, we show the conditional-between and conditional-within migrant contributions of each migrant groups after adjusting for age, sex and employment status. Because some of the overall inequality are accounted for by between-age/between-sex/between-employment status contributions, the sum of the conditional-migrant group contributions will not add up to overall inequality.

conditional within-group contributions will not add up to overall inequality because instead of explaining the contributions of all factors, as most studies that use regression decomposition do, we focus exclusively on "explaining" overall income inequality in terms of the contribution of the eight migrant groups and how accounting for age, sex, and employment status changes the contributions.

Table 4.7: Mean-group contribution of migrant groups to inequality with and without accounting for age, sex and employment status in all urban areas combined

	Basic regression-based decomposition of inequality level and change							Adjusted regression-based decomposition of inequality level and change						
Migrant status	1986	1991	1996	2001	2006	2013	Contri to change(δ_k) MLD points	1986	1991	1996	2001	2006	2013	Contri to change(δ_k) MLD points
	Between-group contribution							**Conditional between-group contribution**						
HS NZ-born	11.7%	13.5%	12.6%	13.8%	14.2%	14.0%	0.0086	12.9%	15.1%	13.8%	15.1%	15.5%	15.0%	0.0079
M/LS NZ-born	-7.3%	-7.3%	-5.7%	-6.5%	-6.7%	-6.5%	0.0027	-9.3%	-9.5%	-7.1%	-8.0%	-7.8%	-7.3%	0.0070
HS Ret. NZ-born	0.7%	0.8%	0.8%	0.8%	1.3%	1.0%	0.0009	0.8%	0.9%	0.9%	0.9%	1.5%	1.1%	0.0009
M/LS Ret. NZ-born	-0.2%	-0.2%	-0.2%	-0.2%	-0.1%	-0.2%	0.0000	-0.2%	-0.2%	-0.3%	-0.2%	-0.2%	-0.2%	0.0001
HS Earlier	3.2%	3.6%	3.2%	3.5%	3.6%	4.1%	0.0034	3.5%	4.0%	3.5%	3.9%	4.0%	4.4%	0.0034
HS New	0.9%	1.2%	0.2%	0.4%	0.3%	0.2%	-0.0023	1.0%	1.4%	0.3%	0.5%	0.4%	0.2%	-0.0025
M/LS Earlier	-1.5%	-2.2%	-2.1%	-2.4%	-3.3%	-3.9%	-0.0087	-1.8%	-2.9%	-2.6%	-3.1%	-4.0%	-4.5%	-0.0095
M/LS New	-0.3%	-0.6%	-0.7%	-0.9%	-1.3%	-0.9%	-0.0022	-0.4%	-0.7%	-1.0%	-1.2%	-1.6%	-1.1%	-0.0026
Overall between	**7.3%**	**9.0%**	**8.2%**	**8.5%**	**8.1%**	**7.9%**	**0.0024**	**6.5%**	**8.2%**	**7.4%**	**8.0%**	**7.8%**	**7.7%**	**0.0047**
	Within-group contribution							**Conditional within-group contribution**						
HS NZ-born	12.2%	13.5%	18.1%	20.1%	20.9%	25.8%	0.0485	9.9%	11.0%	15.8%	17.4%	17.6%	21.5%	0.0416
M/LS NZ-born	57.6%	54.4%	49.1%	45.6%	41.7%	34.9%	-0.0795	35.2%	35.7%	36.4%	34.5%	31.7%	25.9%	-0.0324
HS Ret. NZ-born	0.9%	1.0%	1.3%	1.3%	2.1%	2.0%	0.0037	0.7%	0.9%	1.1%	1.1%	1.8%	1.6%	0.0033
M/LS Ret. NZ-born	1.8%	1.6%	1.6%	1.3%	1.6%	1.1%	-0.0024	1.2%	1.1%	1.2%	1.1%	1.3%	0.9%	-0.0009
HS Earlier	3.5%	3.9%	5.3%	6.9%	8.7%	12.7%	0.0331	2.8%	3.1%	4.6%	5.9%	7.3%	10.6%	0.0280
HS New	1.4%	2.0%	3.1%	3.3%	4.1%	3.6%	0.0080	1.1%	1.6%	2.5%	2.8%	3.4%	2.9%	0.0066
M/LS Earlier	13.3%	12.2%	10.9%	10.3%	10.0%	10.1%	-0.0111	8.2%	8.1%	8.0%	7.8%	7.5%	7.5%	-0.0021
M/LS New	2.0%	2.5%	2.5%	2.6%	2.8%	2.0%	0.0001	1.4%	1.8%	2.0%	2.0%	2.2%	1.6%	0.0007
Overall Within	**92.7%**	**91.0%**	**91.8%**	**91.5%**	**91.9%**	**92.1%**	**0.0003**	**60.4%**	**63.3%**	**71.6%**	**72.5%**	**72.8%**	**72.5%**	**0.0448**
MLD	0.3538	0.3402	0.3596	0.3664	0.3395	0.3565		0.3538	0.3402	0.3596	0.3664	0.3395	0.3565	

Note: Results are the between- and within-group contribution of migrant groups to inequality with and without accounting for age, sex and employment status in all urban areas combined. Contri to change(δ_k) is the contribution to change in MLD between 1986 and 2013 and is calculated using $\delta_k = S_{k,t+1} * I_{t+1} - S_{k,t} * I_t$

Table 4.7 reports the contribution to inequality in all urban areas combined for each migrant group using the regression-based decomposition approach. As explained earlier, we consider two variations. The first variation (hereafter referred to as the basic decomposition) reported in the first panel of Table 4.7 uses only migrant groups as explanatory variables. Because we treat all migrant groups as a block (as if they are one single explanatory variable), the Shapley value decomposition procedure coincides with the standard Fields and Yoo approach i.e. with only one block of explanatory variable; the marginal contribution does not depend on the order in which it is introduced in the regression.

In the second panel in Table 4.7 (hereafter referred to as the adjusted decomposition), we account for age, sex and employment status, in our regression framework and examine what effect these characteristics have on the contributions of each migrant group to inequality. Here, the between-group contributions depend on the ordering and the reported contributions are the average of the marginal contributions from all possible orderings. The within-group contributions do not depend on the orderings and are calculated using the Fields and Yoo approach.

Although the results from the regression decompositions represent a decomposition of the variance of income, Shorrocks (1982) shows that the calculated contributions are invariant to the choice of inequality measure as long as the inequality measure satisfies a set of six axioms[97]. Thus, it is possible to apply the calculated level contributions to the MLD to derive the contribution to change in MLD between 1986 and 2013. The contribution to change (δ_k) is calculated using the formula:

$$\delta_k = S_{k,t+1} * I_{t+1} - S_{k,t} * I_t$$

We compare the within- and between-group contribution to change from the basic regression approach to the within- and between-group contribution to change from the Mookherjee and Shorrocks change decomposition approach.

In the basic regression decomposition, all groups except the High Skilled Newly Arrived, Medium/Low Skilled Earlier and Medium/Low Skilled Newly Arrived make inequality-increasing between-group contributions to inequality change between 1986 and 2013. This is in contrast to the results using the Mookherjee

[97] Popular measures like MLD, Gini, and Theil satisfies these six axioms.

and Shorrocks approach, where all low skilled groups (except for Medium/Low Skilled Newly Arrived) make inequality-reducing between-group contributions to inequality change. For within-group inequality change contributions, the patterns in the regression-based decomposition and Mookherjee and Shorrocks sub-group change decomposition are the same in terms of direction of change except for the Medium/Low Skilled Earlier group. In the Mookherjee and Shorrocks approach, Medium/Low Skilled Earlier made an inequality-increasing contribution but in the regression approach, its contribution to change is inequality-reducing.

Focusing on the immigrant groups (all other groups except High Skilled New Zealand-born and Medium/Low Skilled New Zealand-born), High Skilled Earlier, High Skilled Returning New Zealand-born and Medium/Low Skilled Returning New Zealand-born make inequality-increasing between- and within-group contributions to change in contrast to Medium/low Skilled groups, which make inequality-reducing within-group contributions except for the Medium/Low Skilled Newly Arrived.

Accounting for age, sex and employment status, in the adjusted regressions, the overall between- and within-group contributions to the level of inequality decrease. This implies that accounting for these factors, migrant groups are closer together in terms of average incomes while within-group contributions are lower because some of the within-group inequality is accounted for by differences in age, sex and employment status across groups. With respect to the contribution to change, the basic decomposition results imply that most of the change between 1986 and 2013 is from between-group contributions. However, when age, sex and employment status are accounted for as in the adjusted regressions, the results show that changes in within-group inequality make a greater contribution to overall change in inequality between 1986 and 2013.

Finally, to end this section, we summarise the results from all the decomposition approaches. Table 4.8 summarises the results of the contributions to inequality in levels in 1986 and 2013 from the decomposition techniques. Table 4.9 presents the by-group contribution to changes from the Mookherjee and Shorrocks sub-group decomposition and the basic regression decomposition approaches for all urban areas. Table 4.10 summarises the overall within- and between-group contributions from each method by area.

Summary of decomposition results

Table 4.8: Summary of the contributions to the LEVEL of inequality

Table	Decomposition Method	1986 Sum of between-group prop.	1986 Sum of within-group	2013 Sum of Between-group prop.	2013 Sum of within-group prop.
All urban areas combined					
4.6	Sub-group decomposition	4%	96%	7%	93%
4.6	Regression-based	7%	93%	8%	92%
4.7	Regression-based with covariates	6%	60%	8%	73%
Non-metropolitan					
Appendix 5	Sub-group decomposition	3%	97%	6%	94%
Appendix 5	Regression-based	7%	93%	6%	94%
Appendix 7	Regression-based with covariates	6%	58%	6%	71%
Metropolitan					
Appendix 6	Sub-group decomposition	4%	96%	8%	92%
Appendix 6	Regression-based	7%	93%	8%	92%
Appendix 8	Regression-based with covariates	7%	61%	8%	73%

Note: Results are the overall between- and within-group contributions in 1986 and 2013 using sub-group decomposition and regression decomposition

Table 4.9: By-migrant group contribution to CHANGE in inequality between 1986 to 2013

All urban areas						
	Sub-group change decomposition (approx)			**Regression decomposition of inequality change**		
	Contribution to between	Contribution to within	Total change (approx.)	Contribution to between	Contribution to within	Total change
HS NZ-born	0.1230	0.0324	0.1554	0.0086	0.0485	0.0571
M/LS NZ-born	-0.2192	-0.0882	-0.3074	0.0027	-0.0795	-0.0768
HS Ret. NZ-born	0.0084	0.0025	0.0109	0.0009	0.0037	0.0046
M/LS Ret. NZ-born	-0.0114	-0.0035	-0.0149	0.0000	-0.0024	-0.0024
HS Earlier	0.0871	0.0275	0.1146	0.0034	0.0331	0.0365
HS Newly Arrived	0.0260	0.0109	0.0369	-0.0023	0.0080	0.0057
M/LS Earlier	-0.0104	0.0049	-0.0055	-0.0087	-0.0111	-0.0198
M/LS Newly Arrived	0.0112	0.0053	0.0165	-0.0022	0.0001	-0.0021
Overall	**0.0148**	**-0.0082**	**0.0066**	**0.0024**	**0.0003**	**0.0027**

Note: Results are the overall between- and within-group contributions to change between 1986 and 2013 in all urban areas combined using the sub-group decomposition and regression decomposition

Table 4.10: Summary of the group contributions to CHANGE in inequality between 1986 and 2013: Sub-group decomposition and regression approach

		1986-2013				
Table		Overall contribution from within-group inequality	Overall contribution from between-group inequality	Approx. total contribution	Actual change	Decomposition error
	Sub-group change decomposition (Mookherjee & Shorrocks)					
4.5	All urban areas	-0.0082	0.0148	0.0066	0.0027	0.0043
4.5	Non-metropolitan	-0.0463	0.0082	-0.0381	-0.0412	0.0032
4.5	Metropolitan	0.0033	0.0164	0.0197	0.0156	0.0044
	Change contribution based on Regression decomposition					
4.7	All urban areas	0.0003	0.0024		0.0027	
Appx 4.A.7	Non-metropolitan	-0.0380	-0.0032		-0.0412	
Appx 4.A.8	Metropolitan	0.0117	0.0039		0.0156	
	Change contribution based on Regression based decomposition with covariates					
4.7	All urban areas	0.0448	0.0047		0.0027	
Appx 4.A.7	Non-metropolitan	0.0163	-0.0006		-0.0412	
Appx 4.A.8	Metropolitan	0.0517	0.0059		0.0156	

Note: Results are the overall between- and within-group contributions to change between 1986 and 2013 across areas using the sub-group decomposition and regression decomposition approaches

4.6 Conclusion

Debates on the various socio-economic impacts of immigration in destination countries continue to take centre stage in most western countries. There is a lot of evidence on the impact of immigration on several social and economic outcomes, but the implications for the distribution of personal incomes remain relatively under-researched, particularly in New Zealand, where the emphasis is more commonly on mean income differences between groups of migrants and the local-born. Using New Zealand data, we focus in this paper on the distributional impact of migration on incomes at the sub-national level[98]. A large part of the immigration flow into New Zealand is meant to address skill shortages and while there is evidence of its minimal impact on average incomes, there has previously been little evidence relating to the impact of skilled immigration on income

[98] We use the positive income of people between the ages of 25 to 64 as a proxy for labour income.

inequality. Using multiple decomposition methodologies, we contribute to the literature by examining two channels through which migration status may affect the distribution of income in New Zealand (namely the group size and within-group distribution effects) and provide evidence on the role of migration on changes in the distribution of income between 1986 and 2013 – a period of relatively high immigration and diversification of the type of immigrants in New Zealand.

We find that in all urban areas combined, income inequality rose by about 1% for the population aged 25 to 64 years earning positive incomes. This small increase masks notable spatial differences. In metropolitan areas, the inequality of this population rose by about 5% while in non-metropolitan areas, inequality fell by 11%.

In all urban areas combined, immigrants increased from around 25% of the population aged 25 to 64 years in 1996 to 35% in 2013. The national figures mask the spatial selectivity in the location of immigrants. The immigrant share of the population in metropolitan areas is almost double that in non-metropolitan areas. Also, across areas there are big differences in the patterns of change among immigrants with respect to length of stay and skill level. For example, in all urban areas the number of High Skilled Earlier immigrants in 2013 had increased by around 694% relative to the 1986 number while the number of Low/Medium Skilled Earlier immigrants increased by only around 33% relative to the 1986 number.

We used two decomposition approaches to analyse the effect of these changes on the distribution of income between 1986 and 2013. Using the Mookherjee and Shorrocks sub-group decomposition of inequality change, we examine two channels through which changes in immigration may affect the distribution of income – the composition effect and the migrant-specific distribution effect. In all urban areas, changes from migration have had an inequality-increasing composition effect and an inequality-reducing migrant-specific distribution effect. This composition effect slightly dominated the migrant-specific distribution effect; this is why inequality increased by around 1%. Spatially, the pattern is different with the inequality-reducing migrant-specific distribution effect dominating the inequality-increasing composition effect in non-metropolitan areas, which is why inequality declined in non-metropolitan areas.

We provide an extension to the standard regression decomposition methodology that allows us to express the contributions of migration groups into within- and between-group contributions to the level of inequality, and thus to estimate the contributions to inequality change. This allows us to reconcile the regression decomposition approach with the sub-group decomposition method. We show that the results from both methods are comparable but the difference in the way the MLD and Variance treat groups above/below the mean imply that they give opposing signs for the year-specific mean-group contributions to the level of inequality. In the MLD change decomposition, migrant groups above the overall mean will make inequality-reducing mean group contributions to the level of inequality, contrary to the regression decomposition.

Examining the data by migrant group, we find that excluding the New Zealand-born group (i.e High Skilled New Zealand-born and Low Skilled New Zealand-born), the High Skilled Earlier Migrants group makes the biggest income inequality-increasing contribution to inequality change. Overall, there seems to be a difference in the contribution of high skilled and medium/low skilled groups (immigrants and New Zealand-born). High Skilled groups generally tend to make inequality-increasing contributions while medium/low skilled groups tend to be inequality-decreasing. This is because high skilled groups have high levels of within-group inequality, increased as a share of the total population, as well as having high relative incomes. Medium/low skilled groups had a reduction in population share, lower within-group inequality and lower relative incomes, leading to their inequality-reducing contributions. New Arrivals (high skilled and medium/low skilled) are interestingly different: within-group inequality is high for this group and the population share increased for this group regardless of skill level. Thus, the Newly Arrived group made inequality-increasing contributions regardless of skill level.

Spatially, we show that metropolitan and non-metropolitan areas have a different skill mix, with a greater proportion of high-skilled New Zealand-born and immigrants preferring metropolitan areas. In non-metropolitan areas, the inequality-reducing contribution of the medium/low skilled groups dominated the inequality-increasing contributions of the high-skilled groups, so inequality fell in these areas. The opposite is true in metropolitan areas, with the inequality-increasing contributions of the high-skilled groups dominating the inequality-reducing contributions of the low-skilled group in these areas.

In this research we examined the distributional implications of immigration. The approach provided here can be easily replicated in countries such as Australia and Canada, which operate a similar migration policy to New Zealand, or in countries of the European Union that have experienced large scale immigration in recent times and have high quality disaggregated data on individual incomes.

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Appendix Chapter 4

Table 4.A.1: Employment status of New Zealand-born compared to Immigrants

	NZ-born					Immigrants				
	FT Employed	PT Employed	All employed	Unemployed	NILF	FT Employed	PT Employed	All employed	Unemployed	NILF
Non-metropolitan										
1986	61.8%	13.2%	75.0%	3.1%	21.9%	65.4%	11.6%	77.0%	3.0%	20.0%
1991	55.9%	12.9%	68.8%	5.7%	25.5%	57.6%	12.0%	69.6%	5.6%	24.8%
1996	59.0%	15.9%	75.0%	4.4%	20.7%	59.0%	14.7%	73.7%	4.9%	21.4%
2001	62.3%	16.8%	79.2%	4.0%	16.8%	61.4%	16.0%	77.4%	4.1%	18.5%
2006	66.1%	16.6%	82.6%	2.6%	14.8%	67.1%	15.8%	82.9%	2.6%	14.5%
2013	65.2%	16.1%	81.3%	4.1%	14.6%	67.7%	15.7%	83.3%	3.2%	13.4%
Metropolitan										
1986	65.9%	11.7%	77.6%	2.7%	19.7%	69.7%	10.3%	79.9%	2.8%	17.2%
1991	61.5%	11.9%	73.4%	5.0%	21.6%	61.8%	10.2%	72.0%	5.6%	22.3%
1996	64.9%	14.2%	79.1%	3.5%	17.4%	60.6%	12.2%	72.8%	5.8%	21.4%
2001	68.1%	14.5%	82.6%	3.4%	14.0%	63.3%	12.7%	76.0%	4.9%	19.1%
2006	70.1%	14.5%	84.6%	2.2%	13.2%	67.5%	13.1%	80.6%	2.9%	16.5%
2013	69.5%	13.9%	83.4%	3.6%	13.1%	68.3%	12.7%	81.0%	3.8%	15.2%
All urban areas										
1986	64.5%	12.2%	76.7%	2.9%	20.4%	68.8%	10.6%	79.3%	2.9%	17.8%
1991	59.6%	12.3%	71.9%	5.3%	22.8%	61.0%	10.6%	71.6%	5.6%	22.8%
1996	63.0%	14.8%	77.8%	3.8%	18.4%	60.3%	12.6%	72.9%	5.7%	21.4%
2001	66.3%	15.2%	81.6%	3.6%	14.8%	63.0%	13.3%	76.2%	4.8%	19.0%
2006	68.9%	15.1%	84.0%	2.3%	13.7%	67.4%	13.5%	80.9%	2.9%	16.2%
2013	68.1%	14.6%	82.7%	3.7%	13.5%	68.2%	13.1%	81.3%	3.7%	15.0%

Table 4.A.2: Comparison of MLD, relative mean income, and population share for all international migrant groups and New Zealand-born for non-metropolitan area

		NZ-born		Immigrants						
		HS NZ-born	M/LS NZ-born	HS Ret. NZ-born	M/LS Ret. NZ-born	HS Earlier	HS Newly Arrived	M/LS Earlier	M/LS Newly Arrived	Total
		Non-metropolitan								
1986	MLD	0.3054	0.3492	0.3366	0.3462	0.3216	0.4886	0.3235	0.4740	0.3589
	Rel.inc	1.79	0.95	1.64	0.96	1.81	1.81	1.00	1.00	1.00
	Pop Shr	3.8%	79.3%	0.3%	2.2%	1.0%	0.4%	11.6%	1.4%	100.0%
1991	MLD	0.3040	0.3092	0.3369	0.3023	0.3186	0.4124	0.3092	0.4129	0.3275
	Rel.inc	1.91	0.94	1.68	0.90	1.91	1.74	0.97	0.89	1.00
	Pop Shr	4.2%	80.4%	0.2%	1.7%	1.1%	0.5%	10.6%	1.3%	100.0%
1996	MLD	0.3178	0.3078	0.3409	0.2930	0.3643	0.5600	0.3275	0.4556	0.3340
	Rel.inc	1.88	0.94	1.56	0.91	1.83	1.46	0.93	0.86	1.00
	Pop Shr	5.1%	78.9%	0.3%	2.2%	1.4%	0.8%	9.9%	1.4%	100.0%
2001	MLD	0.3093	0.3079	0.3494	0.3095	0.3577	0.4727	0.3398	0.4325	0.3354
	Rel.inc	1.71	0.93	1.50	0.88	1.73	1.46	0.92	0.81	1.00
	Pop Shr	7.1%	77.5%	0.3%	1.5%	1.9%	0.9%	9.2%	1.6%	100.0%
2006	MLD	0.2809	0.2821	0.3223	0.2790	0.3420	0.3999	0.3146	0.3545	0.3065
	Rel.inc	1.51	0.93	1.33	0.91	1.53	1.27	0.89	0.85	1.00
	Pop Shr	9.5%	72.0%	0.7%	2.1%	2.5%	1.6%	8.8%	2.8%	100.0%
2013	MLD	0.2993	0.2870	0.3724	0.3225	0.3436	0.4647	0.3100	0.3986	0.3177
	Rel.inc	1.44	0.91	1.30	0.86	1.43	1.15	0.89	0.78	1.00
	Pop Shr	12.6%	66.8%	0.7%	1.6%	4.3%	1.7%	10.0%	2.4%	100.0%
Abs pop share		8.7%	-12.5%	0.5%	-0.7%	3.3%	1.3%	-1.6%	1.0%	0.0%
Act pop change		281.2%	-2.2%	203.8%	-18.4%	391.3%	431.0%	0.1%	95.7%	16.1%

Note: Absolute and Actual pop (population) changes reported are changes between 1986 and 2013. Absolute change is the percentage point difference in the proportion of each group between 1986 and 2013 (prop2013-prop1986). Actual pop change is the percentage change in the population of each group between 1986 and 2013 calculated as: (Population 2013-population 1986)/population 1986 for each group. HS NZ-born and M/LS NZ-born represent High Skilled and Medium/Low Skilled New Zealand-born respectively; HS Ret. NZ-born and M/LS Ret. NZ-born represent High Skilled and Medium/Low Skilled Returning New Zealand-born; HS Earlier and LS Earlier represent High Skilled and Medium/Low Skilled Earlier migrants; HS N.A and M/LS N.A represent High Skilled and Medium/Low Skilled Newly Arrived

Notes: Results are the by-group MLD, relative mean income and population share of the different categories of migrant groups in Non-metropolitan areas. HS (High skilled) are defined as those with Bachelor's degree or higher and M/LS (Medium/Low skilled) are those with other qualifications below a Bachelor's degree or no qualifications. Newly Arrived are those who arrived in the last inter-censal period and earlier migrant are arrivals prior to the last inter-censal period

Table 4.A.3: Comparison of MLD, relative mean income, and population share for all international migrant groups and New Zealand-born for non-metropolitan area

		NZ-born		Immigrants						
		HS NZ-born	M/LS NZ-born	HS Ret. NZ-born	M/LS Ret. NZ-born	HS Earlier	HS Newly Arrived	M/LS Earlier	M/LS Newly Arrived	Total
		Metropolitan								
1986	MLD	0.3104	0.3437	0.3473	0.3300	0.3186	0.4125	0.3034	0.4023	0.3500
	Rel.inc	1.66	0.94	1.50	0.96	1.61	1.48	0.93	0.88	1.00
	Pop Shr	6.3%	65.3%	0.6%	2.6%	1.9%	0.6%	20.1%	2.5%	100.0%
1991	MLD	0.3148	0.3199	0.3566	0.3105	0.3233	0.3801	0.3096	0.3706	0.3415
	Rel.inc	1.70	0.93	1.63	0.95	1.64	1.46	0.87	0.83	1.00
	Pop Shr	7.3%	64.4%	0.6%	2.2%	2.2%	1.2%	18.5%	3.6%	100.0%
1996	MLD	0.3389	0.3201	0.3488	0.2971	0.3631	0.6235	0.3341	0.5054	0.3651
	Rel.inc	1.72	0.93	1.61	0.92	1.59	1.02	0.84	0.71	1.00
	Pop Shr	8.8%	61.1%	0.7%	2.5%	2.9%	2.1%	18.0%	3.8%	100.0%
2001	MLD	0.3271	0.3212	0.3560	0.3300	0.3838	0.5129	0.3570	0.4866	0.3719
	Rel.inc	1.62	0.92	1.56	0.93	1.44	1.07	0.81	0.68	1.00
	Pop Shr	11.4%	57.6%	0.8%	1.8%	4.4%	2.7%	17.0%	4.4%	100.0%
2006	MLD	0.3021	0.3002	0.3223	0.3005	0.3531	0.4170	0.3426	0.4001	0.3468
	Rel.inc	1.50	0.92	1.49	0.97	1.27	1.01	0.78	0.72	1.00
	Pop Shr	13.5%	49.9%	1.4%	1.9%	6.8%	4.1%	17.0%	5.3%	100.0%
2013	MLD	0.3283	0.3152	0.3643	0.3527	0.3473	0.4349	0.3528	0.4366	0.3656
	Rel.inc	1.45	0.90	1.44	0.93	1.20	1.01	0.75	0.68	1.00
	Pop Shr	16.2%	43.5%	1.3%	1.3%	11.2%	3.5%	19.4%	3.7%	100.0%
Abs pop share		9.9%	-21.8%	0.7%	-1.3%	9.3%	2.8%	-0.8%	1.2%	0.0%
Act pop change		275.7%	-2.3%	221.5%	-25.4%	763.3%	693.8%	41.2%	115.4%	46.7%

Note: Absolute and Actual pop (population) changes reported are changes between 1986 and 2013. Absolute change is the percentage point difference in the proportion of each group between 1986 and 2013 (prop2013-prop1986). Actual pop change is the percentage change in the population of each group between 1986 and 2013 calculated as: (Population 2013-population 1986)/population 1986 for each group. HS NZ-born and M/LS NZ-born represent High Skilled and Medium/Low Skilled New Zealand-born respectively; HS Ret. NZ-born and M/LS Ret. NZ-born represent High Skilled and Medium/Low Skilled Returning New Zealand-born; HS Earlier and LS Earlier represent High Skilled and Medium/Low Skilled Earlier migrants; HS N.A and M/LS N.A represent High Skilled and Medium/Low Skilled Newly Arrived

Notes: Results are the by-group MLD, relative mean income and population share of the different categories of migrant groups in Metropolitan areas. HS (High skilled) are defined as those with Bachelor's degree or higher and M/LS (Medium/Low skilled) are those with other qualifications below a Bachelor's degree or no qualifications. Newly Arrived are those who arrived in the last inter-censal period and earlier migrant are arrivals prior to the last inter-censal period

Table 4.A.4: Between-group and within-group contributions to MLD by area from 1986 to 2013

Between and Within-group contributions for non-metropolitan and metropolitan areas												
	Between-group contributions											
	Non-metropolitan						**Metropolitan**					
	1986	1991	1996	2001	2006	2013	1986	1991	1996	2001	2006	2013
HS NZ-born	-0.0222	-0.0269	-0.0325	-0.0382	-0.0394	-0.0461	-0.0321	-0.0389	-0.0474	-0.0549	-0.0544	-0.0607
M/LS NZ-born	0.0431	0.0473	0.0529	0.0598	0.0555	0.0635	0.0421	0.0456	0.0449	0.0504	0.0408	0.0443
HS Ret. NZ-born	-0.0014	-0.0012	-0.0014	-0.0013	-0.0019	-0.0019	-0.0024	-0.0028	-0.0036	-0.0035	-0.0056	-0.0047
M/LS Ret. NZ-born	0.0008	0.0019	0.0021	0.0019	0.0021	0.0023	0.0011	0.0011	0.0021	0.0014	0.0006	0.0010
HS Earlier Migrants	-0.0060	-0.0071	-0.0083	-0.0103	-0.0108	-0.0153	-0.0091	-0.0109	-0.0134	-0.0159	-0.0162	-0.0208
HS New. Arr. Migrant	-0.0022	-0.0025	-0.0029	-0.0033	-0.0038	-0.0023	-0.0025	-0.0045	-0.0004	-0.0018	-0.0002	-0.0005
M/LS Earlier Migrant	0.0003	0.0036	0.0070	0.0080	0.0098	0.0113	0.0150	0.0249	0.0309	0.0361	0.0427	0.0552
M/LS New. Arr. Migrant	0.0000	0.0016	0.0021	0.0034	0.0045	0.0060	0.0032	0.0067	0.0130	0.0167	0.0175	0.0139
Sum of Between	0.0124	0.0167	0.0190	0.0200	0.0160	0.0175	0.0153	0.0212	0.0261	0.0285	0.0252	0.0277
Prop-Between	3%	5%	6%	6%	5%	6%	4%	6%	7%	8%	7%	8%
Within-group contributions												
	1986	1991	1996	2001	2006	2013	1986	1991	1996	2001	2006	2013
HS NZ-born	0.0117	0.0126	0.0163	0.0219	0.0267	0.0376	0.0197	0.0230	0.0298	0.0374	0.0409	0.0533
M/LS NZ-born	0.2769	0.2485	0.2429	0.2386	0.2031	0.1917	0.2246	0.2060	0.1955	0.1849	0.1499	0.1371
HS Ret. NZ-born	0.0009	0.0008	0.0011	0.0011	0.0021	0.0027	0.0020	0.0020	0.0026	0.0028	0.0045	0.0047
M/LS Ret. NZ-born	0.0077	0.0052	0.0065	0.0047	0.0060	0.0051	0.0085	0.0070	0.0076	0.0060	0.0058	0.0046
HS Earlier Migrants	0.0033	0.0035	0.0050	0.0067	0.0087	0.0147	0.0060	0.0071	0.0105	0.0168	0.0240	0.0388
HS New. Arr. Migrant	0.0018	0.0019	0.0043	0.0041	0.0064	0.0079	0.0026	0.0045	0.0134	0.0136	0.0171	0.0151
M/LS Earlier Migrant	0.0374	0.0329	0.0324	0.0313	0.0276	0.0309	0.0611	0.0574	0.0601	0.0606	0.0584	0.0683
M/LS New. Arr. Migrant	0.0067	0.0055	0.0064	0.0069	0.0099	0.0095	0.0100	0.0133	0.0193	0.0214	0.0211	0.0160
Sum of Within	0.3464	0.3109	0.3149	0.3153	0.2905	0.3001	0.3345	0.3203	0.3388	0.3435	0.3217	0.3379
Prop-Within	97%	95%	94%	94%	95%	94%	96%	94%	93%	92%	93%	92%
Total inequality	0.3588	0.3276	0.3339	0.3353	0.3065	0.3176	0.3498	0.3415	0.3649	0.3720	0.3469	0.3656
Total inequality here is slightly different from the last column in Table 3 in some years (around 0.0001pts difference) due to base 3 rounding												

Note: Results are the between and within-group contributions to overall inequality (as measured by the MLD) for the migrant group categories in Non-metropolitan and Metropolitan areas in each census period from 1986 to 2013

Table 4.A.5: Comparison of between and within-group contributions in Non-metropolitan areas from the regression and sub-group decomposition approach

Non-metropolitan												
	Regression approach						**Sub-group decomposition**					
Migrant status	1986	1991	1996	2001	2006	2013	1986	1991	1996	2001	2006	2013
	Between-group contribution						**Between-group contribution**					
HS NZ-born	10%	12%	11%	12%	12%	12%	-6%	-8%	-10%	-11%	-13%	-15%
M/LS NZ-born	-7%	-7%	-6%	-7%	-8%	-8%	12%	14%	16%	18%	18%	20%
HS Ret. NZ-born	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	-1%	-1%
M/LS Ret. NZ-born	0%	0%	0%	0%	0%	0%	0%	1%	1%	1%	1%	1%
HS Earlier Migrants	3%	3%	3%	3%	3%	4%	-2%	-2%	-2%	-3%	-4%	-5%
HS Newly Arrived Migrant	1%	1%	1%	1%	1%	0%	-1%	-1%	-1%	-1%	-1%	-1%
M/LS Earlier Migrant	0%	-1%	-1%	-1%	-1%	-1%	0%	1%	2%	2%	3%	4%
M/LS Newly Arrived Migrant	0%	0%	0%	0%	-1%	-1%	0%	0%	1%	1%	1%	2%
Overall between-inequality	7%	8%	7%	7%	6%	6%	3%	5%	6%	6%	5%	6%
	Within-group contribution						**Within-group contribution**					
HS NZ-born	66%	65%	61%	60%	57%	49%	3%	4%	5%	7%	9%	12%
M/LS NZ-born	1%	1%	1%	1%	1%	1%	77%	76%	73%	71%	66%	60%
HS Ret. NZ-born	2%	1%	1%	1%	2%	1%	0%	0%	0%	0%	1%	1%
M/LS Ret. NZ-born	3%	3%	4%	5%	5%	8%	2%	2%	2%	1%	2%	2%
HS Earlier Migrants	1%	1%	2%	2%	3%	3%	1%	1%	1%	2%	3%	5%
HS Newly Arrived Migrant	10%	9%	8%	8%	7%	7%	1%	1%	1%	1%	2%	2%
M/LS Earlier Migrant	2%	1%	1%	1%	2%	2%	10%	10%	10%	9%	9%	10%
M/LS Newly Arrived Migrant	93%	92%	93%	93%	94%	94%	2%	2%	2%	2%	3%	3%
Overall within-inequality proportion	66%	65%	61%	60%	57%	49%	97%	95%	94%	94%	95%	94%

*Note: Results are the between- and within-group contributions in Non-metropolitan areas from the regression and sub-group decomposition approaches. The sub-group decomposition contributions are based on converting the contributions in Table 4.4 to percentages ((by-group contribution)/(overall inequality)*100). The regression approach contributions are based on the formulae presented in Section 4.3.2*

Table 4.A.6: Comparison of between and within-group contributions in Metropolitan areas from the regression and sub-group decomposition approach

Metropolitan												
	Regression approach						**Sub-group decomposition**					
Migrant status	1986	1991	1996	2001	2006	2013	1986	1991	1996	2001	2006	2013
	Between-group contribution						**Between-group contribution**					
HS NZ-born	12%	14%	13%	14%	15%	14%	-9%	-11%	-13%	-15%	-16%	-17%
M/LS NZ-born	-7%	-6%	-5%	-5%	-5%	-5%	12%	13%	12%	14%	12%	12%
HS Ret. NZ-born	1%	1%	1%	1%	1%	1%	-1%	-1%	-1%	-1%	-2%	-1%
M/LS Ret. NZ-born	0%	0%	0%	0%	0%	0%	0%	0%	1%	0%	0%	0%
HS Earlier Migrants	3%	4%	3%	3%	3%	4%	-3%	-3%	-4%	-4%	-5%	-6%
HS Newly Arrived Migrant	1%	1%	0%	0%	0%	0%	-1%	-1%	0%	0%	0%	0%
M/LS Earlier Migrant	-2%	-3%	-3%	-3%	-4%	-5%	4%	7%	8%	10%	12%	15%
M/LS Newly Arrived Migrant	0%	-1%	-1%	-1%	-2%	-1%	1%	2%	4%	4%	5%	4%
Overall between-inequality	7%	9%	8%	9%	8%	8%	4%	6%	7%	8%	7%	8%
	Within-group contribution						**Within-group contribution**					
HS NZ-born	13%	15%	19%	21%	22%	27%	6%	7%	8%	10%	12%	15%
M/LS NZ-born	55%	51%	46%	42%	38%	32%	64%	60%	54%	50%	43%	38%
HS Ret. NZ-born	1%	1%	1%	1%	2%	2%	1%	1%	1%	1%	1%	1%
M/LS Ret. NZ-born	2%	2%	2%	1%	2%	1%	2%	2%	2%	2%	2%	1%
HS Earlier Migrants	4%	4%	6%	8%	10%	14%	2%	2%	3%	5%	7%	11%
HS Newly Arrived Migrant	1%	2%	3%	4%	4%	4%	1%	1%	4%	4%	5%	4%
M/LS Earlier Migrant	15%	13%	12%	11%	11%	11%	17%	17%	16%	16%	17%	19%
M/LS Newly Arrived Migrant	2%	3%	3%	3%	3%	2%	3%	4%	5%	6%	6%	4%
Overall within-inequality proportion	93%	91%	92%	91%	92%	92%	96%	94%	93%	92%	93%	92%

*Note: Results are the between- and within-group contributions in Metropolitan areas from the regression and sub-group decomposition approaches. The sub-group decomposition contributions are based on converting the contributions in Table 4.4 to percentages ((by-group contribution)/(overall inequality)*100). The regression approach contributions are based on the formulae presented in Section 4.3.2*

Table 4.A.7: Mean-group contribution of migrant groups to inequality with and without accounting for age, sex and employment status in all non-metropolitan areas

	Basic decomposition							Adjusted decomposition						
Migrant status	1986	1991	1996	2001	2006	2013	Contri to change(δ_k) MLD points	1986	1991	1996	2001	2006	2013	Contri to change(δ_k) MLD points
	Between-group contribution							**Between-group contribution**						
HS NZ-born	9.7%	11.8%	11.1%	11.7%	11.9%	12.2%	0.0041	10.7%	13.1%	12.2%	12.9%	13.4%	13.6%	0.0048
M/LS NZ-born	-7.2%	-7.1%	-6.2%	-7.2%	-8.0%	-8.4%	-0.0009	-9.3%	-9.4%	-8.0%	-9.0%	-9.7%	-9.9%	0.0019
HS Ret. NZ-born	0.5%	0.4%	0.3%	0.3%	0.5%	0.4%	-0.0005	0.6%	0.5%	0.4%	0.4%	0.6%	0.5%	-0.0006
M/LS Ret. NZ-born	-0.1%	-0.3%	-0.2%	-0.2%	-0.3%	-0.3%	-0.0004	-0.2%	-0.3%	-0.3%	-0.3%	-0.4%	-0.3%	-0.0002
HS Earlier	2.7%	3.1%	2.7%	3.2%	3.3%	4.0%	0.0031	2.9%	3.5%	3.0%	3.5%	3.7%	4.4%	0.0036
HS New	1.0%	1.0%	0.7%	0.8%	0.9%	0.4%	-0.0022	1.1%	1.1%	0.8%	0.9%	1.0%	0.5%	-0.0024
M/LS Earlier	-0.1%	-0.6%	-0.8%	-0.9%	-1.3%	-1.5%	-0.0044	-0.1%	-0.7%	-1.1%	-1.2%	-1.6%	-1.7%	-0.0050
M/LS New	0.0%	-0.2%	-0.2%	-0.3%	-0.6%	-0.6%	-0.0020	0.0%	-0.3%	-0.3%	-0.4%	-0.7%	-0.8%	-0.0025
Overall between	6.5%	8.2%	7.3%	7.3%	6.4%	6.4%	-0.0032	5.8%	7.4%	6.7%	6.9%	6.3%	6.3%	-0.0008
	Within-group contribution							**Within-group contribution**						
HS NZ-born	9.2%	10.3%	14.2%	15.7%	17.0%	21.4%	0.0348	7.5%	8.5%	12.5%	13.4%	14.1%	17.5%	0.0287
M/LS NZ-born	66.4%	65.2%	60.9%	59.5%	56.8%	49.5%	-0.0810	38.9%	41.6%	43.6%	43.2%	41.6%	35.2%	-0.0278
HS Ret. NZ-born	0.6%	0.5%	0.6%	0.7%	1.0%	1.2%	0.0015	0.5%	0.4%	0.5%	0.6%	0.9%	0.9%	0.0011
M/LS Ret. NZ-born	1.7%	1.2%	1.4%	1.1%	1.5%	1.2%	-0.0022	1.0%	0.8%	1.0%	0.8%	1.1%	0.9%	-0.0007
HS Earlier	2.6%	2.8%	3.9%	4.5%	5.3%	8.1%	0.0167	2.1%	2.3%	3.4%	3.9%	4.5%	6.8%	0.0141
HS New	1.4%	1.3%	2.1%	2.0%	2.7%	2.9%	0.0045	1.1%	1.0%	1.8%	1.7%	2.3%	2.5%	0.0040
M/LS Earlier	9.8%	9.2%	8.0%	7.8%	7.2%	7.5%	-0.0114	5.8%	6.0%	5.8%	5.9%	5.4%	5.6%	-0.0030
M/LS New	1.8%	1.4%	1.5%	1.4%	2.1%	1.7%	-0.0009	1.2%	1.0%	1.2%	1.1%	1.6%	1.4%	0.0001
Overall within	93.5%	91.8%	92.7%	92.7%	93.6%	93.6%	-0.0380	58.2%	61.7%	69.8%	70.6%	71.5%	70.9%	0.0164
MLD	0.3589	0.3275	0.334	0.3354	0.3065	0.3177		0.3589	0.3275	0.334	0.3354	0.3065	0.3177	

Note: Results are the between- and within-group contribution of migrant groups to inequality with and without accounting for age, sex and employment status in Non-metropolitan areas. Contri to change(δ_k) is the contribution to change in MLD between 1986 and 2013 and is calculated using $\delta_k = S_{k,t+1} * I_{t+1} - S_{k,t} * I_t$

Table 4.A.8: Mean-group contribution of migrant groups to inequality with and without accounting for age, sex and employment status in metropolitan areas

	Basic decomposition							Adjusted decomposition						
Migrant status	1986	1991	1996	2001	2006	2013	Contri to change(δ_k) MLD points	1986	1991	1996	2001	2006	2013	Contri to change(δ_k) MLD points
	Between-group contribution							Between-group contribution						
HS NZ-born	12.2%	13.8%	12.8%	14.0%	14.6%	14.3%	0.0097	13.5%	15.4%	13.9%	15.3%	15.7%	15.1%	0.0080
M/LS NZ-born	-6.8%	-6.5%	-4.8%	-5.4%	-5.2%	-5.1%	0.0050	-8.6%	-8.4%	-5.9%	-6.5%	-6.0%	-5.6%	0.0096
HS Ret. NZ-born	0.8%	0.9%	0.9%	0.8%	1.5%	1.1%	0.0012	0.9%	1.0%	1.0%	0.9%	1.6%	1.2%	0.0012
M/LS Ret. NZ-born	-0.2%	-0.2%	-0.2%	-0.2%	-0.1%	-0.1%	0.0002	-0.2%	-0.2%	-0.3%	-0.2%	-0.1%	-0.1%	0.0003
HS Earlier	3.3%	3.7%	3.2%	3.4%	3.4%	3.7%	0.0019	3.6%	4.1%	3.5%	3.8%	3.7%	3.9%	0.0017
HS New	0.8%	1.3%	0.0%	0.2%	0.0%	0.1%	-0.0026	0.9%	1.4%	0.1%	0.3%	0.0%	0.1%	-0.0028
M/LS Earlier	-2.4%	-3.2%	-2.8%	-3.2%	-4.3%	-4.8%	-0.0094	-2.9%	-4.2%	-3.6%	-4.0%	-5.1%	-5.4%	-0.0096
M/LS New	-0.5%	-0.8%	-0.9%	-1.2%	-1.6%	-1.1%	-0.0022	-0.6%	-1.1%	-1.3%	-1.6%	-1.9%	-1.2%	-0.0023
Overall Between	7.3%	9.0%	8.2%	8.5%	8.3%	8.1%	0.0039	6.6%	8.1%	7.4%	8.0%	8.0%	7.9%	0.0058
	Within-group contribution							Within-group contribution						
HS NZ-born	13.3%	14.5%	19.2%	21.2%	21.8%	26.6%	0.0507	10.7%	11.8%	16.7%	18.2%	18.3%	22.1%	0.0433
M/LS NZ-born	54.6%	51.2%	46.0%	42.5%	38.4%	31.8%	-0.0751	34.0%	34.0%	34.5%	32.5%	29.5%	23.9%	-0.0316
HS Ret. NZ-born	1.1%	1.2%	1.4%	1.5%	2.3%	2.1%	0.0040	0.8%	1.0%	1.2%	1.3%	1.9%	1.8%	0.0038
M/LS Ret. NZ-born	1.9%	1.7%	1.6%	1.4%	1.6%	1.1%	-0.0025	1.2%	1.2%	1.2%	1.1%	1.3%	0.9%	-0.0009
HS Earlier	3.8%	4.2%	5.7%	7.5%	9.5%	13.8%	0.0371	3.0%	3.4%	4.9%	6.4%	8.0%	11.4%	0.0312
HS New	1.4%	2.2%	3.3%	3.7%	4.4%	3.8%	0.0089	1.1%	1.8%	2.7%	3.0%	3.7%	3.0%	0.0071
M/LS Earlier	14.6%	13.2%	11.7%	10.9%	10.7%	10.7%	-0.0118	9.0%	8.6%	8.5%	8.2%	8.0%	7.9%	-0.0026
M/LS New	2.1%	2.8%	2.8%	2.9%	3.0%	2.1%	0.0004	1.4%	2.0%	2.2%	2.2%	2.3%	1.6%	0.0009
Overall Within	92.7%	91.0%	91.8%	91.5%	91.7%	91.9%	0.0117	61.2%	63.8%	72.0%	73.0%	73.0%	72.7%	0.0516
MLD	0.3500	0.3415	0.3651	0.3719	0.3468	0.3656		0.3500	0.3415	0.3651	0.3719	0.3468	0.3656	

Note: Results are the between- and within-group contribution of migrant groups to inequality with and without accounting for age, sex and employment status in Metropolitan areas. Contri to change(δ_k) is the contribution to change in MLD between 1986 and 2013 and is calculated using $\delta_k = S_{k,t+1} * I_{t+1} - S_{k,t} * I_t$

Table 4.A.9: Definition of Variables used in regression decomposition method

Variable	Definition
Income	The income data represent total personal income before tax of people earning positive income in the 12 months before census night. It consists of income from all sources such as wages and salaries, self-employment, investments, and superannuation. It excludes social transfers in kind, such as public education or government-subsidised health care services. Income is captured in bands
Migration status	Country of birth is used to determine migration status. We identify international migrants in each Census as people who are usually resident in New Zealand but whose country of birth is outside of New Zealand (i.e., the foreign-born). We divide this group, by their length of stay, into newly arrived and earlier migrants. Newly Arrived are migrants who arrived during the last inter-censal period. We use the information on place of residence five years ago to identify a group of "Returning New Zealand-born"- these are New Zealand-born people who had been overseas five years before the census date and were resident in New Zealand at the time of the census.
Sex	This represent the gender of the individual either male or female.
Employment Status	This represents the employment status of the individual, whether employed, unemployed or not in the labour force
Age	This represent the age in years of the individual

Chapter Five: Article 4 - Who partners up? Educational Assortative Matching and the Distribution of Income in New Zealand[99]

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[99] Alimi, Maré and Poot (2018) - This work co-authored with Emeritus Prof. Jacques Poot and Dr. Dave Maré is available as a Motu Working Paper: Alimi, O., Maré, D. C., & Poot, J. (2018). *Who partners up? Educational Assortative Matching and the Distribution of Income in New Zealand.* (Working Paper: 18_13.) Wellington, New Zealand: Motu Economic and Public Policy Research. This chapter has also been submitted to the journal *Demography*

Abstract

Educational assortative matching among couples, i.e., the phenomenon whereby the highly-educated have partners who are also highly-educated, has gained attention in popular media and academic research as a driver of recent changes in the distribution of household income. We examine the effect of educational assortative matching on the distribution of household income in New Zealand - a country that has experienced rising inequality, increased educational attainment and a relatively low, and falling, wage premium for higher levels of education. Using data from the 1986, 1991, 1996, 2001, 2006 and 2013 Census of Population and Dwellings and a counterfactual randomisation methodology that accounts for secular changes in educational distribution, we find that educational assortative matching has increased but, contrary to some evidence overseas, this increase was driven by increased matching in the middle of the educational distribution. Spatially, we find higher and increasing levels of educational assortative matching in metropolitan areas compared to non-metropolitan areas, where assortative matching is lower and decreasing. We find that educational assortative matching has had an inequality-increasing impact on the distribution of income, especially for the full-time employed, for whom the matching impact is around 20 percent of the Mean Log Deviation measure of inequality. Additionally, sorting on observable characteristics such as age and location (with the more highly educated being disproportionally attracted to the metropolitan areas) are also inequality-increasing and sorting on unobservable characteristics that impact on income can play an important role as well.

Disclaimer

Access to the data used in this study was provided by Statistics New Zealand (SNZ) under conditions designed to give effect to the security and confidentiality provisions of the Statistics Act 1975. All frequency counts using Census data were subject to base three rounding in accordance with SNZ's release policy for census data.

Acknowledgements

We are grateful to Ben Davies of Motu, and Robert Didham and Tyler Northern from Statistics New Zealand for their help with the New Zealand Census Data.

5.1 Introduction

Changes in the distribution of income continue to be of concern in New Zealand[100]. At the household level, inequality rose rapidly in the mid-1980s and 1990s but stabilised at this higher level in the 2000s (Perry, 2017, Easton, 2013, Ball and Creedy, 2016). For New Zealand, as well as other countries in the developed world that have experienced growing income inequality since the 1980s, there is a large literature explaining these distributional changes. Attention has mainly focused on the role of economic drivers such as sectoral shifts, pay at the top, globalisation and skill-biased technological change (Autor, Levy & Murnane, 2003, Michaels, Natraj & Van Reenen, 2014, Blum, 2008 and Henze, 2014). As well as the economic factors, there is also growing evidence that socio-demographic changes like ageing, migration and changes in the patterns of family formation have played a role in influencing the distribution of income (see OECD, 2008 for a review of the international evidence; and Ball and Creedy, 2016 and Hyslop and Maré, 2005 for New Zealand evidence). One important socio-demographic mechanism that received considerable attention overseas but less in New Zealand is the role of educational assortative matching of couples in driving household inequality[101]. Broadly defined, assortative matching is the selection of partners based on how similar they are with respect to certain characteristics. Traditionally, partner selection has been based on characteristics such as age and ethnicity. Educational assortative matching is the partnering of people with similar educational levels. Since education is often a significant predictor of income, patterns of partnering and changes to these patterns may influence the distribution of income at the family or household level. In both academic and popular media[102], the increasing sorting of couples into educationally homogenous relationships has been touted as a strong driver of growing inequality in the distribution of income at the household/family level. The argument goes as follows: education is typically a significant predictor of income; hence if people with similar levels of education increasingly partner up, this will lead to an increase in inter-household inequality driven by the gap that is created between

[100] See Collins (2014) and Edwards (2017).
[101] The descriptive studies by Callister and Didham (2010, 2014) are an exception.
[102] For popular media, see the Cowen (2015) article in the *New York Times* and the Worstall (2015) article in the *Forbes* magazine. The next section reviews the academic literature.

highly-educated, high-income households and less-educated, low-income households. Thus, reduction in intra-household inequality may be increasing inter-household inequality.

The study of assortative matching and its effect on the distribution of income is important because the process of partnering not only has implications for cross-sectional inequality but is important for the future of inequality as well. If couples are sorting on characteristics that are increasingly correlated with income, this will affect the current distribution of income and influence the inter-generational transmission of inequality, depending on how resources are passed down to the next generation and the extent to which any form of advantage is conferred on offspring. For example, Schwartz (2013) argues that when both partners of a couple are highly-educated, this is positively related to child outcomes. Ermisch, Francesconi and Siedler (2006) use German and British data to show that on average about 40–50% of the covariance between parents' income and own family income can be attributed to the person to whom one is married. In New Zealand, Maré and Stillman (2010) provide evidence that children with more highly educated parents do better on cognitive tests. Assortative matching not only has potential consequences for the current generation; it is one of the structural change factors that may lead to, and perpetuate, permanent differences.

Intuitively, the role of assortative matching on household income distribution seems direct but identifying the effect of assortative matching on the distribution of income is trickier due to the presence of many confounding factors[103]. Earlier studies used one or more of the following as evidence of educational assortative matching: changes in the correlation of educational attainment between couples, changes in the correlation of earnings between couples, and changes in the proportion of couples with the same level of education/earnings. However, this approach is flawed because trends such as changes in educational distribution can increase the correlation in couples' education or the proportion of couples with the same level of education, while increased labour force participation rates of women can influence the correlation

[103] See Eika, Mogstad and Zafar (2014) for a review of factors that can confound the measure of assortative matching and Pestel (2017) for an explanation of how endogenous labour supply responses influence estimates of assortative matching.

between couples' earnings. As well as these secular[104]. trends that can confound the identification of the effect of assortative matching, another issue in the analysis of the effect of assortative matching on the distribution of income is the endogeneity that arises from joint labour supply responses. Couples typically make joint decisions to participate in the labour force. Incomes are determined not only by educational level (as a proxy for earning potential) but also by hours worked. An individual's decision on hours worked may be influenced by the income or educational level of their partner. Thus, a high-earning, highly-educated person partnered with another high-earning, highly-educated person may decide to work fewer hours. An example is a doctor who partners with another doctor and then works fewer hours than if partnered with a teacher. These secular trends and labour supply responses will affect estimates of educational assortative matching on income distribution if they are not taken into account.

In this study, we analyse the trends and changes in the patterns of educational assortative matching in New Zealand using individual unit record data from each Census from 1986 to 2013[105]. This period is particularly interesting because both inequality and the proportion of couples living in educationally homogenous households increased. In addition, there was a large increase in average educational attainment, a decline in the gender pay gap, and increases in the labour force participation of females over this period. This study makes four important contributions: first, to the best of our knowledge, it is the first study to formally examine the effect of assortative matching on the distribution of income in New Zealand. While there is descriptive evidence in New Zealand of growing assortative matching (see Callister and Didham, 2010, 2014), its impact on household inequality has not been examined. In the last few decades, New Zealand has shared similarities with the US and some European countries in terms of growing inequality and changes in educational distribution. However, New Zealand has a lower educational/skill premium and there is recent evidence that

[104] Other secular changes include delay in the formation of partnership (evidenced by the increase in marriage age). Delay in forming partnerships due to people spending more time in education will imply that people are partnering when they are on a higher income/have higher educational qualifications. This will likely magnify the impact of assortative matching on income inequality, as it will increase the gap between high-educated pairs and those without education. Furthermore, if places of higher education serve as a meet market, this will increase educational assortative matching and inequality.

[105] New Zealand Censuses were held in 1986, 1991, 1996, 2001, 2006, and 2013.

this premium has declined further[106]. We provide evidence on the role of assortative matching on the distribution of income in this interesting and unique context. Secondly, we take a spatial approach, which is unique in the extant literature. Typically, studies of assortative matching are at the national level but one important mechanism for inequality at the sub-national level could be the inter-relationship between city size, assortative matching and household income. Because bigger cities attract more people, especially educated people in the prime of their lives, it is expected that there may be more assortative matching in bigger cities[107]. These patterns may translate to higher inequality in metropolitan areas and differences in rates of assortative matching may explain some of the variation in inequality across space already documented in New Zealand[108]. Thirdly, we show that concentration ratios (the ratios of actual matching to random matching), which are very popular in the literature to describe changes in assortative matching, are influenced by population proportions. This may lead to wrong conclusions on the patterns and trends of assortative matching. We present a new index that overcomes the limitations of concentration ratios. Finally, past research on the impact of assortative matching on household inequality has been imperfect because it has ignored the confounding effect of endogenous joint labour supply responses and changes in educational distribution not being taken into account. Through a counterfactual randomisation methodology, we address the changing educational distribution issue and by focusing on couples working full-time, we try to limit the possibility of joint labour supply responses[109]. This means that our results reflect the best available direct evidence on the effect of educational assortative matching on the distribution of income in New Zealand.

Our results will also have implications for policies meant to address inequality. If significant differences in inequality across areas are driven by what is happening in the patterns of matching, then we might want to revise our expectations of the capability of government policies to address inequality, unless

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[106] See Zuccollo, Maani, Kaye-Blake and Zeng (2013) for OECD comparison of skill premiums and Maré (2018) for evidence on trends of the New Zealand skill premium.

[107] In addition, in New Zealand, all eight universities, which may function as a "meet market", are in the largest urban areas.

[108] See Karagedikli, Maré and Poot (2000, 2003) and Alimi, Maré and Poot (2016, 2018a).

[109] Even among full time workers, there is still the possibility of interacting labour supply responses of partners in terms of hours worked or choice of occupation. Some studies have adopted formal techniques to model these endogenous labour supply responses. For example, see Pestel (2017).

of course the government is somehow given the means to intervene in the partnering market, which is extremely unlikely in a liberal and democratic society. Instead, policy is more likely to be aiming at enhancing geographic labour mobility to the extent that immobility imposes an economic disadvantage. In this study, we therefore examine assortative matching across space and focus on differences between metropolitan and non-metropolitan areas in partnering and its effect on the distribution of income.

We focus on opposite sex couples[110] aged between 25 and 64 earning positive income and find that assortative matching for this group in all urban areas has increased. Contrary to popular opinion and overseas evidence, educational assortative matching fell at the extremes of the educational distribution (highly-educated and poorly-educated) but increased in the middle of the educational distribution (other-educated). Spatially, assortative matching increased in metropolitan areas but fell in non-metropolitan areas. In all periods, educational assortative matching has an inequality-increasing impact on the distribution of income (around 20 percent of observed inequality in each period for those working full-time). Spatially, we find that the effect of assortative matching on income inequality is larger and increased faster in metropolitan areas as well.

While our study focuses on the correlation between changes in educational assortative matching and changes in the distribution of income, the results cannot be given a clear causal interpretation[111]. Indeed, our method can be interpreted as representing an accounting approach that can only be regarded as a first-order approximation of the effect of assortative matching on the distribution of income. However, other recent work, such as that of Eika, Mogstad and Zafar (2014), Greenwood, Guner, Kocharkov and Santos (2014) and Kuhn and Ravazzini (2017) takes the same approach.

[110] At the 2006 census, less than one percent of people living in couple families reported being in a same-sex partnership (see Statistics New Zealand, 2010). Also, the statistical coding of couple families as either opposite-sex or same-sex couples began with the 1996 census. For Censuses pre-1996, if a household consisted of an adult male and an adult female it was difficult to separate whether they were in a relationship, or were a brother and sister living together, or were just flatmates.

[111] While assortative matching is likely to impact on the distribution of household income, changes in the distribution of income for other reasons may trigger changes in educational assortative matching as well. For example, personal income influences the social networks a person belongs to, which in turn affects partner selection.

The rest of the study proceeds as follows: the next section discusses the existing literature on the relationship between assortative matching and the distribution of income; Section 3 introduces the data and methodology; Section 4 provides descriptive evidence and results from our counterfactual randomisation methodology; and section 5 concludes.

5.2 Literature Review

The literature on assortative matching is extensive[112]. Interest in the role of educational assortative matching has a long history that can be traced back to Becker's (1973, 1981) seminal work on marriage and the family; and empirical studies like those of Blackburn and Bloom (1987, 1994), and Cancian and Reed (1998, 1999), which explain changes in the distribution of family income. In this review, we present evidence from the earlier studies and discuss the limitations of their approaches. We examine the different methodological approaches that are common in recent studies and what the differences in approach imply for the evidence of assortative matching's effects on inequality. Finally, we review the available descriptive evidence on educational assortative matching in New Zealand.

Assortative matching can be based on other characteristics such as age, ethnicity, religion, or earnings. Our study focuses on educational assortative matching and its impact on the distribution of income, thus our review is limited to a subset of studies focusing on educational assortative matching. For a broader review of the literature on assortative matching, see Kalmijn (1998) and Schwartz (2013).

Early studies of educational assortative matching typically used the correlation between couples' level of education and the proportion of couples with the same level of education as evidence of assortative matching[113]. For example, Schwartz and Mare (2005) examined educational assortative matching in marriages from 1940 to 2003 in the United States using Census and survey data.

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[112] This topic has generated interest from sociologists, demographers and economists. Aside from its effect on income inequality, sociologists are typically also interested in assortative matching because of its implications for social rigidity, exclusion and social openness (see Blossfeld, 2009)
[113] Another important thing to note with earlier studies is that they were mostly focused on legally married couples, so most of the literature is framed in terms of husbands and wives. More recent studies have focused on legal marriage as well as people who are in de-facto relationships and cover both same-sex and different-sex couples (e.g. Verbakel and Kalmijn on Dutch couples in 2014 Journal of Marriage and Family)

They found increasing resemblance between spouses in terms of educational attainment. They showed that educational homogamy decreased from 1940 to 1960 but increased from 1960 to 2003. Their conclusion was supported in earlier studies by Kremer (1997) and Pencavel (1998), who focused on the same period in the US.

Blossfeld and Timm (2003) provided evidence from 12 European countries and the United States. In eight countries, they compared observed rates of marriage to random marital matching in each birth cohort. They found evidence of increased homogamy in marriage; specifically, they concluded that people seem to prefer to a large extent to marry an equally educated partner in these countries. Macfarlane (2016) also conducted a comparative analysis of assortative matching in European countries using data from 29 countries in the 2012 European Social Survey and found evidence of assortative matching in each country.

Alongside the descriptive studies, earlier studies that linked assortative matching to the distribution of income focused on the effect of changing correlations of husband-wife earnings on overall income inequality. For example, Burtless (1999) found that around 13% of the rise in household inequality was due to an increase in the correlation of husbands' and wives' earnings. Other studies have adopted a decomposition approach, especially of the Coefficient of Variation measure[114]. Changes in the inequality of household earnings are decomposed into parts resulting from changes in the earning inequality of husbands, changes in the earning inequality of wives and the correlation between husband and wives' earnings. The changes due to the correlation between husband and wife earnings are taken as evidence of assortative matching. Other things being equal, an increase in the correlation of earnings between husband and wife will increase overall household inequality. Cancian, Danziger and Gottschalk (1993) and Blackburn and Bloom (1994) presented evidence of such inter-spousal correlation coefficient increases.

Schwartz (2010) noted the limitation of the changes in correlation coefficient approach as a measure of changing association between spousal earnings. She proposed a modelling approach that "differentiates between earners

[114] See Cancian, Danziger and Gottschalk (1993), Blackburn and Bloom (1994), and Cancian and Reed (1999) for further evidence. Breen and Andersen (2012) and Breen and Salazar (2011) use a counterfactual decomposition technique based on decomposing generalised entropy measures such as the Theil measure and Mean Log Deviation (MLD).

and non-earners and incorporates measures of shrinking economic differences between spouses ... in terms of their earnings relative to other members of their own sex" (p.1526). Depending on the measure of inequality used, her study found a stronger association of earnings between couples was responsible for around 25-30% of the increase in inequality. Furthermore, Gihleb and Lang (2016) made an important point on the use of the correlation coefficient of educational levels of partners as a measure of assortative matching. They argued that due to the ordinal nature of most educational classifications, rank correlation measures are typically employed, but these measures, such as the Spearman Rank correlation measure, do not perform well in measuring association in data with lots of ties, such as ordinal educational levels. Further criticisms of assortative matching studies based on measures of association of income or education between spouses are based on the argument that other factors such as changes in the educational distribution and increased labour force participation of women could also be responsible for increased inter-spousal correlation in education and/or earnings (see Eika et al. 2014).

Recent studies have addressed the limitation of earlier studies by adopting a counterfactual randomisation approach to measuring assortative matching and its effect on income inequality (Greenwood et al., 2014, Eika et al., 2014, Hrysho, Juhn and McCue, 2017). An increase in the number of couples with the same level of education does not imply an increase in assortative matching because factors such as secular increase in educational attainment will increase the marginal distribution of educated people and thus increase the chances of couples being in the same educational group even though the rate of assortative matching has not changed. For example, in New Zealand, our data show that the proportion of people with higher education increased from 9% in 1986 to 32% in 2013. Hence even if the rate of assortative matching has not changed, there will be more couples where both have a high level of education, simply because there are more educated people.

These studies compare the actual changes to what would have happened if there was random partnering. If the ratio of actual to random partnering is greater than one, it means the proportion of couples in the same educational category is greater than what could be expected if matching was random, and there is thus evidence of sorting of couples into that category. Eika et al. (2014) used a similar approach and created a sorting parameter S_{ij} based on the ratio of the observed probability that a husband with educational level i is married to a wife with educational level j relative to the probability under random matching with respect to education. By comparing the actual probability to the probability if matching was random, this method accounts for changes in the marginal distribution of education.

However, there are two distinct approaches in counterfactual randomisation methodology; the additional randomisation approach and the imputation randomisation approach (Harmenberg, 2014). The key differences between these approaches are well noted in Harmenberg (2014) and in Frémeaux and Lefranc (2017) and are summarised here. In the additional randomisation approach, individual incomes are held constant and treated like a fixed individual characteristic. The randomised counterfactual in this approach is based on a distribution where individuals are randomly matched into couples but keep their actual observed income. This approach is limited because it does not allow for endogenous labour supply responses. This method assumes income and labour supply decisions are independent of household formation. Instead, there is in reality no reason to believe that, for example, a nurse partnered to a teacher will work the same hours and thus earn the same income as if that same nurse was partnered to a plastic surgeon.

The imputation randomisation approach accounts for these endogenous labour supply responses by taking household income as given, instead of individual incomes. In this approach, individuals are randomly matched into couples and their household income is imputed based on the household income of actual couples with the same observed characteristics. For example, assuming that we create by randomisation a pseudo-household consisting of one lawyer and one doctor, the household income of this pseudo-household will be decided by randomly selecting from the household income of actual households with the same characteristics i.e. households in the actual distribution consisting of a lawyer and a doctor. This approach is limited by how well labour supply decisions are driven by the observed characteristics of couples. Harmenberg (2014) gives an important illustration in this regard – “there are strong reasons to believe that young men with no high school degree who are married to older women with more than a college degree are systematically different from young men with no high school degree married to young women with no high school degree" (p.2). In addition, there is also the possibility that we might have randomised pseudo-households for which there are no actual households with the same actual characteristics.

Other studies, such as those of Pestel (2017) and Frémeaux and Lefranc (2017) have suggested other approaches to account for endogenous labour supply decisions. Pestel (2017) accounted for endogenous labour supply by developing a structural model of household labour supply decisions using conditional logit while Frémeaux and Lefranc (2017) suggested using potential earnings instead of annual income. Potential earnings are in this case defined as the earnings which an individual would receive if he/she worked full-time. The benefit of using potential earning is its independence from joint labour supply decisions, since it is not dependent on hours worked, unlike actual observed earnings.

The implication of the differences in randomisation techniques, when estimating the assortative matching impact on the distribution of income, may not be trivial. It depends on the extent of endogenous labour supply responses. Estimates from the additional randomisation approach will be smaller since endogenous labour supply responses typically dampen the effect of assortative matching (Harmenberg, 2014). Evidence from Pestel (2017) showed that assortative matching had a pronounced effect after adjusting for joint labour supply behaviour in West Germany.

Empirical evidence on the effect of educational assortative matching is mixed. Hryshko et al. (2017) and Eika et al. (2014) found a small positive effect of assortative matching on income inequality in the US. This is contrary to the evidence from Breen and Salazar (2011) for the US, where they found educational assortative matching to have a small negative effect on income inequality. In Brazil, where inequality fell, Hakak and Firpo (2017) found assortative matching reduced between 1990 and 2015 and this had very little effect on income inequality over this period. Evidence from Denmark in Breen and Andersen (2012) suggests that changes in educational distribution rather than educational assortative matching drove the growing inequality in Denmark between 1987 and 2006.

Given the methodological issues, it is unsurprising that evidence on the role of assortative matching on income inequality seems inconclusive. Blossfeld

(2009) highlighted issues that lead to inconsistent findings. First, most studies are based on arbitrary classification of educational levels, and aggregation of educational levels might distort measures of educational homogamy[115]. Secondly, most studies are based on cross-sectional data. While some focus on first marriage, others often use the whole marriage stock. Analysis using the whole marriage stock may be reflecting the combined effect of other factors that drive re-marriage (Blossfeld, 2009, p.517).

We conclude this section by reviewing the available descriptive New Zealand evidence on educational assortative matching and changes in the educational distribution. To date, no study has linked educational assortative matching to income inequality in New Zealand. Callister and Didham (2010, 2014) used Census data for the 25-34 age group to document changes in educational distribution as well as education assortative matching. They found that between 1986 and 2013, the proportion of couples aged 25 to 34 years where both had a degree or higher had significantly increased, from 4.2% to 23.1%, while the proportion of couples in this age group where neither held a formal qualification had declined from 14% to 3.3%. In the 20-year period between 1986 and 2006, there was a complete reversal in the ratio of educational attainment between men and women. In 1986, 45% more males than females were holders of a Bachelor's degree or higher. By 2006, there had been a complete reversal with 45% more women holding a Bachelor's degree than men and by 2013, there were 53 percent more women with Bachelor's degrees than men. On assortative matching, Callister and Didham concluded that it is the well-educated who are most likely to be partnered, and if partnered, they tend to have similarly qualified partners. At the same time, those with no formal education are less likely to be partnered, but if partnered they were, in 2013, more likely to be with an unqualified partner. They concluded that these patterns and changes will have significant implications for income inequality in New Zealand. In this paper we extend Callister and Didham's (2010, 2014) analysis to the population aged 25-64 and link educational assortative matching to the distribution of income.

The next section details the data and methodology used.

[115] Gihleb and Lang (2016) also made a similar point.

5.3 Data and Methodology

5.3.1 Data

The data used are from the unit records of the usually resident New Zealand population from each of the six Censuses of Population and Dwellings between 1986 and 2013[116]. New Zealand Census data capture information on a host of socio-demographic characteristics including qualifications, income, partnership status and location. Our target population was couples residing in the 40 Main and Secondary urban areas[117]. We define couples as male-female partners who are usually resident in the same household. We focus on male-female couples because the censuses (especially the earlier ones) did not ask questions about the gender of partners, which makes it impossible to separate those in a same-sex relationship from people of the same sex merely living in the same dwelling. Specifically, we identify couples from the answer to the "role in the family" question (if either parent and/or spouse). We limit our analysis to those in the 25 to 64 age group working full-time and earning positive income, to make our analysis reflective of labour market earnings. The age restriction is because the effect of education on income is likely to work through the labour market; we expect this mechanism to be most at play in the 25-64 age range as most of the under-25 age group are either in education or training while the 65s and over will largely be out of the labour force. We limit the study to those working full-time in an attempt to limit joint labour supply responses through hours worked that may affect our estimates of the effect of assortative matching. Thus, the reported effect may be seen as an upper bound to the effect that would result when endogenous labour supply responses are taken into account.

Education is measured in terms of qualifications achieved, and we have three categories: High-educated (those with a Bachelor's degree and above), Other-educated (those with other forms of qualification but below the Bachelor level) and Low-educated (those with no qualification). The inconsistencies in

[116] New Zealand Censuses were held in 1986, 1991, 1996, 2001, 2006, and 2013.
[117] The 40 urban areas were grouped into metropolitan and non-metropolitan areas. Metropolitan areas are the urban areas in the six largest cities of Auckland, Christchurch, Wellington, Hamilton, Tauranga and Dunedin. We use the 2013 Statistics New Zealand definition of urban areas for all periods. The metropolitan areas account for about three quarters of all urban population. The rural population, which is excluded from the data, accounts for only about 14 percent of New Zealand's population.

qualification classification over different censuses prevented using a more detailed educational grouping[118].

Our income measure is the sum of personal income of individuals in couples. New Zealand Census income is typically captured in bands with the top income band open-ended[119]. We assume each individual earns the average of the income band he or she belongs to[120], and we assume a Pareto distribution for the top open-ended band. The average in the top band is calculated using the Stata RPME command developed by von Hippel et al. (2016). Our measure of inequality is the Mean Log Deviation, which is one of the generalised entropy measures. A full description of this measure and its properties can be found in Shorrocks (1980) or Bourguignon (1979) and this measure has been used to examine changes in the distribution of income in New Zealand in Alimi et al. (2018a, 2018b).

One important feature of the present study is that we examine the effect of assortative matching on income distribution at the sub-national level. Previous studies have been at the national level but the inter-relationship between self-selection of educated people into cities, assortative matching and household income may have implications for spatial differences in the distribution of income. In addition to examining all urban areas combined, we focus on metropolitan areas (defined as the urban areas that make up the six largest cities in New Zealand) as well as non-metropolitan areas (all other urban areas).

5.3.2 Methodology

We followed the additional randomisation counterfactual methodology. The advantages of this methodology are well detailed in Harmenberg (2014). We favoured this methodology due to its directness and lack of requirement for imputation of income based on observed characteristics. In the additional randomisation approach, household income is assumed to be given and the effect of assortative matching on the distribution of income is estimated by comparing the observed distribution of income with a counterfactual distribution where

[118] The proportion of the population in each census period who are couples working full-time and living in urban areas are reported in Appendix Table 5.A.25

[119] The issue with top open-ended bands are well known. For example, see Breen and Salazar (2011) for US data and Karagedikli et al. (2000) for New Zealand census data.

[120] The availability of income in bands may have implications for our measure of inequality. The MLD assumes every individual earns the midpoint of the income band it occupies. Not accounting for within-band variation may lead to under-estimation of actual inequality.

matching is random. Although the method has been criticised for not accounting for endogenous labour supply responses, we limited some of the impact of this issue in our study by focusing only on couples where both partners are working full-time.[121]. Everyone working full time is classified into one of the three educational categories described earlier and education is measured as a household attribute.

For each Census period, let $f_Y^M(y;x)$ represent the distribution of income in an area *M* where *M* could be all urban areas combined, or a metropolitan area or a non-metropolitan area, then $f_Y^M(y;x) = \int f_{y|x}^M \; dF_X^M$ where $f_{y|x}^M$ respresents the education-specific conditional distribution and dF_X^M represents the prevalence of different household-level education mixes between couples. To illustrate, given our three levels of education – High Educated (H), Other Educated (O) and Low Educated (L), there are six types of education mixes for couples[122,123]:

- HH- two highly-educated partners
- HO /OH - one highly-educated partner and one other-educated partner
- HL /LH - one highly-educated partner and one low-educated partner
- OL /LO - one other-educated partner and one low-educated partner
- OO - two other-educated partners
- LL- two low-educated partners

Assortative matching on education and changes in the educational distribution will affect the prevalence rate of household-education types i.e. dF_X^M.

By comparing the actual distribution to a counterfactual distribution based on randomisation of partnering, we can net out the effect of changes in the educational distribution. The counterfactual distribution is the distribution of income in area *M* based on randomising the different types of educational pairing i.e. $\breve{f}_Y^{M|R} = \int f_{y|x}^M \, dF_{RX}^M$, where dF_{RX}^M represents prevalence of household-education types based on random matching. The effect of educational assortative matching is the difference between these two distributions:

[121] Although one may argue that there could be endogenous responses in terms of type of job taken even if hours do not change

[122] There will be 9 types of couples if we account for ordering i.e. male=L and female=H is seen as different from male= H and female=L. The distinction could matter when there a large gender pay gap, given education. In New Zealand, the gap had reduced to 9.4 percent by 2017 (Ministry of Women; women.govt.nz, accessed 2/8/2018. Ignoring the gender assignment in the education paring is unlikely to have affected the conclusions of this paper.

[123] Note that if there is a large gender gap in earnings, HO and OH have different expected levels of income. Ditto for HL/LH and OL/LO

$$f_Y^M - \check{f}_Y^{M|R}$$

We use the MLD as a summary measure for the observed f_Y^M and counterfactual distribution $\check{f}_Y^{M|R}$ and the differences in this measure for the two distributions are compared. As well as the unconditional randomisation, we perform several other conditional randomisations where we hold observed characteristics such as age, qualification and location constant. These conditional randomisations give us an estimate of the effect of sorting on these observed characteristics. Our conditional randomisations are:

- Age conditional: randomising but holding the actual age distribution constant i.e. partnering is random but people are randomly partnered with someone else with the same age as their observed partner
- Qualification conditional: randomising but holding the actual qualification distribution constant i.e. partnering is random but people are randomly partnered with someone else with the same education as their actual observed partner
- Age and qualification conditional: randomising but holding both the actual age and education distribution constant i.e. partnering is random but people are randomly partnered with someone else with the same age and education as their actual observed partner
- Age, qualification and location conditional: randomising but holding the actual age, qualification and spatial distribution (urban area) constant i.e. partnering is random, but people are randomly partnered with someone else with the same age, education, and location as their actual observed partner.

As in Kuhn and Ravazzini (2017), we also provide some approximate estimates of the potential of assortative matching on the distribution of income by assuming extreme levels of assortative matching. We sort the population first on education and then on income bands, i.e. we rank the population from the highest educated to the lowest educated and then sort on income within each education category. We consider two additional counterfactual distributions: in the first counterfactual, we partner the highest ranked male with the highest ranked female, the second highest ranked male with the second highest ranked female and so on. This gives an estimate of what the distribution of income will be like under maximum assortative matching. In the second counterfactual, we partner the highest ranked male by education and income with the lowest ranked female, the second highest ranked male with the second lowest ranked female and so on. This represents a scenario of maximum disassortative matching and we examine what the distribution of income will be like under this assumption.

In the next section we provide descriptive evidence on educational assortative matching as well as results from our counterfactual randomisation methodology.

5.4 Results: Educational Assortative Matching and Income Inequality in New Zealand

We begin this section by describing the distribution of individual income of those participating in the labour force (full-time employed, part-time employed and unemployed). While we will focus on assortative matching of those in full-time employment only, we first consider everybody in the labour force, including those employed part-time and those unemployed, to show the important contribution of those working full-time to inequality. Next, we shift the level of analysis to couples and focus on the income distribution of male-female couples working full-time[124] and earning positive income, and finally we examine descriptive evidence on the patterns and changes in educational assortative matching. Aside from education, we also provide some evidence on occupational assortative matching using the 1-digit New Zealand Standard Classification of Occupation (NZSCO99). In the final section, we link assortative matching to the distribution of income.

5.4.1 Patterns and changes in the personal income distribution for individuals participating in the labour force

The trends and patterns in income distribution of the 25 to 64 age group earning positive income have already been described in Alimi et al. (2018b). Inequality in individual incomes increased by around 1% in all urban areas. This figures hides

[124] Increase in full-time employment of prime age females increased the number of people in our analysis as we have an increase in couples where both partners are working full time. The increase in full-time employment of prime age females will also have an effect of lowering intra-household inequality but increasing inter-household inequality; higher educated females are more likely to work full-time and earn more to increase the gap between high income- high-educated couples and others.

the spatial disparity, inequality felt in non-metropolitan areas (-11%) and the rise in inequality in metropolitan areas (4%) between 1986 to 2013[125].

For those participating in the labour force (i.e full-time employed, part-time employed and unemployed), we find higher rates of growth in inequality of individual incomes. From 1986 to 2013, personal income inequality increased by around 23% in all urban areas, mostly driven by increases in metropolitan areas (27%) and to a lesser extent by increases in non-metropolitan areas (8%).

We decompose the inequality in each census period by labour force status. Inequality among the full-time employed is a important component of inequality for those earning labour income. We find that within-labour force status group inequality accounts for most of the overall inequality (around 78-84% , see Table 5.1) and those working full-time contribute around two-thirds of the within-labour force status group inequality. Between-labour force status group inequality accounts for around 17-22% of overall inequality. Not suprisingly, given the large differences in income between full-time workers, part-time workers and the unemployed, this percentage share is higher than in the case of between-age inequality reported in Alimi et al. (2018a) or between-migrant group inequality in Alimi et al. (2018b). In Table 5.1, we present the decomposition of overall inequality into between and within components and the contribution of each labour force group for all urban areas[126].

[125] See Appendix 5.A.1 for summary from Alimi et al. (2018).

[126] Decomposition results for Non-metropolitan and Metropolitan areas are available in Appendix B and Appendix C respectively.

Table 5.1: Decomposition of personal income inequality (MLD) by labour-force groups: All urban areas combined

Labour force groups	**1986**	**1991**	**1996**	**2001**	**2006**	**2013**
			National			
			Between-group contribution			
Full-time	-0.0945	-0.1081	-0.1120	-0.1109	-0.0951	-0.1028
Part-time	0.1108	0.1036	0.1219	0.1259	0.1148	0.1151
Unemployed	0.0351	0.0609	0.0517	0.0468	0.0264	0.0423
Sum between-group	0.0514	0.0564	0.0616	0.0618	0.0461	0.0546
Between as a proportion of total	21.5%	22.0%	20.6%	20.3%	16.5%	18.6%
			Within-group contribution			
Full-time	0.1226	0.1302	0.1588	0.1667	0.1610	0.1651
Part-time	0.0493	0.0506	0.0641	0.0613	0.0619	0.0564
Unemployed	0.0158	0.0189	0.0151	0.0146	0.0106	0.0171
Sum within-group	0.1877	0.1997	0.2380	0.2426	0.2335	0.2386
Full-time as a proportion of sum within-group	65.3%	65.2%	66.7%	68.7%	69.0%	69.2%
Total (sum between-group + sum within-group)	0.2392	0.2561	0.2997	0.3044	0.2795	0.2932
Sum within as a proportion of total-inequality	78.5%	78.0%	79.4%	79.7%	83.5%	81.4%

Notes: Results are the between- and within-group contributions to overall inequality (as measured by the MLD) for those participating in the labour force in all urban areas combined (full-time employed, part-time employed and unemployed)

5.4.2 Patterns and changes in the distribution of income of male-female couples working full-time

We shift our level of analysis to couples and examine the patterns and changes in the distribution of total income of male-female couples working full-time. In Table 5.2, we present the trend in average incomes and the MLD for the different types of couples (classified by their education levels) from 1986 to 2013 for all urban areas[127]. For all couples working full-time (regardless of educational level), real average income increased by 38% between 1986 and 2013. Unsuprisingly, couples where both partners were highly educated had the highest mean incomes while couples with two low education partners had the lowest average incomes in all periods. Indicative of the gap between high-educated and low-educated couples, the average income in couples with two high-educated partners was more than double that of low-educated partners in all periods except in 1986. The gap between highly-educated and low-educated couples widened over time; between 1986 and 2013, highly-educated couples had the highest growth in average incomes at 19% compared to 6% for low-educated couples.

As measured by the MLD, overall inequality for all couples working full time grew by around 49%. This masks the variation across couple types. Within-group inequality grew the most for couples with two highly-educated partners at 55% compared to 1% growth for couples with a mix of one highly-educated and one low-educated partner (HL/LH)[128]. In all periods, within-group inequality was lowest among couples with a mix of an other-educated and a low-educated partner (OL/LO). Prior to 1996, couples with a mix of a high-educated and a low-educated partner had the highest within-group inequality but from 1996, high-educated couples had the highest within-group inequality.

[127] Tables for Non-metropolitan and Metropolitan Areas are available in Appendix 5.A.4 and Appendix 5.A.5 respectively.
[128] Note that there may be a slight difference between HL and LH that is not being considered here.

Table 5.2: Mean and inequality statistics by couple type in each census period for all urban areas combined

All urban areas combined						
1986	HH	HO/OH	OO	HL/LH	OL/LO	LL
Overall-mean				$95,696		
Group-mean	$144,627	$126,924	$99,873	$114,930	$87,853	$77,594
Rel. mean income	1.51	1.33	1.04	1.20	0.92	0.81
By-group MLD	0.0895	0.0849	0.0766	0.0969	0.0712	0.0747
Pop share	4.0%	8.3%	35.1%	1.0%	30.3%	21.3%
Overall MLD				0.0895		
1991	HH	HO/OH	OO	HL/LH	OL/LO	LL
Overall mean				$101,260		
Group-mean	$158,934	$136,119	$101,400	$117,485	$87,594	$75,510
Rel. mean income	1.57	1.34	1.00	1.16	0.87	0.75
By-group MLD	0.0981	0.0953	0.0898	0.1133	0.0845	0.0859
Pop share	5.7%	10.3%	43.3%	0.9%	26.3%	13.5%
Overall MLD				0.1089		
1996	HH	HO/OH	OO	HL/LH	OL/LO	LL
Overall mean				$111,133		
Group-mean	$164,184	$141,788	$109,434	$124,748	$94,672	$80,782
Rel. mean income	1.48	1.28	0.98	1.12	0.85	0.73
By-group MLD	0.1235	0.1078	0.0921	0.1171	0.0909	0.0916
Pop share	8.6%	13.2%	39.1%	1.4%	24.2%	13.6%
Overall MLD				0.1179		
2001	HH	HO/OH	OO	HL/LH	OL/LO	LL
Overall mean				$120,852		
Group-mean	$175,377	$149,102	$113,880	$127,878	$97,652	$83,046
Rel. mean income	1.45	1.23	0.94	1.06	0.81	0.69
By-group MLD	0.1257	0.1170	0.1050	0.1142	0.0931	0.0946
Pop share	10.1%	17.0%	45.3%	1.3%	18.5%	7.8%
Overall MLD				0.1278		
2006	HH	HO/OH	OO	HL/LH	OL/LO	LL
Overall mean				$125,310		
Group-mean	$167,719	$144,913	$116,647	$125,936	$100,984	$83,589
Rel. mean income	1.34	1.16	0.93	1.00	0.81	0.67
By-group MLD	0.1347	0.1159	0.1086	0.1039	0.0938	0.0977
Pop share	14.2%	20.6%	41.5%	1.6%	16.0%	6.1%
Overall MLD				0.1285		
2013	HH	HO/OH	OO	HL/LH	OL/LO	LL
Overall mean (2013$)				$131,754		
Group-mean	$172,684	$145,312	$117,609	$123,541	$101,156	$82,252
Rel. mean income	1.31	1.10	0.89	0.94	0.77	0.62
By-group MLD	0.1391	0.1180	0.1097	0.0978	0.0900	0.1045
Pop share	18.8%	25.1%	39.0%	1.8%	11.4%	3.9%
Overall MLD				0.1333		
All reported mean and group-mean are in 2013$						

Notes: Results are the mean, relative mean income, MLD and population share for each educational pair and the overall mean income in all urban areas combined in each census period. Abbreviations: HH- two high-educated partners; HO /OH - one high-educated partner and one other-educated partner; OO - two other-educated partners; HL/LH - one high-educated partner and one low-educated partner; OL /LO - one other-educated partner and one one low-educated partner; LL - two low-educated partners

Table 5.3: Inequality of total income of male-female couples working full-time and aged 25-64 from 1986 to 2013

Area	1986	1991	1996	2001	2006	2013	Growth 1986-2013
Non-metro	0.0837	0.0999	0.1039	0.1121	0.1109	0.1092	30%
Metro	0.0906	0.1093	0.1194	0.1290	0.1308	0.1372	51%
All urban areas	0.0895	0.1089	0.1179	0.1278	0.1285	0.1333	49%

Notes: Results are MLD by area for each census period from 1986 to 2013. Metropolitan areas are the six largest New Zealand cities (in order of size): Auckland, Wellington, Christchurch, Hamilton, Tauranga and Dunedin. All other urban areas are considered non-metropolitan areas

Table 5.3 summarises the Mean Log Deviation (MLD) by area from 1986 to 2013. Inequality among couples working full-time was lower than the personal income inequality of everyone in the labour force (compare Tables 5.1 and 5.3) but grew faster. In all urban areas combined, inequality in total income of couples grew faster than the national total household income inequality reported in Ball and Creedy (2016) and Perry (2017). In all urban areas combined, inequality in total income of couples working full-time grew by around 49% between 1986 and 2013, whereas national total household income inequality growth over the same period in Ball and Creedy (2016) was around 14%. Spatially, income inequality for full-time couples earning positive income grew in both metropolitan and non-metropolitan areas, with growth between 1986 and 2013 in metropolitan areas (51%) higher than in non-metropolitan areas (30%).

Our focus in this study is to examine the role of assortative matching in these patterns of inequality. Before we address the evidence on the contribution of educational assortative matching to inequality, we provide descriptive evidence of changes in the educational distribution and rates of assortative matching in all census periods and across the three spatial areas considered.

5.4.3 Patterns of educational assortative matching among male-female couples in New Zealand

As noted earlier, inter-temporal studies of assortative matching need to account for secular changes in the educational distribution in all urban areas. In Table 5.4, we show the changes in educational attainment for males and females in couples[129]. We begin with all urban areas combined and proceed to examine the differences between metropolitan and non-metropolitan areas.

The secular increase in educational attainment is evident. In 1986, only 9% of the individuals who were married or in a de facto relationship could be classified as high-educated. By 2013, this proportion had increased to 32%. Educational attainment has risen faster for females. In 1986, there were 51% more males than females that were highly educated; by 2013 this proportion had reversed with 36% more females than males[130]. These changes in educational distribution are significant and imply that even if underlying rates of assortative matching have not changed, there will be more couples where both are highly educated, simply because there is a huge increase in the number of educated individuals (both males and females).

[129] Tables for Non-metropolitan and Metropolitan Areas are available in Appendix 5.A.6 and Appendix 5.A.7

[130] Note that the figures reported are different from the ones reported in Callister and Didham (2010, 2014). Both studies by Callister and Didham focused on the whole population aged 25-34 while we focus on the population aged 25-64 in male-female couples, earning positive income and working full-time.

Table 5.4: Educational distribution for individuals in couples aged 25-64 in all urban areas from 1986 to 2013

	Total (Male + Female)	Prop	Male	Prop.	Female	Prop	Ratio of Male/Female
			1986				
High-Education	20,913	9%	12,588	10%	8,325	7%	151%
Other-Education	130,974	54%	67,485	56%	63,489	53%	106%
Low-Education	88,902	37%	40,323	33%	48,579	40%	83%
Total specified	240,789	100%	120,393	100%	120,393	100%	
			1991				
High-Education	28,758	11%	16,329	13%	12,426	10%	131%
Other-Education	157,134	62%	78,474	62%	78,663	62%	100%
Low-Education	69,126	27%	32,706	26%	36,420	29%	90%
Total specified	255,021	100%	127,509	100%	127,512	100%	
			1996				
High-Education	39,495	16%	21,285	17%	18,210	15%	117%
Other-Education	143,787	58%	69,582	56%	74,208	60%	94%
Low-Education	65,754	26%	33,651	27%	32,103	26%	105%
Total specified	249,039	100%	124,521	100%	124,518	100%	
			2001				
High-Education	58,554	19%	28,899	19%	29,658	19%	97%
Other-Education	191,853	63%	93,885	62%	97,971	64%	96%
Low-Education	53,838	18%	29,340	19%	24,495	16%	120%
Total specified	304,245	100%	152,121	100%	152,124	100%	
			2006				
High-Education	100,119	25%	45,429	23%	54,693	28%	83%
Other-Education	236,940	60%	120,261	61%	116,679	59%	103%
Low-Education	59,265	15%	32,475	16%	26,793	14%	121%
Total specified	396,327	100%	198,165	100%	198,162	100%	
			2013				
High-Education	132,855	32%	56,268	27%	76,584	37%	73%
Other-Education	235,983	57%	124,716	61%	111,267	54%	112%
Low-Education	43,350	11%	25,107	12%	18,240	9%	138%
Total specified	412,185	100%	206,094	100%	206,094	100%	

Notes: Results are the number and proportion by gender in each educational group in all urban areas combined for each census period. High-Education represents those with Bachelor's degrees and above, Other-Education are those with other forms of qualification but below the Bachelor level, and Low-Education are those with those with no qualification

In Table 5.5, we present contingency tables showing in proportions, the actual pairing of couples with respect to their highest educational attainment and in Table 5.6, we present what the pairing would have been under an assumption of random matching. The random matching contingency tables are the average of 250 replications of randomisation with the standard errors in brackets.[131]

[131] Non-metropolitan area tables are available in Appendix 5.A.8 and Appendix 5.A.9 and Metropolitan area tables in Appendix 5.A.10 and Appendix 5.A.11.

Table 5.5: Actual proportion of couples in each educational pairing from 1986 to 2013: All urban areas combined

Female	**Male**		
	High-education	Other-education	Low-education
		1986	
High-Education	4.0%	2.5%	0.4%
Other-Education	5.8%	35.1%	11.8%
Low-Education	0.7%	18.4%	21.3%
		1991	
High-Education	5.7%	3.6%	0.4%
Other-Education	6.7%	43.3%	11.7%
Low-Education	0.5%	14.6%	13.5%
		1996	
High-Education	8.6%	5.4%	0.7%
Other-Education	7.8%	39.1%	12.7%
Low-Education	0.7%	11.5%	13.6%
		2001	
High-Education	10.1%	8.6%	0.8%
Other-Education	8.4%	45.3%	10.7%
Low-Education	0.4%	7.8%	7.8%
		2006	
High-Education	14.2%	12.2%	1.2%
Other-Education	8.3%	41.5%	9.0%
Low-Education	0.4%	7.0%	6.1%
		2013	
High-Education	18.8%	16.9%	1.5%
Other-Education	8.2%	39.0%	6.8%
Low-Education	0.3%	4.6%	3.9%

Notes: Results are the actual proportion of male-female couples in each educational pairing in all urban areas combined for each census period. High-Education represents those with Bachelor's degrees and above, Other-Education are those with other forms of qualification but below the Bachelor level, and Low-Education are those with those with no qualification.

Table 5.6: Proportion of couples in each educational pairing from 1986 to 2013 under randomisation: All urban areas combined

Random pairing- All urban areas			
Female	**Male**		
	High-education	Other-education	Low-education
1986			
High-Education	0.7% (0.02%)	3.9% (0.04%)	2.3% (0.04%)
Other-Education	5.5% (0.05%)	29.6% (0.07%)	17.7% (0.07%)
Low-Education	4.2% (0.05%)	22.6% (0.07%)	13.5% (0.07%)
1991			
High-Education	1.3% (0.03%)	6.0% (0.04%)	2.5% (0.04%)
Other-Education	7.9% (0.05%)	38.0% (0.06%)	15.85% (0.06%)
Low-Education	3.7% (0.04%)	17.6% (0.06%)	7.35% (0.05%)
1996			
High-Education	2.5% (0.04%)	8.2% (0.05%)	4.0% (0.04%)
Other-Education	10.2% (0.05%)	33.3% (0.08%)	16.1% (0.07%)
Low-Education	4.4% (0.05%)	14.4% (0.07%)	7.0% (0.06%)
2001			
High-Education	3.7% (0.04%)	12.0% (0.05%)	3.8% (0.04%)
Other-Education	12.2% (0.05%)	39.7% (0.06%)	12.4% (0.05%)
Low-Education	3.1% (0.04%)	9.9% (0.04%)	3.1% (0.04%)
2006			
High-Education	6.3% (0.04%)	16.7% (0.05%)	4.5% (0.04%)
Other-Education	13.5% (0.05%)	35.7% (0.06%)	9.7% (0.04%)
Low-Education	3.1% (0.03%)	8.2% (0.04%)	2.2% (0.03%)
2013			
High-Education	10.1% (0.05%)	22.5% (0.06%)	4.5% (0.03%)
Other-Education	14.7% (0.05%)	32.7% (0.06%)	6.6% (0.03%)
Low-Education	2.4% (0.03%)	5.4% (0.03%)	1.1% (0.02%)

Notes: Results are the proportion of male-female couples in all urban areas combined in each educational pairing in each census period under randomised matching. High-Education represents those with Bachelor's degrees and above, Other-Education are those with other forms of qualification but below the Bachelor level, and Low-Education are those with those with no qualification

The actual pairings show a relatively large proportion of couples with the same level of educational attainment, i.e. couples along the diagonal. Education-matched couples represent about 60-63% of all couples. Interestingly, there is no clear upward trend in this percentage. Examining changes in the proportions along the diagonal over time will lead to an incorrect conclusion that assortative matching has increased for the highly educated and decreased for the poorly educated. Although the proportion of couples where both partners are highly educated increased from 4% in 1983 to 19% in 2013, while the proportion of couples where both are poorly educated reduced from 21.3% in 1983 to 3.9% in 2013, these changes reflect the combined effect of changes in assortative matching and changes in educational distribution. Indeed, looking at the numbers from the random distribution (Table 5.6), we find that if matching was entirely random, the proportion of couples where both partners are highly educated would have increased from around 1% in 1986 to 10% in 2013 while couples with no qualification would have fallen from 14% in 1986 to 1% in 2013. Even without assortative matching, changes in the educational distribution would have led to a large increase in the proportion of couples with a high level of education attainment and a reduction in those with low levels of educational attainment.

To disentangle the changes in educational distribution from the role of assortative matching, the standard approach in the literature is to calculate the concentration ratio; i.e., the ratio of the actual pairing to random pairing in each educational pair[132]. A ratio greater than one is indicative of a greater concentration than would be expected under random matching, and thus evidence of assortative matching. This ratio for all urban areas, reported in Table 5.7[133], reveals the extent to which each educational pairing occur above what would have happened if matching was random given the educational distribution. However, we argue that the concentration ratio is rather strongly influenced by the population proportions in relatively rare education pairings and may lead to misleading conclusions about the trend in educational assortative matching.

[132] See Callister and Didham (2010,2014) and Greenwood et al. (2014)
[133] See Appendix 5.A.12 for Non-metropolitan ratios and Appendix 5.A.13 for Metropolitan ratios

Table 5.7: Concentration ratio: All urban areas combined

Female	Male		
	High-Education	Other-Education	Low-Education
1986			
High-Education	5.6	0.7	0.2
Other-Education	1.1	1.2	0.7
Low-Education	0.2	0.8	1.6
1991			
High-Education	4.5	0.6	0.2
Other-Education	0.8	1.1	0.7
Low-Education	0.1	0.8	1.8
1996			
High-Education	3.4	0.7	0.2
Other-Education	0.8	1.2	0.8
Low-Education	0.2	0.8	2.0
2001			
High-Education	2.7	0.7	0.2
Other-Education	0.7	1.1	0.9
Low-Education	0.1	0.8	2.5
2006			
High-Education	2.2	0.7	0.3
Other-Education	0.6	1.2	0.9
Low-Education	0.1	0.9	2.8
2013			
High-Education	1.9	0.8	0.3
Other-Education	0.6	1.2	1.0
Low-Education	0.1	0.9	3.6

Notes: Results are the concentration ratio i.e. ratio of actual proportion to random proportion of male-female couples in each educational group in each census period for all urban areas combined. High-Education represents those with Bachelor’s degrees and above, Other-Education are those with other forms of qualification but below the Bachelor level, and Low-Education are those with those with no qualification

We can conclude from Table 5.7 that between 1986 and 2013, assortative matching fell considerably – relative to random sorting – for highly educated pairs (from 5.6 to 1.9), remained constant for other-educated pairs (from 1.2 to 1.2) and increased considerably for poorly educated pairs (from 1.6 to 3.6). This conclusion may, however, be misleading. The concentration ratio for groups with large population proportions will have a smaller range than for groups with small proportions and thus it is easier to conclude that smaller groups have undergone bigger changes.

To see this clearly, let us assume, for ease of explanation, a contingency table with just 2 groups: high-educated and low-educated. The minimum the concentration ratio can be is 0, i.e. if the frequency of a pairing is zero. It will be 1 when the actual proportion is equal to the random proportion. However, the maximum value of the concentration ratio depends on the maximum possible homogamy that can be achieved given the educational distribution.

$$Max\ concentration\ ratio = \frac{\text{Max Homogamy}}{\text{Random}}$$

The maximum homogamy for each pair is the minimum of the male and female population proportion in that pair; i.e. if there are 20% of males with high educational levels and 15% of females with high educational levels, the maximum possible proportion of people in the high-education pair (maximum homogamy) is 15%. In general, max homogamy= Min[$\mathrm{P}(\mathrm{F}_H)$), $\mathrm{P}(\mathrm{M}_H)$)].

Under random matching, the proportion of people in the highly educated group is $\mathrm{P}(\mathrm{F}_H) * \mathrm{P}(\mathrm{M}_H)$.

Since maximum homogamy is the minimum of the male and female proportions in that pair, the maximum possible value for the concentration ratio will be the inverse of the group with the larger proportions. [134]

This implies that:

- The ratio will be larger when both groups are small.
- If one or both groups are large, the ratio will be small

Since ratios are influenced by the population proportion, this may affect the conclusion we draw about the rates and trend in assortative matching. This has implications for our New Zealand data - the other-educated group has a large population proportion (see Table 5.5) and will always have smaller ratios compared to the other groups that have smaller proportions. Focusing on changes in the concentration ratios over time may lead to incorrect conclusions on the trends in educational assortative matching.

[134] For example, if $\mathrm{P}(\mathrm{F}_H) < \mathrm{P}(\mathrm{M}_H)$ then the Max Homogamy fraction equals $\mathrm{P}(\mathrm{F}_H)$ and the random fraction equals $\mathrm{P}(\mathrm{F}_H) * \mathrm{P}(\mathrm{M}_H)$. Therefore the Max concentration ratio = $\mathrm{P}(\mathrm{F}_H)$/($\mathrm{P}(\mathrm{F}_H)$* $\mathrm{P}(\mathrm{M}_H)$) = 1/ $\mathrm{P}(\mathrm{M}_H)$. Similarly, when $\mathrm{P}(\mathrm{F}_H) > \mathrm{P}(\mathrm{M}_H)$,the Max concentration ratio is 1/ $\mathrm{P}(F_H)$)).

Due to the effect population proportions can have on the concentration ratio, we propose a new measure of assortative matching. Our proposed index is calculated as :

$$Index = \frac{Actual - Random}{Max\ homogamy - Random}$$

As described previously, $Max\ Homogamy$ is the maximum possible pairing for each educational pair. For example, in 1986, in all urban areas about 7% of the population were highly educated females and 10% were highly educated males, thus the maximum possible pairing for highly educated people in this year is 7%; i.e. if all highly educated people were partnered with each other, we would only have 7% of the population in the highly educated pairs. Our index normalises the calculation of concentrations in each educational pair and is not influenced by the population proportions. It will range between 0 and 1 for the same educational pairings (along the diagonals) [135]. Our index is equal to 0 if matching is entirely random and equal to 1 under if actual patterns of matching are equal to what would happen under maximum homogamy.

Like the concentration ratio reported in Table 5.7, we calculate our index for all educational pairs in all urban areas in Table 5.8 with standard errors in brackets.[136,137]. Our interest is in the diagonals (pairs with the same educational levels).

[135] It is possible to get negative values for our index on the off-diagonal cells. Negative values on the off-diagonal cells are consistent with assortative matching while positive values in the off-diagonals are consistent with non-assortative matching, or even disassortative matching, which may also occur concurrently with assortative matching.
[136] See Appendix 5.A.14 for Non-metropolitan areas and Appendix 5.A.15 for Metropolitan areas
[137] Standard errors are the standard deviations from 250 replications of randomisation.

Table 5.8: Assortative matching index by educational group: All urban areas combined

Female	Male		
	High-education	Other-education	Low-education
1986			
High-Education	0.53	-0.44	-0.42
	(0.2%)	(1.8%)	(1.1%)
Other-Education	0.06	0.24	-0.37
	(0.9%)	(0.2%)	(0.6%)
Low-Education	-0.57	-0.24	0.39
	(1.2%)	(0.5%)	(0.2%)
1991			
High-Education	0.52	-0.63	-0.29
	(0.2%)	(1.8%)	(0.7%)
Other-Education	-0.25	0.23	-0.42
	(1.2%)	(0.2%)	(0.8%)
Low-Education	-0.35	-0.27	0.34
	(0.6%)	(0.7%)	(0.2%)
1996			
High-Education	0.50	-0.44	-0.30
	(0.2%)	(1.1%)	(0.5%)
Other-Education	-0.35	0.26	-0.31
	(1.1%)	(0.2%)	(0.8%)
Low-Education	-0.29	-0.26	0.35
	(0.5%)	(0.7%)	(0.2%)
2001			
High-Education	0.42	-0.47	-0.19
	(0.2%)	(1.0%)	(0.3%)
Other-Education	-0.56	0.25	-0.26
	(1.1%)	(0.2%)	(0.9%)
Low-Education	-0.20	-0.34	0.36
	(0.3%)	(1.0%)	(0.2%)
2006			
High-Education	0.47	-0.42	-0.28
	(0.1%)	(0.6%)	(0.4%)
Other-Education	-0.55	0.25	-0.09
	(0.8%)	(0.2%)	(0.6%)
Low-Education	-0.26	-0.23	0.35
	(0.4%)	(1.0%)	(0.2%)
2013			
High-Education	0.50	-0.38	-0.40
	(0.1%)	(0.6%)	(0.6%)
Other-Education	-0.52	0.30	0.04
	(0.6%)	(0.2%)	(0.6%)
Low-Education	-0.33	-0.21	0.37
	(0.6%)	(1.1%)	(0.2%)

Notes: Results are the educational assortative matching index calculated as $\frac{Actual - Random}{Max\ homogamy - Random}$ for each educational pairing for all urban areas combined in each census period. Standard errors in brackets (standard errors are the standard deviation of 250 replications of randomisation). High-Education represent those with Bachelor's degrees and above, Other-Education are those with other forms of qualification but below the Bachelor level, and Low-Education are those with those with no qualification

As in Table 5.7, we conclude on the basis of our relative homogamy index that assortative matching of those with high levels of education has declined and of those with other-education has increased, when comparing 1986 with 2013. However, contrary to the results from the concentration ratio, between 1986 and 2013, our index shows that assortative matching declined for the poorly educated. In all cases, the index changes are relatively small as compared with the concentration ratio changes that suggested dramatic shifts in assortative matching. For the highly educated, our index declines from 0.53 in 1986 to 0.50 in 2013. For the low education group, it declines from 0.39 in 1986 to 0.37 in 2013, while it increases from 0.24 to 0.30 for the other-educated. Our results are partially consistent with evidence from the US presented by Eika et al. (2014), which reported decreasing levels of assortative matching among college graduates [138]. However, they reported increasing assortative matching among those with no high school diploma, whereas in the NZ case assortative matching among the low education group appears to be declining. Our findings are contrary to public commentary, which suggests increases in assortative matching in recent years, especially for those at the top of the educational distribution[139].

Table 5.9 presents the index for the diagonal educational pairs for all areas (standard errors in brackets). Besides the diagonal educational pairs, we also present a composite measure of assortative matching in each period. This is calculated as the weighted average of the index numbers for each same education pair (along the diagonals) and the weights are the actual proportions of each educational pair in the actual distribution.

[138] Chiappori, Salanie and Weiss (2017) reports increased assortative matching for highly educated Whites in the US.

[139] For popular media, see the Cowen (2015) article in the *New York Times* and the Worstall (2015) article in the *Forbes* magazine.

Table 5.9: Assortative matching index by educational group for all areas

Educational assortative matching index						
Non-metro						
	1986	1991	1996	2001	2006	2013
High-Education	0.53	0.50	0.46	0.37	0.42	0.47
	(0.4%)	(0.3%)	(0.3%)	(0.3%)	(0.3%)	(0.3%)
Other-Education	0.23	0.22	0.24	0.22	0.18	0.21
	(0.4%)	(0.4%)	(0.5%)	(0.4%)	(0.4%)	(0.4%)
Low-Education	0.35	0.30	0.33	0.34	0.31	0.33
	(0.4%)	(0.3%)	(0.4%)	(0.4%)	(0.3%)	(0.4%)
All (Composite)	0.29	0.26	0.28	0.26	0.23	0.27
	(0.4%)	(0.4%)	(0.4%)	(0.4%)	(0.3%)	(0.3%)
Metro						
High-Education	0.53	0.52	0.51	0.42	0.47	0.50
	(0.2%)	(0.2%)	(0.2%)	(0.2%)	(0.2%)	(0.2%)
Other-Education	0.24	0.23	0.26	0.26	0.27	0.31
	(0.3%)	(0.2%)	(0.3%)	(0.2%)	(0.2%)	(0.2%)
Low-Education	0.40	0.35	0.36	0.37	0.35	0.38
	(0.2%)	(0.2%)	(0.2%)	(0.2%)	(0.2%)	(0.2%)
All (Composite)	0.32	0.28	0.32	0.30	0.33	0.38
	(0.2%)	(0.2%)	(0.2%)	(0.2%)	(0.2%)	(0.2%)
All urban areas						
High-Education	0.53	0.52	0.50	0.42	0.47	0.50
	(0.2%)	(0.2%)	(0.2%)	(0.2%)	(0.1%)	(0.1%)
Other-Education	0.24	0.23	0.26	0.25	0.25	0.30
	(0.2%)	(0.2%)	(0.2%)	(0.2%)	(0.2%)	(0.2%)
Low-Education	0.39	0.34	0.35	0.36	0.35	0.37
	(0.2%)	(0.2%)	(0.2%)	(0.2%)	(0.2%)	(0.2%)
All (Composite)	0.31	0.28	0.31	0.29	0.31	0.36
	(0.2%)	(0.2%)	(0.2%)	(0.2%)	(0.2%)	(0.2%)

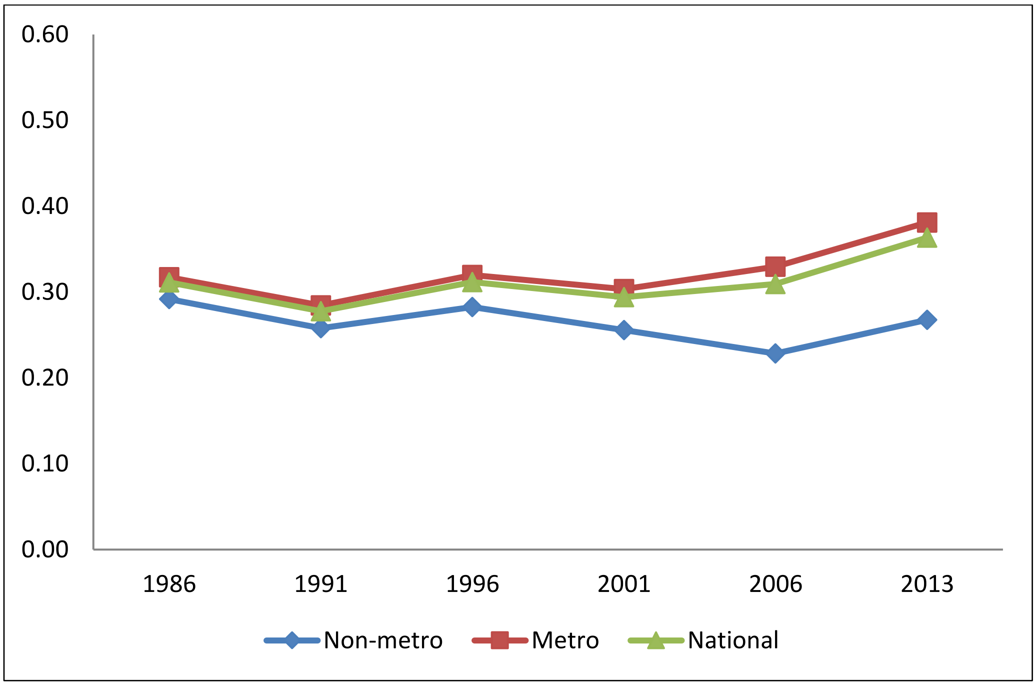
Notes: Results are the educational assortative matching index for couples with same level of education in each period. Index is calculated as : $\frac{Actual-Random}{Max\ homogamy-Random}$. Standard errors in brackets (standard errors are the standard deviation of 250 replications of randomisation). High-Education represents those with Bachelor’s degrees and above, Other-Education are those with other forms of qualification but below the Bachelor level, and Low-Education are those with those with no qualification

The composite index indicates overall increases in assortative matching in all urban areas from 0.31 in 1986 to 0.36 in 2013. As shown by educational group, this increase is due to changes in the other-educated group (0.24 to 0.30) rather than changes for the high-educated or low-educated groups.

Spatially, between 1986 and 2013, assortative matching fell in non-metropolitan areas while it rose in metropolitan areas. In both areas, the changes in assortative matching are similar for the high-educated and the low-educated groups: assortative matching fell. Nonetheless, there are some differences between metropolitan and non-metropolitan areas: firstly, assortative matching increased for the other-educated group in metropolitan areas, contrary to non-metropolitan areas where it fell. The increase in assortative matching for the other-educated group in metropolitan areas meant assortative matching increased overall in metropolitan areas. It is the increase in assortative matching for the other-educated in metropolitan areas that actually drove the overall rise in assortative matching in all urban areas combined. Secondly, apart from 1986, in each educational group, assortative matching was higher in metropolitan areas than non-metropolitan areas and the difference across areas seems to be growing over time, especially for the high-educated and other-educated groups. This is unsurprising given that young educated people are attracted to metropolitan areas and in New Zealand, the metropolitan areas are also where universities are located, which may function as a meet-market.

Figure 5.1 summarises the trend in assortative matching in by area in all periods.

Figure 5.1: Assortative matching index for couples with same category of education by area in all periods



Notes: Figure 5.1 presents educational assortative matching index for couples with the same level of education in each area in each census period. The index is calculated as $\frac{Actual-Random}{Max\ homogamy-Random}$. Metropolitan areas are the six largest New Zealand cities (in order of size): Auckland, Wellington, Christchurch, Hamilton, Tauranga and Dunedin. All other urban areas are considered non-metropolitan areas.

To conclude, with regard to the descriptive patterns of educational assortative matching in New Zealand, in all urban areas, we find evidence of increasing rates of educational assortative matching over time, driven by increases in the assortative matching for the other-educated. By educational group, assortative matching has declined for both the high-educated and low-educated groups. Spatially, we find higher and increasing rates of assortative matching in metropolitan areas compared to non-metropolitan areas.

As well as educational assortative matching, we examine occupational assortative matching over the 1986 to 2013 period. This is useful in the present context because occupation is a strong predictor of income. We use a consistent 1-digit classification of occupations of the 1999 New Zealand Standard Classification of Occupations in all census periods[140]. We use our new index to examine the overall trend in occupational assortative matching in each census period by area[141]. We report the composite occupational assortative matching index by area in Table 5.10.

Table 5.10: Assortative matching index of occupational pairings of couples from 1986 to 2013 by area

	Occupational assortative matching index					
	1986	1991	1996	2001	2006	2013
Non-metropolitan						
All (Composite)	0.29	0.28	0.25	0.24	0.20	0.19
	(0.2%)	(0.2%)	(0.2%)	(0.2%)	(0.2%)	(0.2%)
Metropolitan						
All (Composite)	0.24	0.24	0.22	0.21	0.19	0.17
	(0.2%)	(0.1%)	(0.2%)	(0.1%)	(0.1%)	(0.1%)
All urban areas						
All (Composite)	0.26	0.25	0.23	0.22	0.19	0.18
	(0.1%)	(0.1%)	(0.1%)	(0.1%)	(0.1%)	(0.1%)

Notes: Results are the occupational assortative matching index for couples with same occupational classification in each census period by area. The index is calculated as : $\frac{Actual-Random}{Max\ homogamy-Random}$. Standard errors are the standard deviations from 250 replications of randomisation. Metropolitan areas are the six largest New Zealand cities (in order of size): Auckland, Wellington, Christchurch, Hamilton, Tauranga and Dunedin. All other urban areas are considered non-metropolitan areas.

[140] The 1- digit classifies occupation into 9 categories - Legislators, Administrators and Managers; Professionals; Technicians and Associate Professionals; Clerks; Service and Sales Workers; Agriculture and Fishery Workers; Trades Workers; Plant and Machine Operators and Assemblers, and Elementary occupations (incl. Residual)

[141] In Appendix 5.A.16 and Appendix 5.A.17, we present the actual occupational parings for all urban areas respectively. Actual and random occupational pairings for Non-metropolitan areas are presented in Appendix 5.A.18 and Appendix 5.A.19 and Appendix 5.A.20 and 5.A.21 present the actual and random occupational areas for Metropolitan areas. Appendices 5.A.22-5.A.24 present our assortative matching index for all urban areas, non-metropolitan areas, and metropolitan areas respectively

Unlike educational assortative matching, occupational assortative matching has decreased over time in all areas. Spatially, occupational assortative matching is higher in non-metropolitan areas than metropolitan areas, which is also contrary to the results from educational assortative matching. Apart from 1986, educational assortative matching is higher than occupational assortative matching in all areas. This result possibly reflects the diversity of economic opportunities in metropolitan areas compared to non-metropolitan areas and is consistent with the co-location hypothesis of Costa and Kahn (2000). If cities solve the co-location problem of highly educated couples by offering more potential job matches, permitting specialisation and offering a wide range of economic activities, then we may expect educational assortative matching to be higher than occupational assortative matching.

Given these results, in the next section, we link assortative matching to income distribution and examine the implications of the patterns of assortative matching for income inequality from 1986 to 2013 and across areas.

5.4.4 The impact of assortative matching on income inequality among couples working full-time in New Zealand

In this section we examine what the patterns and trends in assortative matching discussed in the previous section imply for the distribution of income. Even when we find evidence that rates of educational assortative matching have not changed much, the effect on inequality may be different over time. Other factors, such as return to education, may interact with patterns of partnering and influence its implications for income inequality. For example, with increasing returns to education, the gap between highly educated couples and those with no education may increase even when the underlying patterns of assortative matching have not changed[142].

To show evidence of assortative matching on income inequality for male-female couples participating in the labour force, we compare the Mean Log Deviation (MLD) in the observed distribution to the MLD in the random counterfactual distribution. The Mean Log Deviation is defined as $\frac{1}{N}\sum_{i=1}^{N} ln\bar{x} -$

[142] Furthermore, assortative matching will have a multiplicative effect on household income. Percentage change in household income = percentage change in male income + percentage change in female income. When there is educational assortative matching and the rate of return to education increases, inequality in household income grows faster than inequality in individual income.

lnx_i in which N is the number of couples, $\bar{x}$ is the average income of all couples and x_i is the income of couple i (defined by the respective education levels of each partner and by their location). It is useful to note that *MLD* is invariant to the total number of couples if the relative frequencies remain constant, and to the unit of measurement of income (e.g. nominal or real).

The MLDs for the random counterfactual distribution are averages of 250 replications of randomisation with standard errors reported in brackets. For each census period and area, we simulate the randomisation 250 different times and report the average of the MLD from all the 250 different distributions. The standard errors are quite small and range from 0.02% to 0.04%. We can be confident of the estimated differences between the actual MLD and each of the counterfactual distributions. Our data is from the total population, not surveys as in most other studies, which helps to pinpoint our estimates.

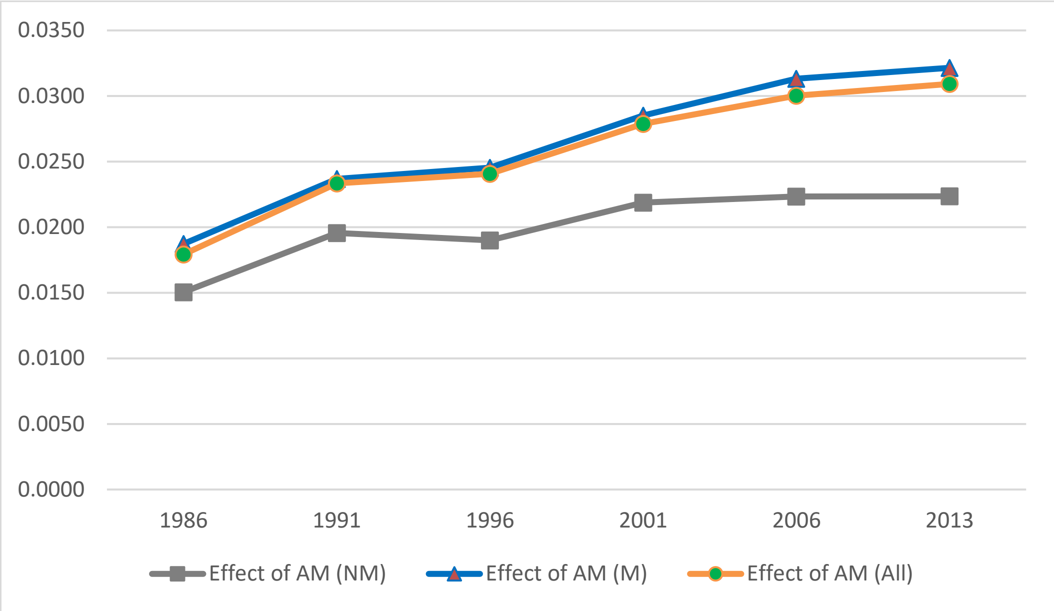
If inequality in the random distribution is lower (higher) than the actual distribution, this implies that the assortative matching is income inequality-increasing (inequality-reducing). Table 5.11 presents the results of the comparison of MLDs for the actual and random distributions for each area and in Figure 5.2 we plot the role of assortative matching over time (difference in MLDs between the actual and counterfactual random distribution).

Table 5.11: Effect of educational assortative matching on the distribution of income of couples working full-time in each Census period by area: MLDs

Age 25-64	1986	1991	1996	2001	2006	2013	Changes between 1986 and 2013
Non-metropolitan							
Observed	0.0837	0.0999	0.1039	0.1121	0.1109	0.1092	30%
Unconditional randomisation	0.0685	0.0803	0.0844	0.0903	0.0889	0.0877	28%
Standard errors	0.03%	0.04%	0.04%	0.03%	0.03%	0.03%	
Effect of assortative matching (MLD points)	0.0152	0.0196	0.0195	0.0218	0.0220	0.0215	0.0063
Effect as a proportion of observed inequality	18%	20%	19%	19%	20%	20%	
Metropolitan							
Observed	0.0906	0.1093	0.1194	0.129	0.1308	0.1372	51%
Unconditional randomisation	0.0719	0.0855	0.0948	0.1006	0.0992	0.1048	46%
Standard errors	0.02%	0.02%	0.02%	0.02%	0.02%	0.02%	
Effect of assortative matching (MLD points)	0.0187	0.0238	0.0246	0.0284	0.0316	0.0324	0.0137
Effect as a proportion of observed inequality	21%	22%	21%	22%	24%	24%	
All urban areas combined							
Observed	0.0895	0.1089	0.1179	0.1278	0.1285	0.1333	49%
Unconditional randomisation	0.0715	0.0854	0.0938	0.1000	0.0984	0.1026	44%
Standard errors	0.02%	0.02%	0.02%	0.02%	0.02%	0.02%	
Effect of assortative matching (MLD points)	0.0180	0.0235	0.0241	0.0278	0.0301	0.0307	0.0127
Effect as a proportion of observed inequality	20%	22%	21%	22%	23%	23%	

Notes: Results are the MLD measure of inequality for the actual and the randomised counterfactual distribution of income of couples working full-time in each census period. Standard errors are the standard deviations from 250 replications of randomisation. Metropolitan areas are the six largest New Zealand cities (in order of size): Auckland, Wellington, Christchurch, Hamilton, Tauranga and Dunedin. All other urban areas are considered non-metropolitan areas

Figure 5.2: Effect of educational assortative matching on the distribution of income of couples working full-time in each Census period by area: MLDs



Notes: Figure 5.2 shows the difference between the MLD for the actual and the randomised counterfactual distribution. The difference represents the effect of assortativ ematching on the distribution of income. Metropolitan areas are the six largest New Zealand cities (in order of size): Auckland, Wellington, Christchurch, Hamilton, Tauranga and Dunedin. All other urban areas are considered non-metropolitan areas. Abbreviations: AM (NM) – Assortative Matching (Non-metropolitan); AM (M) – Assortative Matching (Metropolitan); AM (All) – Assortative Matching (All urban areas).

Table 5.11 shows that assortative matching has a notable impact on income inequality. In all urban areas combined, the effect of assortative matching on income inequality in all periods ranges from 0.0180 MLD points in 1986 to 0.0307 MLD points in 2013. To put this information in context, these numbers represent 20% of the actual observed inequality in 1986 and 23% in 2013.

Reflecting the higher rates of assortative matching in metropolitan areas, assortative matching had a larger inequality-increasing impact in metropolitan areas than in non-metropolitan areas. Also reflecting the increase in assortative matching in metropolitan areas between 1986 and 2013, the inequality-increasing effect rose more in metropolitan areas than non-metropolitan areas. This is a factor that has contributed to the growing differences in income inequality between metropolitan and non-metropolitan areas reported in earlier New Zealand research (e.g. Alimi et al. 2016).

Due to differences in measures of inequality, the MLD results are not directly comparable with evidence from the US and certain European countries as reported by Eika et al. (2014) and Greenwood et al. (2014). These studies reported smaller effects of assortative matching on inequality. Eika et al. (2014) found assortative matching contributed 2%in 1980 and 5% in 2007 while Greenwood (2014) reported the effect of assortative matching to be around 2% of actual inequality in both 1960 and 2005. Using Gini coefficients as in these studies, we find that the contribution of assortative matching in New Zealand ranges from 9% in 1986 to 11% of actual inequality in 2013.

Table 5.12 reports both Ginis and MLDs used to estimate the effect of assortative matching for all couples participating in the labour force; i.e full-time, part-time and unemployed. Table 5.12 presents the results for everyone in the labour force and allows us to compare our results with some of the evidence overseas most of which are not limited to the subset of the population working full-time

Table 5.12: Effect of educational assortative matching on the distribution of income of couples working full-time and everyone in the labour force, using Gini coefficients and MLD

	Full-time (Gini)						
	1986	**1991**	**1996**	**2001**	**2006**	**2013**	**Growth 1986-2013**
Actual	0.2261	0.2524	0.2655	0.2782	0.2761	0.2801	24%
Unconditional randomisation	0.2049	0.2266	0.2390	0.2485	0.2461	0.2503	22%
Effect of Assortative Matching	0.0212	0.0258	0.0265	0.0298	0.03	0.0298	
Effect as a prop of actual	9%	10%	10%	11%	11%	11%	
	All labour force (Gini)						
Actual	0.2677	0.3095	0.3159	0.3231	0.3193	0.3261	22%
Unconditional randomisation	0.2586	0.292	0.2876	0.2934	0.2958	0.3047	18%
Effect of Assortative Matching	0.0091	0.0175	0.0283	0.0297	0.0235	0.0214	
Effect as a prop of actual	3%	6%	9%	9%	7%	7%	
	All labour force (MLD)						
Actual	0.1216	0.1649	0.1719	0.1792	0.1815	0.1916	58%
Unconditional randomisation	0.1154	0.1491	0.1376	0.1425	0.1504	0.1606	39%
Effect of Assortative Matching	0.0062	0.0158	0.0343	0.0366	0.0311	0.031	
Effect as a prop of actual	5%	10%	20%	20%	17%	16%	

Notes: Results are the Gini and MLD measures of inequality for the actual and the randomised distribution of income of couples working full-time and the whole labour force (full-time employed, part-time employed, and unemployed) in each census period.

Using the same measure of inequality, namely the Gini coefficient, the effect of assortative matching in New Zealand is greater than in the US. This may be because we focus on the population working full-time while other studies did not restrict the labour force status. We have already shown that within-group inequality is higher for those working full-time. Also, by focusing on those working full-time, we limit to some extent the effect of endogenous joint labour supply responses. Endogenous joint labour supply responses are likely to dampen the effect of assortative matching on inequality (see Pestel, 2017). Indeed when we do not restrict the investigation to those working full-time and focus on the total population aged 25 to 64 earning positive income, we find lower effects of assortative matching of between 3% and 7% using Ginis and 5% and 16% using Mean Log Deviations (see Table 5.12). The difference in the reference population between our studies and previous studies means care needs to be taken before concluding that assortative matching contributes more to inequality in New Zealand than in the US[143]. We know that partnering isn't entirely random and couples sort based on certain observable and unobservable characteristics. We account for sorting on these characteristics by preserving the actual distribution of these characteristics of couples in our randomised counterfactuals. We use conditions based on age, education, and location as well as combinations of these factors. For example, in our age-conditional randomisation, we preserve the age distribution of couples; i.e. this counterfactual distribution is based on randomisation of partners but we partner people up with another random partner with the same age as their actual partner. In Table 5.13, we present the results of the actual, unconditional, and the difference between the unconditional randomisation and each of the conditional randomisations. As with the descriptive statistics on randomisation, the randomisation results are the average of 250 replications of randomisation. The standard errors for these results are small and range from 0.01% to 0.04%, so we can be quite confident about the estimated differences between actual MLDs and each of the counterfactual distributions.

[143] Greenwood et al. (2014) focused on singles and married couples aged 25-54 and Eika et al. (2014) focused on husband-and-wife couples earning positive income with mean ages between 26 and 60 years.

Table 5.13: Effect of educational assortative matching on the distribution of income of couples working full-time under unconditional and conditional randomisations using MLDs by area

Non-metropolitan						
Distribution	**1986**	**1991**	**1996**	**2001**	**2006**	**2013**
Actual	0.0837	0.0999	0.1039	0.1121	0.1109	0.1092
Unconditional randomisation	0.0685	0.0803	0.0844	0.0903	0.0889	0.0877
Difference between the unconditional randomisation and conditional randomisation						
Age conditional	-0.0002	+0.0000	+0.0001	+0.0004	+0.0004	+0.0006
Education conditional	+0.0023	+0.0034	+0.0036	+0.0038	+0.0032	+0.0028
Age and Education	+0.0024	+0.0037	+0.0041	+0.0045	+0.0041	+0.0042
Location conditional	+0.0005	+0.0007	+0.0007	+0.0008	+0.0006	+0.0007
Age, education and location	+0.0037	+0.0055	+0.0061	+0.0064	+0.0058	+0.0060
Maximum Assortative	+0.0364	+0.0533	+0.0399	+0.0465	+0.0393	+0.0370
Maximum disassortative	-0.0207	-0.0288	-0.0243	-0.0307	-0.0392	-0.0283
Metropolitan						
Distribution	**1986**	**1991**	**1996**	**2001**	**2006**	**2013**
Actual	0.0906	0.1093	0.1194	0.1290	0.1308	0.1372
Unconditional randomisation	0.0719	0.0855	0.0948	0.1006	0.0992	0.1048
Difference between the unconditional randomisation and conditional randomisation						
Age conditional	-0.0003	0.0000	+0.0001	+0.0002	+0.0004	+0.0011
Education conditional	+0.0035	+0.0050	+0.0050	+0.0047	+0.0039	+0.0041
Age and Education	+0.0034	+0.0051	+0.0055	+0.0053	+0.0049	+0.0062
Location conditional	+0.0011	+0.0020	+0.0022	+0.0027	+0.0023	+0.0021
Age, education and location	+0.0044	+0.0067	+0.0072	+0.0073	+0.0067	+0.0079
Maximum assortative	+0.0341	+0.0441	+0.0508	+0.0612	+0.0476	+0.0455
Maximum disassortative	-0.0229	-0.0324	-0.0320	-0.0341	-0.0277	-0.0326
All urban areas						
Distribution	**1986**	**1991**	**1996**	**2001**	**2006**	**2013**
Actual	0.0895	0.1089	0.1179	0.1278	0.1285	0.1333
Unconditional randomisation	0.0715	0.0854	0.0937	0.1000	0.0984	0.1026
Difference between the unconditional randomisation and conditional randomisation						
Age conditional	-0.0003	-0.0001	+0.0001	+0.0002	+0.0003	+0.0009
Education conditional	+0.0033	+0.0048	+0.0049	+0.0049	+0.0041	+0.0042
Age and Education	+0.0033	+0.0050	+0.0054	+0.0055	+0.0050	+0.0061
Location conditional	+0.0013	+0.0025	+0.0027	+0.0033	+0.0028	+0.0026
Age, education and location	+0.0045	+0.0072	+0.0078	+0.0082	+0.0074	+0.0083
Maximum assortative	+0.0352	+0.0472	+0.0484	+0.0584	+0.0463	+0.0443
Maximum disassortative	-0.0240	-0.0323	-0.0310	-0.0503	-0.0303	-0.0300

Notes: Results are the MLD measure of inequality for the actual and unconditional randomised distributions, and the difference in the MLD measure of the unconditional distribution and the conditional-randomised distribution. All distributions are for couples working full-time in each census period. Metropolitan areas are the six largest New Zealand cities (in order of size): Auckland, Wellington, Christchurch, Hamilton, Tauranga and Dunedin. All other urban areas are considered non-metropolitan areas

Our conditional randomisation indicates the role that sorting on these observed characteristics plays in inequality. We compare all conditional randomisations with the unconditional randomisation in each period. If the conditional randomisation results are higher than the unconditional randomisation, this implies that the observed pattern of sorting on this characteristic is inequality-increasing; i.e. the way people sort on this characteristic increase inequality more than if sorting on this characteristic was random. Apart from a few exceptions in the age-conditional randomisation[144], in all variants of our conditional randomisation, inequality is higher in the conditional distributions than the purely random unconditional distribution. Hence, inequality increases when we preserve the observed distribution of these characteristics. The effects are smaller in non-metropolitan areas than metropolitan areas[145].

The conditional counterfactuals show that patterns of age sorting are almost always inequality-increasing in all periods and all areas. The exceptions are in 1986. Unsurprisingly, patterns of sorting on education are inequality-increasing and larger in magnitude than age sorting in all areas. We also find that location is important. Patterns of sorting on location are inequality-increasing and have bigger effects than age sorting but less than educational sorting. In all urban areas, inequality in the counterfactual distribution that preserves the actual distribution of all three factors is around 85% of actual inequality in 1986 but 83% in 2013. This indicates that sorting on unobservable characteristics is also important and has become slightly more important over time.

Finally, we follow Kuhn and Ravazzini (2017) and consider two counterfactual distributions that assume extreme levels of assortative matching. We sort individuals in couples based on our ordinal measure of education and income (income bands). In the maximum assortative matching counterfactual, we match the highest educated males in the highest income bands to females with the highest education in the highest income band, and so on. This gives us an estimate of what inequality would look like under extreme maximum assortative matching. Conversely, we match the highest educated-highest income males to the lowest educated-lowest-income females and so on for an estimate of maximum disassortative matching. The results show that the potential of assortative

[144]In 1986 and 1991, patterns of age sorting are inequality-decreasing in all areas combined
[145] The only exception is in age randomisation in 2001

matching with measures of inequality under the assumptions of maximum assortative matching is around double that under minimum assortative matching[146]. These are reported in the last 2 rows of the results by area in Table 5.13.

[146] Although actual inequality is closer to the results under maximum assortative matching than maximum disassortative matching, this effect isn't purely due to assortative matching as results under pure randomisation are closer to maximum assortative matching than maximum disassortative. The actual results are closer to maximum assortative matching than maximum disassortative matching because income does not follow a normal distribution but is right-skewed (see Kuhn and Ravazzini, 2017).

5.5 Conclusion

Changes in the distribution of income in most western countries continue to receive considerable attention. While most of the focus has been on the role of economic variables, there is growing evidence that socio-demographic factors have been crucial as well.

One socio-demographic factor that is important in determining household income is the role of educational assortative matching. Patterns of partnering will have a direct effect on household income. Early studies of assortative matching and popular opinion have suggested that there has been an increase in assortative matching over time, especially at the top of the educational distribution. In this paper we examined the patterns of assortative matching for couples working full time in New Zealand. We found that rates of assortative matching have increased. However, and contrary to earlier evidence and popular discourse, assortative matching has fallen at the top and bottom of the educational distribution but increased in the middle (other-educated). Earlier studies of assortative matching often just took increases in correlation of levels of education between couples or changes in the proportion of couples with similar levels of education as evidence of assortative matching. These methods did not account for changes in the educational distribution and often failed to differentiate the impact of changes in educational distribution and changes in rates of assortative matching. Changes in educational distribution will influence the correlation of educational achievement between couples or observed proportions of couples with identical levels of education.

Accounting for changes in the distribution of education using a counterfactual randomisation approach, our study provides evidence from the New Zealand context. The New Zealand context is unique because, unlike the US and Europe, New Zealand has a combination of increasing inequality and increasing educational attainment, but a low and falling educational premium. We take an accounting approach and link assortative matching to inequality.

Although our study does not account for all possible endogenous labour supply issues through formal modelling, we limit endogenous joint labour supply responses by focusing on those working full-time. We find that educational assortative matching has slightly increased in all urban areas and spatially, educational assortative matching is higher in metropolitan areas, where it increased over the 1986 to 2013 period, than in non-metropolitan areas, where it decreased over this period.

We find that assortative matching has had a non-neglible effect on the distribution of total income of male-female couples in New Zealand. We go beyond the national level analysis of educational assortative matching in most studies and take a spatial approach. We find notable variation by area. Assortative matching and its impact on the distribution of income is larger and has risen faster in metropolitan than non-metropolitan areas.

Finally, partnering is selective on certain observable and unobservable characteristics. We present evidence on the role of sorting on education, age and location. By also simulating extreme levels of assortative matching, we show that assortative matching has a large potential to affect the distribution of income.

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Appendix Chapter 5

Table 5.A.1: Summary of MLD changes by area for the individual population 25-64. Source: Alimi et al. (2018)

Area	1986	1991	1996	2001	2006	2013	Percentage Change 1986-2013
Non-metropolitan	0.3589	0.3275	0.3340	0.3354	0.3065	0.3177	-11%
Metropolitan	0.3500	0.3415	0.3651	0.3719	0.3468	0.3656	4%
All urban area	0.3538	0.3402	0.3596	0.3664	0.3395	0.3565	1%

Notes: Results are the MLD measure of inequality for the individual population aged 25-64 in each census period. Metropolitan areas are the six largest New Zealand cities (in order of size): Auckland, Wellington, Christchurch, Hamilton, Tauranga and Dunedin. All other urban areas are considered non-metropolitan areas

Table 5.A.2: Decomposition of personal income inequality by labour-force groups: Non-metropolitan areas

	1986	1991	1996	2001	2006	2013
			Non-Metropolitan			
			Between-group contributions			
Full-time	-0.1020	-0.1170	-0.1195	-0.1196	-0.1030	-0.1101
Part-time	0.1192	0.1136	0.1333	0.1377	0.1258	0.1237
Unemployed	0.0368	0.0644	0.0494	0.0463	0.0262	0.0427
Sum between-group	0.0540	0.0610	0.0632	0.0644	0.0490	0.0563
Between as a prop. of	22.2%	24.1%	22.3%	22.8%	19.1%	21.4%
			Within-group contributions			
Full-time	0.1155	0.1205	0.1399	0.1427	0.1371	0.1369
Part-time	0.0565	0.0543	0.0675	0.0636	0.0623	0.0558
Unemployed	0.0177	0.0176	0.0130	0.0116	0.0085	0.0141
Sum within-group	0.1897	0.1924	0.2204	0.2179	0.2079	0.2068
Full-time as a prop. of	60.9%	62.6%	63.5%	65.5%	65.9%	66.2%
Total (sum between-	0.2437	0.2533	0.2836	0.2823	0.2570	0.2632
Sum within as prop of	77.8%	76.0%	77.7%	77.2%	80.9%	78.6%

Notes: Results are the between- and within-group contribution to overall inequality (as measured by the MLD) for those participating in the labour force in Non-metropolitan area (full-time employed, part-time employed and unemployed). Metropolitan areas are the six largest New Zealand cities (in order of size): Auckland, Wellington, Christchurch, Hamilton, Tauranga and Dunedin. All other urban areas are considered non-metropolitan areas

Table 5.A.3: Decomposition of personal income inequality by labour-force groups: Metropolitan areas

	1986	1991	1996	2001	2006	2013
Metropolitan						
Between-group contributions						
Full-time	-0.0909	-0.1037	-0.1080	-0.1066	-0.0916	-0.0994
Part-time	0.1066	0.0985	0.1157	0.1195	0.1094	0.1105
Unemployed	0.0342	0.0589	0.0522	0.0467	0.0263	0.0420
Sum between-group	0.0499	0.0537	0.0599	0.0596	0.0441	0.0531
Between as a prop. of total	21.1%	21.2%	19.9%	19.4%	15.6%	17.7%
Within-group contributions						
Full-time	0.1250	0.1323	0.1635	0.1721	0.1665	0.1721
Part-time	0.0462	0.0486	0.0622	0.0597	0.0610	0.0561
Unemployed	0.0150	0.0193	0.0160	0.0156	0.0113	0.0180
Sum within-group	0.1862	0.2002	0.2417	0.2474	0.2388	0.2462
Full-time as a prop. of sum	67.1%	66.1%	67.6%	69.6%	69.7%	69.9%
Total (sum between-group +	0.2360	0.2539	0.3014	0.3068	0.2829	0.2992
Sum within as prop of total-	78.9%	78.8%	80.2%	80.6%	84.4%	82.3%

Notes: Results are the between- and within-group contribution to overall inequality (as measured by the MLD) for those participating in the labour force in Metropolitan area (full-time employed, part-time employed and unemployed). Metropolitan areas are the six largest New Zealand cities (in order of size): Auckland, Wellington, Christchurch, Hamilton, Tauranga and Dunedin. All other urban areas are considered non-metropolitan areas.

Table5.A.4: Mean and inequality statistics by couple type in each census period for Non-metropolitan areas

	Non-metropolitan area					
1986	HH	HO/OH	OO	HL/LH	OL/LO	LL
Overall mean			$89,377			
Group mean	$136,930	$120,380	$94,538	$108,655	$83,943	$75,861
Rel. mean income	1.53	1.35	1.06	1.22	0.94	0.85
By-group MLD	0.0935	0.0879	0.0718	0.0940	0.0701	0.0747
Pop share	0.03	0.06	0.34	0.01	0.33	0.24
Overall MLD			0.0837			
1991	HH	HO/OH	OO	HL/LH	OL/LO	LL
Overall mean			$90,608			
Group mean	$146,973	$127,284	$92,719	$104,222	$82,086	$72,621
Rel. mean income	1.62	1.40	1.02	1.15	0.91	0.80
By-group MLD	0.0870	0.0962	0.0835	0.1144	0.0840	0.0864
Pop share	0.03	0.07	0.43	0.01	0.30	0.16
Overall MLD			0.0999			
1996	HH	HO/OH	OO	HL/LH	OL/LO	LL
Overall mean			$98,052			
Group mean	$150,843	$131,772	$98,790	$113,377	$87,925	$77,545
Rel. mean income	1.54	1.34	1.01	1.16	0.90	0.79
By-group MLD	0.1028	0.0984	0.0826	0.0971	0.0870	0.0929
Pop share	0.05	0.10	0.40	0.01	0.29	0.16
Overall MLD			0.1039			
2001	HH	HO/OH	OO	HL/LH	OL/LO	LL
Overall mean			$105,003			
Group mean	$163,771	$136,730	$102,986	$113,769	$90,356	$78,852
Rel. mean income	1.56	1.30	0.98	1.08	0.86	0.75
By-group MLD	0.1034	0.1079	0.0919	0.0942	0.0919	0.0945
Pop share	0.05	0.12	0.47	0.01	0.24	0.10
Overall MLD			0.1121			
2006	HH	HO/OH	OO	HL/LH	OL/LO	LL
Overall mean			$109,935			
Group mean	$159,717	$131,887	$107,087	$115,999	$93,743	$80,834
Rel. mean income	1.45	1.20	0.97	1.06	0.85	0.74
By-group MLD	0.1195	0.1040	0.0948	0.0898	0.0874	0.0914
Pop share	0.07	0.16	0.45	0.02	0.22	0.08
Overall MLD			0.1109			
2013	HH	HO/OH	OO	HL/LH	OL/LO	LL
Overall mean			$115,013			
Group mean	$160,884	$131,635	$108,024	$117,180	$96,166	$81,200
Rel. mean income	1.40	1.14	0.94	1.02	0.84	0.71
By-group MLD	0.1293	0.0991	0.0906	0.0811	0.0817	0.0894
Pop share	0.10	0.21	0.45	0.02	0.17	0.06
Overall MLD			0.1092			

Notes: Results are the mean, relative mean income, MLD and population share for each educational pair and the overall mean income in Non-metropolitan areas in each census period. Abbreviations: HH- two high-educated partners; HO /OH - one high-educated partner and one other-educated partner; OO - two other-educated partners; HL/LH - one high-educated partner and one low-educated partner; OL /LO - one other-educated partner and one one low-educated partner; LL - two low-educated partners. Metropolitan areas are the six largest New Zealand cities (in order of size): Auckland, Wellington, Christchurch, Hamilton, Tauranga and Dunedin. All other urban areas are considered non-metropolitan areas

Table 5.A.5: Mean and inequality statistics by couple type in each census period for Metropolitan areas

			Metropolitan area			
1986	HH	HO/OH	OO	HL/LH	OL/LO	LL
Overall mean			$98,123			
Group mean	$146,262	$128,585	$101,830	$116,695	$89,540	$78,372
Rel. mean income	1.49	1.31	1.04	1.19	0.91	0.80
By-group MLD	0.0883	0.0837	0.0776	0.0972	0.0711	0.0746
Pop share	5%	9%	36%	1%	29%	20%
Overall MLD			0.0906			
1991	HH	HO/OH	OO	HL/LH	OL/LO	LL
Overall mean			$105,307			
Group mean	$161,187	$138,226	$104,628	$121,044	$90,105	$76,946
Rel. mean income	1.53	1.31	0.99	1.15	0.86	0.73
By-group MLD	0.0996	0.0944	0.0902	0.1108	0.0834	0.0851
Pop share	7%	11%	44%	1%	25%	12%
Overall MLD			0.1093			
1996	HH	HO/OH	OO	HL/LH	OL/LO	LL
Overall mean			$115,835			
Group mean	$166,467	$144,208	$113,324	$127,910	$97,737	$82,283
Rel. mean income	1.44	1.24	0.98	1.10	0.84	0.71
By-group MLD	0.1264	0.1093	0.0931	0.1211	0.0910	0.0904
Pop share	10%	14%	39%	2%	23%	13%
Overall MLD			0.1194			
2001	HH	HO/OH	OO	HL/LH	OL/LO	LL
Overall mean			$126,080			
Group mean	$177,091	$151,851	$117,628	$132,544	$101,115	$85,073
Rel. mean income	1.40	1.20	0.93	1.05	0.80	0.67
By-group MLD	0.1286	0.1180	0.1074	0.1179	0.0916	0.0937
Pop share	12%	18%	45%	1%	17%	7%
Overall MLD			0.1290			
2006	HH	HO/OH	OO	HL/LH	OL/LO	LL
Overall mean			$130,388			
Group mean	$168,878	$148,034	$120,148	$129,836	$104,688	$84,979
Rel. mean income	1.30	1.14	0.92	1.00	0.80	0.65
By-group MLD	0.1367	0.1175	0.1119	0.1077	0.0950	0.1004
Pop share	16%	22%	40%	2%	14%	5%
Overall MLD			0.1308			
2013	HH	HO/OH	OO	HL/LH	OL/LO	LL
Overall mean			$136,938			
Group mean	$174,369	$148,711	$121,162	$126,143	$103,775	$82,778
Rel. mean income	1.27	1.09	0.88	0.92	0.76	0.60
By-group MLD	0.1401	0.1212	0.1150	0.1038	0.0933	0.1119
Pop share	22%	26%	37%	2%	10%	3%
Overall MLD			0.1372			

Notes: Results are the mean, relative mean income, MLD and population share for each educational pair and the overall mean income in Non-metropolitan areas in each census period. Abbreviations: HH- two high-educated partners; HO /OH - one high-educated partner and one other-educated partner; OO - two other-educated partners; HL/LH - one high-educated partner and one low-educated partner; OL /LO - one other-educated partner and one one low-educated partner; LL - two low-educated partners. Metropolitan areas are the six largest New Zealand cities (in order of size): Auckland, Wellington, Christchurch, Hamilton, Tauranga and Dunedin. All other urban areas are considered non-metropolitan areas

Table 5.A.6: Educational distribution for individuals in couples aged 25-64 in Non-metropolitan areas from 1986 to 2013

Educational distribution: Non- Metropolitan areas	Total	Prop.	Male	Prop.	Female	Prop.	Ratio of
1986							
High-Education	3,990	6%	2,502	7%	1,491	4%	168%
Other-Education	35,697	53%	18,393	55%	17,304	52%	106%
Low-Education	27,123	41%	12,513	37%	14,610	44%	86%
Total specified	66,813	100%	33,408	100%	33,408	100%	
1991							
High-Education	5,067	7%	2,937	8%	2,130	6%	138%
Other-Education	42,975	61%	21,336	61%	21,636	62%	99%
Low-Education	22,185	32%	10,839	31%	11,346	32%	96%
Total specified	70,224	100%	35,112	100%	35,112	100%	
1996							
High-Education	6,693	10%	3,669	11%	3,021	9%	121%
Other-Education	38,637	59%	18,435	56%	20,202	61%	91%
Low-Education	20,523	31%	10,821	33%	9,699	29%	112%
Total specified	65,850	100%	32,925	100%	32,928	100%	
2001							
High-Education	9,135	12%	4,410	12%	4,725	13%	93%
Other-Education	49,047	65%	23,649	63%	25,398	67%	93%
Low-Education	17,286	23%	9,678	26%	7,611	20%	127%
Total specified	75,468	100%	37,734	100%	37,734	100%	
2006							
High-Education	15,894	16%	6,720	14%	9,174	19%	73%
Other-Education	62,700	64%	31,407	64%	31,296	64%	100%
Low-Education	19,797	20%	11,070	23%	8,727	18%	127%
Total specified	98,391	100%	49,197	100%	49,194	100%	
2013							
High-Education	21,042	22%	7,878	16%	13,164	27%	60%
Other-Education	61,863	63%	32,343	66%	29,520	61%	110%
Low-Education	14,547	15%	8,505	17%	6,039	12%	141%
Total specified			48,726	100%	48,726	100%	

Notes: Results are the number and proportion by gender in each educational group in Non-metropolitan areas for each census period. High-Education represents those with Bachelor's degrees and above, Other-Education are those with other forms of qualification but below the Bachelor level, and Low-Education are those with those with no qualification

Table 5.A.7: Educational distribution for individuals in couples aged 25-64 in Metropolitan areas from 1986 to 2013

Educational distribution: Metropolitan area							
	Total	**Prop.**	**Male**	**Prop.**	**Female**	**Prop.**	**Ratio of**
1986							
High-Education	16,920	10%	10,086	12%	6,837	8%	148%
Other-Education	95,274	55%	49,092	56%	46,182	53%	106%
Low-Education	61,779	36%	27,810	32%	33,969	39%	82%
Total specified	173,973	100%	86,988	100%	86,988	100%	
1991							
High-Education	23,694	13%	13,395	14%	10,299	11%	130%
Other-Education	114,162	62%	57,135	62%	57,027	62%	100%
Low-Education	46,944	25%	21,870	24%	25,074	27%	87%
Total specified	184,797	100%	92,400	100%	92,400	100%	
1996							
High-Education	32,805	18%	17,616	19%	15,186	17%	116%
Other-Education	105,153	57%	51,147	56%	54,006	59%	95%
Low-Education	45,231	25%	22,830	25%	22,404	24%	102%
Total specified	183,189	100%	91,596	100%	91,596	100%	
2001							
High-Education	49,419	22%	24,489	21%	24,933	22%	98%
Other-Education	142,806	62%	70,233	61%	72,573	63%	97%
Low-Education	36,552	16%	19,665	17%	16,887	15%	116%
Total specified	228,777	100%	114,390	100%	114,390	100%	
2006							
High-Education	84,228	28%	38,706	26%	45,519	31%	85%
Other-Education	174,237	58%	88,857	60%	85,383	57%	104%
Low-Education	39,468	13%	21,405	14%	18,063	12%	119%
Total specified	297,933	100%	148,968	100%	148,968	100%	
2013							
High-Education	111,813	36%	48,393	31%	63,420	40%	76%
Other-Education	174,120	55%	92,373	59%	81,747	52%	113%
Low-Education	28,803	9%	16,602	11%	12,201	8%	136%
Total specified	314,736	100%	157,368	100%	157,368	100%	

Notes: Results are the number and proportion by gender in each educational group in Metropolitan areas for each census period, High-Education represents those with Bachelor's degrees and above, Other-Education are those with other forms of qualification but below the Bachelor level, and Low-Education are those with those with no qualification

Table 5.A.8: Actual proportion of couples in each educational pairing: Non-metropolitan areas

Female	Actual proportion - Non-metropolitan Male: High-Education	Other-Education	Low-Education
1986			
High-Education	2.5%	1.6%	0.3%
Other-Education	4.4%	34.0%	13.4%
Low-Education	0.5%	19.5%	23.8%
1991			
High-Education	3.3%	2.5%	0.3%
Other-Education	4.8%	42.6%	14.2%
Low-Education	0.3%	15.7%	16.3%
1996			
High-Education	4.7%	3.8%	0.6%
Other-Education	5.8%	39.6%	16.0%
Low-Education	0.6%	12.6%	16.3%
2001			
High-Education	5.3%	6.4%	0.9%
Other-Education	6.0%	46.8%	14.5%
Low-Education	0.4%	9.5%	10.3%
2006			
High-Education	7.2%	9.9%	1.5%
Other-Education	6.1%	44.8%	12.8%
Low-Education	0.4%	9.1%	8.3%
2013			
High-Education	9.9%	15.2%	1.9%
Other-Education	5.9%	44.6%	10.1%
Low-Education	0.3%	6.6%	5.5%

Notes: Results are the proportion of male-female couples in each educational pairing in Non-metropolitan areas for each census period. High-Education represents those with Bachelor's degrees and above, Other-Education are those with other forms of qualification but below the Bachelor level, and Low-Education are those with those with no qualification

Table 5.A.9: Proportion of couples in each educational pairing under randomisation: Non-metropolitan areas

Randomised - Non-metropolitan			
Female	**Male**		
	High-Education	Other-Education	Low-Education
1986			
High-Education	0.3% (0.0003)	2.4% (0.0006)	1.7% (0.0005)
Other-Education	3.9% (0.0007)	28.5% (0.0013)	19.4% (0.0013)
Low-Education	3.3% (0.0008)	24.1% (0.0013)	16.4% (0.0013)
1991			
High-Education	0.5% (0.0003)	3.7% (0.0007)	1.9% (0.0006)
Other-Education	5.2% (0.0007)	37.4% (0.0012)	19.0% (0.0011)
Low-Education	2.7% (0.0006)	19.6% (0.0012)	10.0% (0.0010)
1996			
High-Education	1.0% (0.0005)	5.1% (0.0008)	3.0% (0.0008)
Other-Education	6.8% (0.0009)	34.4% (0.0013)	20.2% (0.0013)
Low-Education	3.3% (0.0008)	16.5% (0.0013)	9.7% (0.0012)
2001			
High-Education	1.5% (0.0005)	7.9% (0.0008)	3.2% (0.0007)
Other-Education	7.9% (0.0008)	42.2% (0.0011)	17.3% (0.0010)
Low-Education	2.4% (0.0007)	12.6% (0.0009)	5.2% (0.0008)
2006			
High-Education	2.5% (0.0006)	11.9% (0.0008)	4.2% (0.0007)
Other-Education	8.7% (0.0007)	40.6% (0.0010)	14.3% (0.0009)
Low-Education	2.4% (0.0006)	11.3% (0.0008)	4.0% (0.0007)
2013			
High-Education	4.4% (0.0007)	17.9% (0.0009)	4.7% (0.0008)
Other-Education	9.8% (0.0008)	40.2% (0.0011)	10.6% (0.0009)
Low-Education	2.0% (0.0005)	8.2% (0.0007)	2.2% (0.0006)

Notes: Results are the proportion of male-female couples in Non-metropolitan areas in each educational pairing in each census period under randomised matching. High-Education represents those with Bachelor's degrees and above, Other-Education are those with other forms of qualification but below the Bachelor level, and Low-Education are those with those with no qualification.

Table 5.A.10: Actual proportion of couples in each educational pairing: Metropolitan areas

Actual proportion - Metropolitan			
Female	**Male**		
	High-Education	Other-Education	Low-Education
1986			
High-Education	4.6%	2.9%	0.4%
Other-Education	6.3%	35.5%	11.2%
Low-Education	0.7%	18.0%	20.3%
1991			
High-Education	6.6%	4.1%	0.5%
Other-Education	7.4%	43.6%	10.8%
Low-Education	0.5%	14.2%	12.5%
1996			
High-Education	10.0%	5.9%	0.7%
Other-Education	8.5%	38.9%	11.6%
Low-Education	0.8%	11.0%	12.6%
2001			
High-Education	11.7%	9.3%	0.8%
Other-Education	9.2%	44.8%	9.4%
Low-Education	0.5%	7.3%	7.0%
2006			
High-Education	16.5%	13.0%	1.1%
Other-Education	9.1%	40.4%	7.8%
Low-Education	0.4%	6.3%	5.4%
2013			
High-Education	21.5%	17.4%	1.3%
Other-Education	8.9%	37.2%	5.8%
Low-Education	0.3%	4.0%	3.4%

Notes: Results are the actual proportion of male-female couples in each educational pairing in Metropolitan areas for each census period. High-Education represents those with Bachelor's degrees and above, Other-Education are those with other forms of qualification but below the Bachelor level, and Low-Education are those with those with no qualification.

Table 5.A.11: Proportion of couples in each educational pairing under randomisation: Metropolitan areas

Randomised - Metropolitan			
Female	**Male**		
	High-Education	Other-Education	Low-Education
1986			
High-Education	0.9% (0.0003)	4.4% (0.0004)	2.5% (0.0004)
Other-Education	6.2% (0.0006)	30.0% (0.0008)	17.0% (0.0007)
Low-Education	4.5% (0.0005)	22.0% (0.0008)	12.5% (0.0007)
1991			
High-Education	1.6% (0.0004)	6.9% (0.0005)	2.6% (0.0005)
Other-Education	8.9% (0.0005)	38.2% (0.0008)	14.6% (0.0007)
Low-Education	3.9% (0.0005)	16.8%(0.0007)	6.4% (0.0006)
1996			
High-Education	3.2% (0.0005)	9.3% (0.0006)	4.1% (0.0006)
Other-Education	11.3% (0.0007)	32.9% (0.0008)	14.7% (0.0007)
Low-Education	4.7% (0.0006)	13.7% (0.0007)	6.1% (0.0006)
2001			
High-Education	4.7% (0.0005)	13.4% (0.0006)	3.7% (0.0005)
Other-Education	13.6% (0.0006)	39.0% (0.0007)	10.9% (0.0005)
Low-Education	3.2% (0.0004)	9.1% (0.0005)	2.5% (0.0004)
2006			
High-Education	7.9% (0.0006)	18.2% (0.0006)	4.4% (0.0005)
Other-Education	14.9% (0.0006)	34.2% (0.0006)	8.2% (0.0005)
Low-Education	3.1% (0.0004)	7.2% (0.0004)	1.7% (0.0003)
2013			
High-Education	12.4% (0.0006)	23.7% (0.0007)	4.3% (0.0004)
Other-Education	16.0% (0.0006)	30.5% (0.0007)	5.5% (0.0004)
Low-Education	2.4% (0.0003)	4.6% (0.0003)	0.8% (0.0002)

Notes: Results are the proportion of male-female couples in Metropolitan areas in each educational pairing in each census period under randomised matching. High-Education represents those with Bachelor's degrees and above, Other-Education are those with other forms of qualification but below the Bachelor level, and Low-Education are those with those with no qualification

Table 5.A.12: Concentration ratio from 1986 to 2013: Non-metropolitan areas

	Concentration ratio		
	High-Education	Other-Education	Low-Education
1986			
High-Education	7.5	0.7	0.2
Other-Education	1.1	1.2	0.7
Low-Education	0.2	0.8	1.5
1991			
High-Education	6.4	0.7	0.2
Other-Education	0.9	1.1	0.7
Low-Education	0.1	0.8	1.6
1996			
High-Education	4.6	0.7	0.2
Other-Education	0.9	1.2	0.8
Low-Education	0.2	0.8	1.7
2001			
High-Education	3.6	0.8	0.3
Other-Education	0.8	1.1	0.8
Low-Education	0.2	0.8	2.0
2006			
High-Education	2.8	0.8	0.4
Other-Education	0.7	1.1	0.9
Low-Education	0.2	0.8	2.1
2013			
High-Education	2.3	0.8	0.4
Other-Education	0.6	1.1	1.0
Low-Education	0.1	0.8	2.5

Notes: Results are the concentration ratios; i.e. ratio of actual proportion to random proportion of male-female couples in each educational group in each census period for Non-metropolitan areas. High-Education represents those with Bachelo’rs degrees and above, Other-Education are those with other forms of qualification but below the Bachelor level, and Low-Education are those with those with no qualification

Table 5.A.13: Concentration ratio from 1986 to 2013: Metropolitan areas

	Concentration ratio		
	High-Education	Other-Education	Low-Education
	1986		
High-Education	5.0	0.7	0.2
Other-Education	1.0	1.2	0.7
Low-Education	0.2	0.8	1.6
	1991		
High-Education	4.1	0.6	0.2
Other-Education	0.8	1.1	0.7
Low-Education	0.1	0.8	1.9
	1996		
High-Education	3.1	0.6	0.2
Other-Education	0.8	1.2	0.8
Low-Education	0.2	0.8	2.1
	2001		
High-Education	2.5	0.7	0.2
Other-Education	0.7	1.2	0.9
Low-Education	0.1	0.8	2.8
	2006		
High-Education	2.1	0.7	0.3
Other-Education	0.6	1.2	0.9
Low-Education	0.1	0.9	3.1
	2013		
High-Education	1.7	0.7	0.3
Other-Education	0.6	1.2	1.1
Low-Education	0.1	0.9	4.2

Notes: Results are the concentration ratios; i.e. ratios of actual proportion to random proportion of male-female couples in each educational group in each census period for Metropolitan areas. High-Education represents those with Bachelor's degrees and above, Other-Education are those with other forms of qualification but below the Bachelor level, and Low-Education are those with those with no qualification

Table 5.A.14: Assortative matching index by educational group for non-metropolitan areas

	Non-metropolitan		
	High-Education	Other-Education	Low-Education
	1986		
High-Education	0.53	-0.41	-0.50
	(0.4%)	(3.9%)	(2.9%)
Other-Education	0.16	0.23	-0.33
	(1.7%)	(0.4%)	(1.0%)
Low-Education	-0.66	-0.23	0.35
	(3.0%)	(0.8%)	(0.4%)
	1991		
High-Education	0.50	-0.52	-0.37
	(0.3%)	(4.1%)	(1.9%)
Other-Education	-0.13	0.22	-0.40
	(2.4%)	(0.4%)	(1.3%)
Low-Education	-0.42	-0.31	0.30
	(1.6%)	(1.2%)	(0.3%)
	1996		
High-Education	0.46	-0.32	-0.39
	(0.3%)	(2.6%)	(1.7%)
Other-Education	-0.23	0.24	-0.33
	(2.5%)	(0.5%)	(1.3%)
Low-Education	-0.34	-0.30	0.33
	2001		
High-Education	0.37	-0.31	-0.25
	(0.3%)	(2.2%)	(0.9%)
Other-Education	-0.48	0.22	-0.33
	(3.0%)	(0.4%)	(1.6%)
Low-Education	-0.21	-0.42	0.34
	(0.9%)	(1.8%)	(0.4%)
	2006		
High-Education	0.42	-0.29	-0.19
	(0.3%)	(1.5%)	(0.6%)
Other-Education	-0.53	0.18	-0.19
	(2.3%)	(0.4%)	(1.3%)
Low-Education	-0.18	-0.35	0.31
	(0.6%)	(1.6%)	(0.3%)
	2013		
High-Education	0.47	-0.30	-0.22
	(0.3%)	(1.3%)	(0.8%)
Other-Education	-0.61	0.21	-0.08
	(2.1%)	(0.4%)	(1.4%)
Low-Education	-0.16	-0.39	0.33
	(0.6%)	(2.3%)	(0.4%)

Notes: Results are the educational assortative matching index calculated as $\frac{Actual-Random}{Max\ homogamy-Random}$ for each educational pairing for Non-metropolitan areas in each census period. Standard errors are in parentheses (standard errors are the standard deviations from 250 replications of randomisation). High-Education represents those with Bachelor’s degrees and above, Other-Education are those with other forms of qualification but below the Bachelor level, and Low-Education are those with those with no qualification

Table 5.A.15: Assortative matching index by educational group for metropolitan areas

	Metropolitan		
	High-Education	Other-Education	Low-Education
	1986		
High-Education	0.53	-0.45	-0.40
	(0.2%)	(1.9%)	(1.1%)
Other-Education	0.03	0.24	-0.38
	(1.0%)	(0.3%)	(0.7%)
Low-Education	-0.54	-0.24	0.40
	(1.1%)	(0.6%)	(0.2%)
	1991		
High-Education	0.52	-0.66	-0.26
	(0.2%)	(2.0%)	(0.7%)
Other-Education	-0.28	0.23	-0.43
	(1.3%)	(0.2%)	(1.1%)
Low-Education	-0.32	-0.25	0.35
	(0.6%)	(0.8%)	(0.2%)
	1996		
High-Education	0.51	-0.46	-0.27
	(0.2%)	(1.3%)	(0.6%)
Other-Education	-0.36	0.26	-0.31
	(1.1%)	(0.3%)	(0.9%)
Low-Education	-0.27	-0.24	0.36
	(0.5%)	(0.8%)	(0.2%)
	2001		
High-Education	0.42	-0.49	-0.22
	(0.2%)	(1.1%)	(0.4%)
Other-Education	-0.56	0.26	-0.24
	(1.1%)	(0.2%)	(1.0%)
Low-Education	-0.23	-0.31	0.37
	(0.5%)	(1.2%)	(0.2%)
	2006		
High-Education	0.47	-0.43	-0.33
	(0.2%)	(0.7%)	(0.6%)
Other-Education	-0.52	0.27	-0.07
	(0.8%)	(0.2%)	(0.8%)
Low-Education	-0.30	-0.19	0.35
	(0.6%)	(1.1%)	(0.2%)
	2013		
High-Education	0.50	-0.37	-0.46
	(0.2%)	(0.5%)	(0.9%)
Other-Education	-0.48	0.31	0.06
	(0.6%)	(0.2%)	(0.7%)
Low-Education	-0.39	-0.17	0.38
	(0.8%)	(1.2%)	(0.2%)

Notes: Results are the educational assortative matching index calculated as $\frac{Actual-Random}{Max\ homogamy-Random}$ for each educational pairing for Metropolitan areas in each census period. Standard errors are in parentheses (standard errors are the standard deviations from 250 replications of randomisation). High-Education represents those with Bachelor's degrees and above, Other-Education are those with other forms of qualification but below the Bachelor level, and Low-Education are those with those with no qualification

Abbreviations for 1999 New Zealand Standard Occupational Classification:

- AD&M – Legislators, Administrators and Managers
- PROF - Professionals
- TECH – Technicians and Associate Professionals
- CLERKS - Clerks
- S&S – Service and Sales Workers
- AGRI - Agriculture and Fishery Workers
- TRADE – Trades Workers
- P&M – Plant and Machine Operators and Assemblers
- ELMT – Elementary occupations (incl. Residual)

Table 5.A.16: Actual occupational pairings in 1986 and 2013: All urban areas

Actual occupational pairings- All urban areas									
Female	**Male**								
	AD&M	PROF	TECH	CLERKS	S & S	AGRI	TRADE	P&M	ELMT
				1986					
AD&M	5.0%	0.8%	0.9%	0.6%	0.6%	0.2%	1.3%	0.7%	0.4%
PROF	2.3%	5.3%	2.2%	1.3%	1.1%	0.3%	2.0%	1.0%	0.6%
TECH	1.2%	1.4%	1.7%	0.8%	0.6%	0.2%	1.3%	0.7%	0.4%
CLERKS	5.3%	3.2%	4.2%	3.6%	2.8%	0.7%	6.7%	3.2%	2.0%
S & S	1.7%	0.8%	1.3%	1.2%	1.9%	0.4%	2.9%	2.3%	1.4%
AGRI	0.1%	0.1%	0.1%	0.1%	0.1%	1.4%	0.2%	0.3%	0.1%
TRADE	0.2%	0.1%	0.2%	0.2%	0.1%	0.1%	0.9%	0.5%	0.2%
P&M	0.5%	0.2%	0.5%	0.7%	0.6%	0.3%	2.1%	2.6%	1.2%
ELMT	0.4%	0.2%	0.3%	0.5%	0.4%	0.2%	1.2%	1.5%	1.2%
				2013					
AD&M	7.3%	3.1%	2.5%	0.8%	1.5%	0.4%	2.5%	1.4%	1.4%
PROF	5.6%	7.9%	3.7%	1.2%	1.9%	0.5%	3.1%	1.6%	1.8%
TECH	3.4%	2.7%	2.8%	0.8%	1.3%	0.3%	2.2%	1.4%	1.3%
CLERKS	3.5%	2.2%	2.1%	1.1%	1.2%	0.3%	2.6%	1.7%	1.4%
S & S	1.8%	1.0%	1.2%	0.5%	1.8%	0.3%	1.8%	1.5%	1.1%
AGRI	0.1%	0.1%	0.1%	0.0%	0.0%	0.4%	0.1%	0.1%	0.1%
TRADE	0.1%	0.1%	0.1%	0.0%	0.1%	0.0%	0.3%	0.1%	0.1%
P&M	0.2%	0.1%	0.1%	0.1%	0.1%	0.1%	0.4%	0.7%	0.3%
ELMT	0.7%	0.5%	0.4%	0.2%	0.3%	0.1%	0.7%	0.8%	1.1%

Notes: Results are the actual proportion of male-female couples in each occupational pairing for all urban areas combined in 1986 and 2013. Abbreviations: AD&M – Legislators, Administrators and Managers; PROF – Professionals; TECH – Technicians and Associate Professionals; CLERKS – Clerks; S&S – Service and Sales Workers; AGRI - Agriculture and Fishery Workers;TRADE – Trades Workers; P&M – Plant and Machine Operators and Assemblers;ELMT – Elementary occupations (incl. Residual)

Table 5.A.17: Occupational pairing under randomisation in 1986 and 2013: All urban areas

Occupational pairing under randomisation- All urban areas									
Female	**Male**								
	AD&	PRO	TEC	CLERK	S &	AGR	TRAD	P&	ELM
1986									
AD&M	1.8%	1.3%	1.2%	0.9%	0.9%	0.4%	1.9%	1.3%	0.8%
PROF	2.7%	2.0%	1.8%	1.4%	1.3%	0.6%	3.0%	2.0%	1.2%
TECH	1.4%	1.0%	1.0%	0.7%	0.7%	0.3%	1.5%	1.1%	0.6%
CLERK	5.3%	3.9%	3.6%	2.8%	2.6%	1.2%	5.8%	4.0%	2.4%
S & S	2.3%	1.7%	1.6%	1.2%	1.2%	0.5%	2.6%	1.8%	1.1%
AGRI	0.4%	0.3%	0.3%	0.2%	0.2%	0.1%	0.5%	0.3%	0.2%
TRADE	0.4%	0.3%	0.3%	0.2%	0.2%	0.1%	0.5%	0.3%	0.2%
P&M	1.5%	1.1%	1.0%	0.8%	0.7%	0.3%	1.6%	1.1%	0.7%
ELMT	1.0%	0.7%	0.7%	0.5%	0.5%	0.2%	1.0%	0.7%	0.4%
2013									
AD&M	4.7%	3.7%	2.7%	1.0%	1.7%	0.5%	2.8%	1.9%	1.8%
PROF	6.2%	4.8%	3.6%	1.3%	2.3%	0.7%	3.7%	2.5%	2.3%
TECH	3.7%	2.8%	2.1%	0.8%	1.3%	0.4%	2.2%	1.5%	1.4%
CLERK	3.6%	2.8%	2.1%	0.8%	1.3%	0.4%	2.2%	1.5%	1.4%
S & S	2.5%	1.9%	1.4%	0.5%	0.9%	0.3%	1.5%	1.0%	0.9%
AGRI	0.2%	0.2%	0.1%	0.0%	0.1%	0.0%	0.1%	0.1%	0.1%
TRADE	0.2%	0.1%	0.1%	0.0%	0.1%	0.0%	0.1%	0.1%	0.1%
P&M	0.5%	0.4%	0.3%	0.1%	0.2%	0.1%	0.3%	0.2%	0.2%
ELMT	1.1%	0.9%	0.6%	0.2%	0.4%	0.1%	0.7%	0.4%	0.4%

Notes: Results are the proportion of male-female couples in each occupational pairing under randomised matching in all urban areas combined in 1986 and 2013. Abbreviations: AD&M – Legislators, Administrators and Managers; PROF – Professionals; TECH – Technicians and Associate Professionals; CLERKS – Clerks; S&S – Service and Sales Workers; AGRI - Agriculture and Fishery Workers;TRADE – Trades Workers; P&M – Plant and Machine Operators and Assemblers;ELMT – Elementary occupations (incl. Residual)

Table 5.A.18: Actual occupational pairings in 1986 and 2013: Non-metropolitan areas

Female	Actual occupational pairing - Non-metropolitan areas								
	Male								
	AD&M	PROF	TECH	Clerks	S & S	AGRI	TRADE	P&M	ELMT
	1986								
AD&M	5.4%	0.6%	0.8%	0.5%	0.6%	0.3%	1.3%	0.9%	0.4%
PROF	1.9%	5.2%	2.0%	1.1%	1.1%	0.6%	2.2%	1.3%	0.7%
TECH	0.8%	1.2%	1.5%	0.6%	0.6%	0.3%	1.3%	0.9%	0.5%
Clerks	4.2%	2.7%	3.5%	2.6%	2.5%	1.1%	6.4%	3.7%	1.7%
S & S	1.7%	0.9%	1.5%	1.3%	2.2%	0.9%	3.6%	3.3%	1.7%
AGRI	0.2%	0.2%	0.2%	0.1%	0.2%	2.3%	0.4%	0.6%	0.3%
TRADE	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.7%	0.3%	0.1%
P&M	0.4%	0.2%	0.4%	0.5%	0.6%	0.5%	1.9%	2.7%	1.0%
ELMT	0.4%	0.1%	0.3%	0.4%	0.3%	0.4%	1.0%	1.5%	1.0%
	2013								
AD&M	6.3%	1.9%	2.1%	0.5%	1.6%	0.8%	2.8%	1.9%	1.6%
PROF	4.2%	5.6%	2.9%	0.8%	2.2%	1.1%	3.6%	2.3%	1.9%
TECH	2.7%	1.8%	2.1%	0.6%	1.3%	0.7%	2.6%	1.9%	1.3%
Clerks	3.3%	1.6%	1.9%	0.8%	1.2%	0.7%	3.1%	2.3%	1.5%
S & S	2.0%	0.8%	1.2%	0.5%	2.1%	0.8%	2.5%	2.3%	1.5%
AGRI	0.2%	0.1%	0.1%	0.0%	0.1%	0.8%	0.2%	0.2%	0.2%
TRADE	0.1%	0.1%	0.1%	0.0%	0.1%	0.0%	0.3%	0.1%	0.1%
P&M	0.2%	0.1%	0.2%	0.1%	0.1%	0.2%	0.4%	1.0%	0.4%
ELMT	0.6%	0.4%	0.3%	0.2%	0.3%	0.3%	0.7%	1.1%	1.2%

Notes: Results are the actual proportion of male-female couples in each occupational pairing for Non-metropolitan areas in 1986 and 2013. Abbreviations: AD&M – Legislators, Administrators and Managers; PROF – Professionals; TECH – Technicians and Associate Professionals; CLERKS – Clerks; S&S – Service and Sales Workers; AGRI - Agriculture and Fishery Workers;TRADE – Trades Workers; P&M – Plant and Machine Operators and Assemblers;ELMT – Elementary occupations (incl. Residual)

Table 5.A.19: Occupational pairing under randomisation in 1986 and 2013: Non-metropolitan areas

Female	**Occupational pairing under randomisation- Non-metropolitan areas** **Male**								
	1986								
	AD&M	PROF	TECH	Clerks	S & S	AGRI	TRADE	P&M	ELMT
AD&M	1.7%	1.2%	1.1%	0.8%	0.9%	0.7%	2.0%	1.7%	0.8%
PROF	2.5%	1.8%	1.7%	1.2%	1.3%	1.1%	3.0%	2.5%	1.2%
TECH	1.2%	0.8%	0.8%	0.6%	0.6%	0.5%	1.4%	1.1%	0.6%
Clerks	4.3%	3.2%	2.9%	2.1%	2.3%	1.9%	5.3%	4.3%	2.1%
S & S	2.6%	1.9%	1.8%	1.3%	1.4%	1.1%	3.2%	2.6%	1.3%
AGRI	0.7%	0.5%	0.5%	0.3%	0.4%	0.3%	0.8%	0.7%	0.3%
TRADE	0.3%	0.2%	0.2%	0.1%	0.1%	0.1%	0.3%	0.3%	0.1%
P&M	1.3%	0.9%	0.9%	0.6%	0.7%	0.5%	1.5%	1.2%	0.6%
ELMT	0.8%	0.6%	0.5%	0.4%	0.4%	0.3%	1.0%	0.8%	0.4%
	2013								
AD&M	3.8%	2.4%	2.1%	0.7%	1.8%	1.1%	3.2%	2.6%	1.9%
PROF	4.8%	3.0%	2.7%	0.9%	2.2%	1.3%	4.0%	3.2%	2.4%
TECH	3.0%	1.9%	1.6%	0.5%	1.4%	0.8%	2.5%	2.0%	1.5%
Clerks	3.2%	2.1%	1.8%	0.6%	1.5%	0.9%	2.7%	2.2%	1.6%
S & S	2.7%	1.7%	1.5%	0.5%	1.2%	0.7%	2.2%	1.8%	1.3%
AGRI	0.4%	0.2%	0.2%	0.1%	0.2%	0.1%	0.3%	0.3%	0.2%
TRADE	0.2%	0.1%	0.1%	0.0%	0.1%	0.0%	0.1%	0.1%	0.1%
P&M	0.5%	0.3%	0.3%	0.1%	0.2%	0.1%	0.4%	0.3%	0.3%
ELMT	1.0%	0.6%	0.6%	0.2%	0.5%	0.3%	0.8%	0.7%	0.5%

Notes: Results are the proportion of male-female couples in each occupational pairing under randomised matching in Non-metropolitan area in 1986 and 2013. Abbreviations: AD&M – Legislators, Administrators and Managers; PROF – Professionals; TECH – Technicians and Associate Professionals; CLERKS – Clerks; S&S – Service and Sales Workers; AGRI - Agriculture and Fishery Workers;TRADE – Trades Workers; P&M – Plant and Machine Operators and Assemblers;ELMT – Elementary occupations (incl. Residual)

Table 5.A.20: Actual occupational pairings in 1986 and 2013: Metropolitan areas

	Actual occupational pairing - Metropolitan areas								
Female	**Male**								
	1986								
1986	AD&M	PROF	TECH	Clerks	S & S	AGRI	TRADE	P&M	ELMT
AD&M	4.9%	0.9%	1.0%	0.6%	0.6%	0.1%	1.3%	0.6%	0.4%
PROF	2.4%	5.3%	2.2%	1.3%	1.2%	0.2%	1.8%	0.8%	0.6%
TECH	1.4%	1.5%	1.8%	0.8%	0.7%	0.1%	1.4%	0.6%	0.4%
Clerks	5.8%	3.4%	4.5%	3.9%	3.0%	0.5%	6.7%	3.0%	2.1%
S & S	1.7%	0.8%	1.3%	1.2%	1.8%	0.3%	2.6%	1.9%	1.2%
AGRI	0.1%	0.1%	0.1%	0.1%	0.1%	1.0%	0.2%	0.1%	0.1%
TRADE	0.3%	0.1%	0.2%	0.2%	0.2%	0.0%	1.0%	0.5%	0.3%
P&M	0.5%	0.3%	0.5%	0.7%	0.6%	0.2%	2.1%	2.6%	1.3%
ELMT	0.3%	0.2%	0.3%	0.5%	0.4%	0.2%	1.3%	1.5%	1.2%
	2013								
AD&M	7.6%	3.4%	2.7%	0.8%	1.5%	0.3%	2.4%	1.2%	1.3%
PROF	6.1%	8.6%	4.0%	1.3%	1.9%	0.4%	2.9%	1.4%	1.7%
TECH	3.6%	2.9%	3.1%	0.9%	1.3%	0.2%	2.1%	1.2%	1.2%
Clerks	3.6%	2.3%	2.1%	1.1%	1.2%	0.2%	2.4%	1.5%	1.4%
S & S	1.8%	1.0%	1.1%	0.5%	1.7%	0.2%	1.6%	1.2%	0.9%
AGRI	0.1%	0.1%	0.1%	0.0%	0.0%	0.3%	0.1%	0.1%	0.0%
TRADE	0.1%	0.1%	0.1%	0.0%	0.1%	0.0%	0.3%	0.1%	0.1%
P&M	0.2%	0.1%	0.1%	0.1%	0.1%	0.0%	0.4%	0.6%	0.3%
ELMT	0.7%	0.6%	0.4%	0.2%	0.3%	0.1%	0.6%	0.7%	1.1%

Notes: Results are the actual proportion of male-female couples in each occupational pairing in Metropolitan areas in 1986 and 2013. Abbreviations: AD&M – Legislators, Administrators and Managers; PROF – Professionals; TECH – Technicians and Associate Professionals; CLERKS – Clerks; S&S – Service and Sales Workers; AGRI - Agriculture and Fishery Workers;TRADE – Trades Workers; P&M – Plant and Machine Operators and Assemblers;ELMT – Elementary occupations (incl. Residual)

Table 5.A.21: Occupational pairing under randomisation in 1986 and 2013: Metropolitan areas

Occupational pairing under randomisation- Metropolitan areas									
Female	Male								
1986									
	AD&M	PROF	TECH	Clerks	S & S	AGRI	TRADE	P&M	ELMT
AD&M	1.8%	1.3%	1.2%	1.0%	0.9%	0.3%	1.9%	1.2%	0.8%
PROF	2.8%	2.0%	1.9%	1.5%	1.3%	0.4%	2.9%	1.9%	1.2%
TECH	1.5%	1.1%	1.0%	0.8%	0.7%	0.2%	1.6%	1.0%	0.7%
Clerks	5.7%	4.1%	3.9%	3.1%	2.8%	0.9%	6.0%	3.9%	2.5%
S & S	2.2%	1.6%	1.5%	1.2%	1.1%	0.3%	2.3%	1.5%	1.0%
AGRI	0.3%	0.2%	0.2%	0.2%	0.2%	0.0%	0.3%	0.2%	0.1%
TRADE	0.5%	0.3%	0.3%	0.3%	0.2%	0.1%	0.5%	0.3%	0.2%
P&M	1.5%	1.1%	1.1%	0.8%	0.7%	0.2%	1.6%	1.0%	0.7%
ELMT	1.0%	0.7%	0.7%	0.5%	0.5%	0.2%	1.1%	0.7%	0.4%
2013									
AD&M	5.0%	4.1%	2.9%	1.1%	1.7%	0.3%	2.7%	1.7%	1.7%
PROF	6.7%	5.4%	3.9%	1.4%	2.3%	0.5%	3.6%	2.2%	2.3%
TECH	3.9%	3.2%	2.3%	0.8%	1.3%	0.3%	2.1%	1.3%	1.3%
Clerks	3.8%	3.1%	2.2%	0.8%	1.3%	0.3%	2.0%	1.3%	1.3%
S & S	2.4%	1.9%	1.4%	0.5%	0.8%	0.2%	1.3%	0.8%	0.8%
AGRI	0.2%	0.1%	0.1%	0.0%	0.1%	0.0%	0.1%	0.1%	0.1%
TRADE	0.2%	0.2%	0.1%	0.0%	0.1%	0.0%	0.1%	0.1%	0.1%
P&M	0.5%	0.4%	0.3%	0.1%	0.2%	0.0%	0.2%	0.2%	0.2%
ELMT	1.1%	0.9%	0.7%	0.2%	0.4%	0.1%	0.6%	0.4%	0.4%

Notes: Results are the proportion of male-female couples in each occupational pairing under randomised matching in Metropolitan area in 1986 and 2013. Abbreviations: AD&M – Legislators, Administrators and Managers; PROF – Professionals; TECH – Technicians and Associate Professionals; CLERKS – Clerks; S&S – Service and Sales Workers; AGRI - Agriculture and Fishery Workers;TRADE – Trades Workers; P&M – Plant and Machine Operators and Assemblers;ELMT – Elementary occupations (incl. Residual)

Table 5.A.22: Assortative matching index of occupational pairings for 1986 and 2013 in all urban areas

	Occupational Index- All urban areas								
Female	**Male**								
	1986								
	AD&M	PROF	TECH	Clerks	S & S	AGRI	TRADE	P&M	ELMT
AD&M	0.37	-0.05	-0.03	-0.04	-0.03	-0.07	-0.08	-0.07	-0.06
	(0.2%)	(0.3%)	(0.3%)	(0.3%)	(0.3%)	(0.5%)	(0.5%)	(0.3%)	(0.4%)
PROF	-0.03	0.32	0.03	-0.02	-0.03	-0.08	-0.08	-0.10	-0.09
	(0.3%)	(0.2%)	(0.3%)	(0.4%)	(0.4%)	(0.7%)	(0.3%)	(0.4%)	(0.5%)
TECH	-0.03	0.05	0.10	0.00	-0.01	-0.04	-0.03	-0.05	-0.03
	(0.5%)	(0.4%)	(0.3%)	(0.3%)	(0.3%)	(0.5%)	(0.4%)	(0.4%)	(0.3%)
Clerks	0.00	-0.08	0.07	0.13	0.03	-0.19	0.06	-0.10	-0.08
	(0.4%)	(0.6%)	(0.5%)	(0.6%)	(0.6%)	(1.2%)	(0.4%)	(0.6%)	(0.8%)
S & S	-0.05	-0.08	-0.03	0.00	0.10	-0.03	0.03	0.05	0.05
	(0.3%)	(0.3%)	(0.3%)	(0.4%)	(0.3%)	(0.6%)	(0.3%)	(0.3%)	(0.4%)
AGRI	-0.15	-0.09	-0.08	-0.06	-0.05	0.53	-0.11	-0.02	-0.02
	(0.9%)	(0.7%)	(0.7%)	(0.6%)	(0.6%)	(0.2%)	(0.9%)	(0.7%)	(0.5%)
TRADE	-0.10	-0.09	-0.04	-0.01	-0.03	-0.01	0.21	0.06	0.03
	(0.9%)	(0.7%)	(0.6%)	(0.6%)	(0.5%)	(0.3%)	(0.7%)	(0.7%)	(0.5%)
P&M	-0.13	-0.11	-0.07	-0.01	-0.02	-0.02	0.06	0.20	0.08
	(0.5%)	(0.3%)	(0.3%)	(0.3%)	(0.3%)	(0.4%)	(0.4%)	(0.3%)	(0.3%)
ELMT	-0.13	-0.11	-0.07	-0.01	-0.02	0.00	0.03	0.15	0.14
	(0.6%)	(0.5%)	(0.4%)	(0.4%)	(0.4%)	(0.4%)	(0.5%)	(0.4%)	(0.3%)
	2013								
AD&M	0.16	-0.04	-0.02	-0.06	-0.03	-0.08	-0.03	-0.07	-0.05
	(0.2%)	(0.3%)	(0.3%)	(0.5%)	(0.4%)	(0.8%)	(0.3%)	(0.4%)	(0.4%)
PROF	-0.03	0.24	0.02	-0.03	-0.05	-0.08	-0.07	-0.14	-0.09
	(0.3%)	(0.2%)	(0.3%)	(0.6%)	(0.5%)	(0.9%)	(0.4%)	(0.5%)	(0.5%)
TECH	-0.02	-0.01	0.07	0.01	-0.01	-0.03	0.00	-0.01	-0.02
	(0.3%)	(0.2%)	(0.2%)	(0.4%)	(0.3%)	(0.6%)	(0.2%)	(0.3%)	(0.3%)
Clerks	-0.01	-0.05	0.00	0.08	-0.02	-0.03	0.04	0.03	0.01
	(0.3%)	(0.3%)	(0.3%)	(0.4%)	(0.3%)	(0.6%)	(0.2%)	(0.3%)	(0.3%)
S & S	-0.08	-0.11	-0.03	0.00	0.12	0.02	0.04	0.06	0.02
	(0.4%)	(0.3%)	(0.2%)	(0.4%)	(0.2%)	(0.5%)	(0.3%)	(0.2%)	(0.2%)
AGRI	-0.17	-0.13	-0.07	-0.03	-0.04	0.40	-0.05	0.03	-0.01
	(1.4%)	(1.2%)	(0.9%)	(0.5%)	(0.7%)	(0.2%)	(1.0%)	(0.6%)	(0.7%)
TRADE	-0.14	-0.11	-0.04	0.00	-0.02	0.00	0.26	0.01	0.02
	(1.6%)	(1.3%)	(1.0%)	(0.5%)	(0.7%)	(0.4%)	(0.7%)	(0.8%)	(0.8%)
P&M	-0.18	-0.15	-0.07	0.01	-0.02	0.00	0.06	0.26	0.06
	(0.9%)	(0.9%)	(0.6%)	(0.3%)	(0.5%)	(0.2%)	(0.6%)	(0.4%)	(0.4%)
ELMT	-0.11	-0.08	-0.05	0.00	-0.02	0.00	0.00	0.08	0.15
	(0.6%)	(0.5%)	(0.4%)	(0.2%)	(0.3%)	(0.3%)	(0.4%)	(0.3%)	(0.2%)

Notes: Results are the occupational assortative matching index for couples in all urban areas combined with same type of occupation in 1986 and 2013. Index is calculated as : $\frac{Actual-Random}{Max\ homogamy-Random}$. Standard errors are in parentheses (standard errors are the standard deviations from 250 replications of randomisation). Abbreviations: AD&M – Legislators, Administrators and Managers; PROF – Professionals; TECH – Technicians and Associate Professionals; CLERKS – Clerks; S&S – Service and Sales Workers; AGRI - Agriculture and Fishery Workers;TRADE – Trades Workers; P&M – Plant and Machine Operators and Assemblers;ELMT – Elementary occupations (incl. Residual)

Table 5.A.23: Assortative matching index of occupational pairings for 1986 and 2013 in non-metropolitan areas

	Index- Non-metropolitan areas								
Female	**Male**								
1986									
	AD&M	PROF	TECH	Clerks	S & S	AGRI	TRADE	P&M	ELMT
AD&M	0.41	-0.06	-0.03	-0.04	-0.03	-0.07	-0.09	-0.08	-0.06
	(0.4%)	(0.6%)	(0.6%)	(0.7%)	(0.7%)	(0.7%)	(0.8%)	(0.8%)	(0.8%)
PROF	-0.04	0.36	0.03	-0.02	-0.04	-0.08	-0.06	-0.09	-0.07
	(0.6%)	(0.5%)	(0.7%)	(0.9%)	(0.9%)	(1.0%)	(0.6%)	(0.6%)	(0.9%)
TECH	-0.06	0.05	0.10	0.01	-0.01	-0.03	-0.02	-0.05	-0.01
	(0.9%)	(0.7%)	(0.6%)	(0.6%)	(0.6%)	(0.6%)	(0.9%)	(0.9%)	(0.5%)
Clerks	-0.01	-0.06	0.07	0.10	0.04	-0.15	0.08	-0.06	-0.07
	(0.8%)	(1.1%)	(1.0%)	(1.1%)	(1.2%)	(1.4%)	(0.6%)	(0.8%)	(1.3%)
S & S	-0.07	-0.11	-0.03	0.01	0.11	-0.04	0.03	0.06	0.07
	(0.7%)	(0.8%)	(0.7%)	(0.9%)	(0.7%)	(0.9%)	(0.5%)	(0.6%)	(0.8%)
AGRI	-0.14	-0.08	-0.07	-0.05	-0.05	0.49	-0.11	-0.01	-0.02
	(1.2%)	(1.0%)	(0.9%)	(0.8%)	(0.8%)	(0.4%)	(1.4%)	(1.1%)	(0.7%)
TRADE	-0.09	-0.08	-0.02	-0.02	-0.03	-0.02	0.23	0.05	0.01
	(1.9%)	(1.5%)	(1.4%)	(1.2%)	(1.3%)	(1.1%)	(1.5%)	(1.7%)	(1.3%)
P&M	-0.12	-0.10	-0.06	-0.01	-0.01	-0.01	0.05	0.20	0.06
	(0.9%)	(0.7%)	(0.6%)	(0.6%)	(0.5%)	(0.6%)	(0.8%)	(0.6%)	(0.5%)
ELMT	-0.09	-0.09	-0.06	0.00	-0.03	0.00	0.00	0.16	0.12
	(1.1%)	(0.8%)	(0.8%)	(0.6%)	(0.7%)	(0.6%)	(1.2%)	(0.9%)	(0.5%)
2013									
AD&M	0.15	-0.05	-0.01	-0.05	-0.02	-0.07	-0.03	-0.06	-0.04
	(0.3%)	(0.6%)	(0.6%)	(1.2%)	(0.8%)	(1.0%)	(0.6%)	(0.6%)	(0.7%)
PROF	-0.04	0.27	0.03	-0.02	-0.01	-0.06	-0.03	-0.10	-0.07
	(0.6%)	(0.5%)	(0.7%)	(1.4%)	(0.8%)	(1.2%)	(0.6%)	(0.7%)	(0.8%)
TECH	-0.02	-0.01	0.05	0.01	-0.01	-0.02	0.01	-0.01	-0.01
	(0.6%)	(0.6%)	(0.5%)	(1.0%)	(0.7%)	(0.8%)	(0.5%)	(0.5%)	(0.6%)
Clerks	0.01	-0.04	0.01	0.07	-0.03	-0.04	0.03	0.01	-0.01
	(0.5%)	(0.6%)	(0.5%)	(0.9%)	(0.7%)	(0.8%)	(0.4%)	(0.5%)	(0.6%)
S & S	-0.06	-0.08	-0.03	0.01	0.11	0.00	0.02	0.05	0.02
	(0.6%)	(0.6%)	(0.5%)	(0.9%)	(0.5%)	(0.7%)	(0.5%)	(0.4%)	(0.6%)
AGRI	-0.14	-0.08	-0.07	-0.02	-0.04	0.41	-0.08	-0.01	-0.01
	(1.9%)	(1.3%)	(1.2%)	(0.6%)	(1.2%)	(0.5%)	(1.6%)	(1.3%)	(1.1%)
TRADE	-0.12	-0.07	-0.04	-0.01	-0.02	-0.01	0.26	0.00	0.03
	(2.7%)	(1.8%)	(1.8%)	(0.9%)	(1.7%)	(1.3%)	(1.6%)	(1.9%)	(1.5%)
P&M	-0.14	-0.10	-0.05	0.00	-0.05	0.01	-0.01	0.27	0.05
	(1.4%)	(1.1%)	(1.0%)	(0.6%)	(0.9%)	(0.6%)	(1.3%)	(0.8%)	(0.8%)
ELMT	-0.10	-0.06	-0.05	0.00	-0.03	0.01	-0.02	0.09	0.15
	(1.0%)	(0.8%)	(0.7%)	(0.5%)	(0.6%)	(0.5%)	(0.8%)	(0.7%)	(0.5%)

Notes: Results are the occupational assortative matching index for couples in Non-metropolitan areas with same type of occupation in 1986 and 2013. Index is calculated as : $\frac{Actual-Random}{Max\ homogamy-Random}$. Standard errors are in parentheses (standard errors are the standard deviations from 250 replications of randomisation). Abbreviations: AD&M – Legislators, Administrators and Managers; PROF – Professionals; TECH – Technicians and Associate Professionals; CLERKS – Clerks; S&S – Service and Sales Workers; AGRI - Agriculture and Fishery Workers;TRADE – Trades Workers; P&M – Plant and Machine Operators and Assemblers;ELMT – Elementary occupations (incl. Residual)

Table 5.A.24: Assortative matching index of occupational pairings for 1986 and 2013 in Metropolitan areas

Female	**Index- Metropolitan areas** **Male**								
	1986								
	AD&M	PROF	TECH	Clerks	S & S	AGRI	TRADE	P&M	ELMT
AD&M	0.36	-0.04	-0.03	-0.04	-0.03	-0.07	-0.08	-0.07	-0.06
	(0.3%)	(0.4%)	(0.4%)	(0.4%)	(0.4%)	(0.8%)	(0.5%)	(0.4%)	(0.4%)
PROF	-0.03	0.31	0.03	-0.02	-0.03	-0.08	-0.08	-0.10	-0.10
	(0.4%)	(0.3%)	(0.4%)	(0.5%)	(0.5%)	(0.9%)	(0.4%)	(0.5%)	(0.6%)
TECH	-0.02	0.05	0.10	0.00	-0.01	-0.04	-0.03	-0.05	-0.04
	(0.5%)	(0.4%)	(0.3%)	(0.4%)	(0.3%)	(0.7%)	(0.5%)	(0.4%)	(0.4%)
Clerks	0.00	-0.09	0.07	0.13	0.03	-0.20	0.06	-0.11	-0.08
	(0.5%)	(0.7%)	(0.6%)	(0.6%)	(0.7%)	(1.8%)	(0.5%)	(0.7%)	(1.0%)
S & S	-0.05	-0.07	-0.02	0.00	0.10	-0.04	0.02	0.04	0.04
	(0.4%)	(0.4%)	(0.4%)	(0.4%)	(0.4%)	(0.8%)	(0.4%)	(0.3%)	(0.4%)
AGRI	-0.16	-0.10	-0.08	-0.07	-0.05	0.57	-0.11	-0.05	-0.03
	(1.4%)	(1.1%)	(1.0%)	(0.9%)	(0.8%)	(0.2%)	(1.4%)	(1.0%)	(0.7%)
TRADE	-0.10	-0.10	-0.04	-0.01	-0.03	-0.01	0.20	0.07	0.03
	(1.1%)	(0.8%)	(0.7%)	(0.6%)	(0.7%)	(0.3%)	(0.8%)	(0.6%)	(0.6%)
P&M	-0.14	-0.11	-0.07	-0.01	-0.02	-0.02	0.07	0.20	0.09
	(0.6%)	(0.4%)	(0.4%)	(0.4%)	(0.4%)	(0.7%)	(0.5%)	(0.3%)	(0.3%)
ELMT	-0.14	-0.11	-0.07	-0.01	-0.02	0.00	0.04	0.15	0.15
	(0.7%)	(0.5%)	(0.5%)	(0.5%)	(0.4%)	(0.5%)	(0.6%)	(0.4%)	(0.3%)
	2013								
AD&M	0.16	-0.04	-0.02	-0.06	-0.04	-0.07	-0.04	-0.08	-0.06
	(0.2%)	(0.3%)	(0.3%)	(0.6%)	(0.4%)	(1.1%)	(0.4%)	(0.5%)	(0.5%)
PROF	-0.03	0.23	0.01	-0.04	-0.07	-0.08	-0.08	-0.15	-0.09
	(0.3%)	(0.3%)	(0.4%)	(0.8%)	(0.5%)	(1.4%)	(0.4%)	(0.6%)	(0.6%)
TECH	-0.03	-0.02	0.07	0.00	-0.01	-0.03	0.00	-0.01	-0.02
	(0.3%)	(0.3%)	(0.3%)	(0.5%)	(0.4%)	(0.8%)	(0.3%)	(0.4%)	(0.4%)
Clerks	-0.02	-0.06	0.00	0.08	-0.01	-0.02	0.04	0.03	0.02
	(0.3%)	(0.3%)	(0.3%)	(0.4%)	(0.4%)	(0.8%)	(0.3%)	(0.4%)	(0.4%)
S & S	-0.08	-0.11	-0.03	0.00	0.13	0.01	0.04	0.05	0.02
	(0.5%)	(0.4%)	(0.3%)	(0.4%)	(0.2%)	(0.7%)	(0.3%)	(0.3%)	(0.3%)
AGRI	-0.17	-0.14	-0.05	-0.03	-0.05	0.39	-0.04	0.03	-0.02
	(2.1%)	(1.6%)	(1.4%)	(0.7%)	(1.0%)	(0.3%)	(1.2%)	(0.9%)	(1.0%)
TRADE	-0.14	-0.13	-0.05	0.00	-0.02	0.00	0.27	0.02	0.02
	(1.7%)	(1.6%)	(1.2%)	(0.7%)	(0.8%)	(0.4%)	(0.8%)	(0.9%)	(0.8%)
P&M	-0.19	-0.16	-0.08	0.01	-0.01	0.00	0.08	0.25	0.06
	(1.1%)	(1.0%)	(0.7%)	(0.4%)	(0.6%)	(0.3%)	(0.7%)	(0.4%)	(0.5%)
ELMT	-0.12	-0.09	-0.05	0.00	-0.01	-0.01	0.01	0.07	0.16
	(0.8%)	(0.6%)	(0.5%)	(0.3%)	(0.3%)	(0.4%)	(0.4%)	(0.3%)	(0.3%)

Notes: Results are the occupational assortative matching index for couples in Metropolitan areas with same type of occupation in 1986 and 2013. Index is calculated as : $\frac{Actual-Random}{Max\ homogamy-Random}$. Standard errors are in parentheses (standard errors are the standard deviations from 250 replications of randomisation). Abbreviations: AD&M – Legislators, Administrators and Managers; PROF – Professionals; TECH – Technicians and Associate Professionals; CLERKS – Clerks; S&S – Service and Sales Workers; AGRI - Agriculture and Fishery Workers;TRADE – Trades Workers; P&M – Plant and Machine Operators and Assemblers;ELMT – Elementary occupations (incl. Residual)

Table 5.A.25: Proportion of total population who are male-female couples working full-time and residing in urban areas.

	1986	1991	1996	2001	2006	2013
Proportion of total population who are couples working full time and residing in urban areas	15%	16%	13%	21%	21%	20%
Total population = 15+, earning positive income excludes those missing mesh block, education, family ID *1996= issue with educational classification meant they assigned the unidentifiable to the nearest qualification group. This unidentifiable group were removed and led to lower numbers in 1996. This matches the approach in Callister and Didham (2010, 2014),						

Chapter Six: Conclusion

The distribution of income widened in the late 1980s and 1990s in New Zealand. Despite having been relatively little change since the early 2000s for some areas and population groups, concerns about the distribution of income continue to be one of the top economic and social issues New Zealanders are concerned about. This thesis examined inequality between and within New Zealand urban areas, taking a sub-national approach: the focus is on patterns and trends in inequality in urban areas. In addition to the very limited evidence on sub-national level inequality in the existing literature, another motive to examine inequality at this level is that the drivers, patterns and trends in inequality at this level may differ from those at the national level and such differences have hitherto not been explored.

The thesis provides descriptive evidence on inequality and also examines the effect of three socio-demographic variables on inequality – age, migration and educational assortative matching. It examines the effect of changes, as well as spatial differences, in these factors on the distribution of income.

The thesis provides a descriptive analysis of personal income inequality between and within New Zealand regions[147] in Chapter 2. Employing administrative regional boundaries, it examines the disparity in income for the population aged 15+ across and within regions. It compares average incomes across regions, tests for convergence between regions and uses multiple measures of inequality to examine the distribution of income within regions. It showed that inequality has increased in New Zealand and there is spatial variation in this trend. Ranking regions by the level of average income reveals persistence at the top and bottom, with Auckland and Wellington leading with the highest levels of income since 1986. The chapter found evidence of convergence in average incomes among regions when Auckland and Wellington are excluded. The patterns in the distribution of income within each region reveal inequality growth from 1981 to 2013 with higher inequality growth in Auckland and Wellington. Both regions

[147] Male income is used in this chapter as a proxy for labour earnings of all full-time workers simply because total income is a function of hours worked and there is much more regional variation in female than male labour force participation and hours worked.

have a rate of inequality growth that is almost double the growth rates in each of the other regions.

Given the evidence of different patterns in inequality across areas, the role of spatial differences in ageing, immigration and assortative matching, and the effect of inter-temporal changes in these factors were considered in the subsequent chapters. The analysis took a simplified spatial view and focused on metropolitan and non-metropolitan areas, as evidence from the descriptive analysis showed a big divide between the large metropolitan areas and elsewhere. Multiple decomposition techniques including the sub-group decomposition approach of Mookherjee and Shorrocks (1982), the density decomposition approach of DiNardo et al. (1996), and the regression-based decomposition approach of Fields and Yoo (2000) are used to examine how ageing and immigration have contributed to the level and change in income inequality through the composition effect and the group-specific distribution effects. For educational assortative matching, a counterfactual randomisation technique is used to examine the role of sorting on education among male-female couples on the distribution of total income of couples.

New Zealand experienced changes in the age structure with additionally spatial variation in the ageing trend. The thesis examined what the effect of these changes and its spatial variation imply for the level and change in income inequality. The analysis was for the population aged 15 and above earning positive income and based on 4 classifications of age (15-24, 25-44, 45-64 and 65+).

The results show most of the cross-sectional inequality is within age groups. Between-age group inequality accounts for around 9-16 percent of overall inequality in all periods between 1986 and 2013. Most evidence from overseas show that ageing (composition effect) increases inequality[148] but the opposite is the case in New Zealand. The inequality-reducing composition effect in New Zealand is interesting because evidence from other countries that have aged typically find an inequality-increasing composition effect. To illustrate why the New Zealand results are different, consider the changes between 1986 and 2013 for the 15-24 and 65+ age groups. There was a reduction in the population share

[148] See Mookherjee and Shorrocks (1982), Cameron (2000), Lin et al. (2015).

of the 15-24 group while the share of the 65+ group increased. Although within-group inequality rose in both groups, the large composition effect from the reduction in the population share ensured that the 15-24 group had an inequality-reducing composition effect. The inequality-reducing contribution from this group was larger than the inequality-increasing composition effect for the 65+.

While inequality increased between 1986 and 2013, most of the changes in inequality over this period were due to changes in the within-age group distribution. Changes in the population composition (ageing of the population) over this period had an inequality-reducing effect.

The results have implications for the future of inequality patterns. All other things being equal, New Zealand is expected to continue to age. This change, coupled with a sustained increase in labour force participation of those in the 65+ group, may imply that the composition effect and within-group distribution of this group will be inequality-increasing going into the future. As the size of the 65+ group increases, the inequality-increasing composition effect of this age group may dominate the inequality-reducing composition effects of the younger age groups. Thus, ageing of the population may increase inequality in the future.

Immigration is an important contributor to population growth in New Zealand, particularly in recent years. The effect of migration status on the distribution of income was examined. The analysis here was limited to the population aged 25 to 64 to capture labour market effects. The total population was classified by place of birth, skill level and length of stay. The results show that between-migrant group differences account for 4-7% of overall cross-sectional inequality[149]. This is smaller than the 9-16% accounted for by between-age group inequality and indicates smaller differences (at least in average income) across migrant groups than age groups.

The study employs both sub-group decomposition and regression decomposition approaches to examine the contributions of various migrant-status groups to changes in the distribution of income between 1986 and 2013. For changes between 1986 and 2013, the results show that high skilled groups (including New Zealand-born and immigrant groups) had inequality-increasing within- and

[149] Using the regression decomposition approach, between migrant group inequality accounts for around 7-9 percent of overall inequality

between-group contributions. These high skilled groups have high relative mean incomes, experienced an increase in population share and within-group inequality. These changes meant these groups made inequality-increasing within- and between-group contributions. Focusing on immigrant groups, High Skilled Earlier migrants and High Skilled Newly Arrived migrants made the highest and second-highest inequality-increasing contributions of all immigrant groups.

The thesis extends the regression decomposition approach to allow the calculation of the contribution of each migrant-group to cross-sectional within-group inequality. Our extension allows us to calculate the within-group contributions to the level of inequality by migrant group. Typically, in the literature, the results from the regression-decomposition approach are not expressed in terms of between- and within-group contributions to the level of inequality, as often the focus is on explaining the contribution of multiple explanatory variables. Chapter 4 reconciles the regression and sub-group decomposition approaches by developing an extension to the regression approach that allows the contribution of factors to inequality to be expressed in terms of within- and between-group inequality. Using migration status as an explanatory variable, it compares the within-group levels contributions from this extension to the within-group levels contributions from the sub-group decomposition of the MLD. The results largely mirror each other although there are slight differences in the signs of the between-group contributions across both methods. This difference can be linked to the way the MLD and the variance treat groups that are above/below the mean[150].

As expected, controlling for age, sex and employment status reduces both the between-group and within-group contributions of each migrant-group. This implies that by accounting for these factors, migrant groups are closer in terms of average incomes and some of the within-group inequality is accounted for by age, sex and employment status.

Apart from examining the role of ageing and immigration on individual incomes, the level of analysis in the thesis shifted from individuals to couples. The process by which people sort into households may affect the distribution of income if people are sorting on income-determining characteristics. The role of educational

[150] Groups with group-mean above (below) the overall mean make negative (positive) between-group contributions in the MLD in contrast to the variance

assortative matching on the distribution of income of male-female couples aged 25 to 64 working full time is examined. The analysis is restricted to the 25 to 64 age group working full-time to capture labour market effects as education is going to influence income through participation in the labour force. The results show that educational assortative matching has increased, driven by increased assortative matching in the middle of the educational distribution. This is contrary to evidence from overseas and public commentary, which imply that assortative matching has increased at the top and bottom of the educational distribution. Spatially, assortative matching is higher and increased over time in metropolitan areas, in contrast to non-metropolitan areas. Instead of using the concentration index – the popular measure of assortative matching in the literature – the thesis shows that results from the concentration index may be misleading as its results may be influenced by group size. A new index of assortative matching is developed that accounts for the limitation of the concentration index.

Assortative matching is linked to the distribution of income using a counterfactual randomisation methodology. The results show that educational assortative matching has an inequality-increasing effect on the distribution of income. Given the higher rates of assortative matching in metropolitan areas, the impact of assortative matching on the distribution of income is higher in these areas compared to non-metropolitan areas. Apart from educational assortative matching, the results show that patterns of sorting on age and location are inequality-increasing, as well as sorting on unobserved characteristics (which have become more important over time).

The results here are particularly important because assortative matching belongs to a class of factors that may lead to or accentuate permanent differences across groups and lead to inter-generational transmission of advantages[151]. The results show that some of the differences in inequality across areas are driven by what is happening in the patterns of matching. This has limiting implications for the potential of policy to address spatial inequality, unless of course the government is somehow given the means to intervene in the partnering market.

[151] See Schwartz (2013) for a review

The thesis makes several important contributions. First, it updates the existing knowledge on sub-national inequality in New Zealand presented in studies by Martin (2000), Smith (2000) and Karagedikli et al. (2000, 2003), which examined income distribution at a sub-national level up to the mid-1990s. The thesis provides an update, especially for the period from the mid-1990s to 2013. In addition, instead of concentrating on regional council levels of analysis, it provides evidence at the urban scale.

Second, it adds to the evidence base on the effect of ageing on the distribution of income. The effect of ageing on the distribution of income is not clear a priori. Empirical evidence on the relationship between changes in the age structure and the distribution of income has been mixed, although most studies find that population ageing increases income inequality. This thesis provides evidence from the New Zealand context, a country that has experienced rapid rates of ageing[152], and finds that changes in the age composition of the population are inequality-reducing, although the widening of the age-specific distributions of income ensured inequality increased. The analysis in this study could be further extended by examining the impact of the continuing participation of the over 65 in the labour force. There is evidence that a growing proportion of older New Zealanders are continuing to work beyond the age they are entitled to the New Zealand Superannuation (65) with New Zealand having one of the highest labour force participation rates for the 65+ group (Khawaja and Boddington, 2009). The increased participation of the 65+ in the labour force will have an effect on the distribution of income at these older ages as well as an effect on the overall distribution of income.

Third, we examine the distributional implications of immigration. The impact of immigration on the average income of various groups is well researched but, to date, no study had examined the distributional implications of immigration in New Zealand. By classifying migrants by their length of stay and skill level, the results show that changes in the high skilled groups have an inequality-increasing effect on the distribution of income. The thesis has focused on the effect of immigration on the distribution of income in urban areas, it is also important to

[152] Although not as rapid as some other OECD countries because of relatively high Total Fertility Rates (TFR) and immigration.

recognise the role of internal migration especially rural-urban and urban-rural migration. Movement between rural and urban areas may respond to and influence income distributions in both rural and urban areas. The impact of this form of migration on income distribution has not been examined in the thesis and particularly remains an interesting issue for New Zealand due to the high internal mobility rates of people.

Fourth, this study is the first to examine the role educational assortative matching on the distribution of income in New Zealand. Studies like those of Callister and Didham (2010, 2014) have provided descriptive evidence of assortative matching but this has not been formally linked to income distribution. This thesis is the first to provide New Zealand evidence that patterns of assortative matching have an inequality-increasing effect. Assortative matching is a particularly important mechanism that can influence both current and subsequent distribution of income in the next generation (intergenerational transmission).

The results from this study have implications for public policy, especially with respect to policies that are meant to address spatial inequality. Most recent policy discussions focus on how to curb the growth of inequality, especially in metropolitan areas. The results of this study show that changes in the age composition are inequality-reducing, with smaller effects in metropolitan areas due to the less pronounced ageing in these areas. If the patterns of ageing in non-metropolitan areas continue and the age-specific distributions continue to widen, we can expect inequality in non-metropolitan areas to continue to fall and there to be an even wider spatial disparity between non-metropolitan and metropolitan areas.

Of the three socio-demographic factors examined, immigration is the easiest to influence with policy. The results, however, show that high skilled groups make inequality-increasing contributions regardless of whether they are New Zealand-born or immigrants, and medium/low skilled groups make inequality-reducing contributions. On assortative matching and the distribution of income, the results show higher rates of assortative matching in metropolitan areas with inequality-increasing effects in this area. Given that it will be difficult to argue for government intervention in the process of partnering, it is expected that this trend will continue to widen the spatial disparity in inequality.

This thesis is not without its limitations. First, we relied on Census data; New Zealand Census provides a snapshot of the total population at a point in time. While it remains the only dataset in New Zealand that has sufficient broad coverage for spatial analysis at the urban area level, it is still a snapshot at a point in time and easily becomes dated due to the time period between successive censuses. The most recent Census period used in this study was 2013. While there was a new census in 2018, the results were not available at the time of this study. Furthermore, the cross-sectional nature of the census limits its usefulness in following individuals over time. Statistics New Zealand is making progress in linking successive censuses and creating a longitudinal census dataset. When this become fully operational, it will be interesting to use this new dataset to follow the same individuals over time and examine their income mobility.

Another limitation arises from the way censuses capture income data. Income data are captured in bands. This generates two issues: 1) due to the absence of actual incomes, for the measure of inequality, the Mean Log Deviation, an individual is assumed to earn the midpoint of the income band they belong to. This assumption may affect our estimates of inequality by under estimating within-band variation. 2) The top band of incomes in censuses are open-ended. While other studies typically exclude observations in this top band, this thesis assumes a Pareto distribution for this top, open ended band. This treatment of the open-ended band may affect measures of inequality.

Another limitation arises from our methodology. These techniques represent an accounting approach and do not attempt to establish a causal relationship between the socio-demographic factors considered and the distribution of income. This must be kept in mind when interpreting the results. However, these accounting approaches represent an important first step prior to formal causal and general equilibrium modelling of the relationships between these factors and the distribution of income.

Future studies examining inequality in New Zealand will benefit from using a continuous measure of income. Available datasets in New Zealand with continuous measure of income do not have enough coverage for spatial analysis but Statistics New Zealand is making important progress in the integration of various data sources. With the linking of census and administrative datasets, future research will be able to take advantage of broad-based datasets like the Census as well as detailed administrative datasets such as Inland Revenue Department (IRD) tax data. These developments by Statistics New Zealand have exciting implications for future research on inequality in New Zealand.

The thesis examined three socio-economic variables that affect the distribution of income. The period of the study from 1986 to 2013 covers a period of many social, demographic and economic changes in New Zealand, which may have had implications for income inequality. Examples include the deregulation and liberalisation of the late 1980s and early 1990s, the global financial crisis of 2007/2008, and the recovery. Future research should focus on examining the effect of these changes on the distribution of income.

Evidence on intergenerational transmission of inequality continues to be missing in New Zealand. Factors like educational assortative matching will not only affect cross-sectional inequality but can lead to the transmission of inequality across generations. Future research should focus on examining the patterns and determinants of inter-generational transmission of income.

Finally, studies of inequality represent a comparison of individuals along the income dimension. For a comprehensive well-being comparison of individuals, other dimensions such as wealth, health and consumption are important. The growing disparity in wealth is attracting increasing attention internationally (e.g. McCain, 2017). Evidence on the distribution of wealth is particularly lacking in New Zealand.

Despite the inevitable limitations, this thesis has provided an important update on the patterns and trends in inequality at the urban area level and has examined the role of key socio-demographic factors in the changes in the distribution of income over time and across areas.

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Appendix – Census question information

Table A. 6.1: Census income question information in each Census from 1986 to 2013

Year	Definition	Question
1986	The income before tax that a person aged 15 years or over receives in the financial year ending 31 March 1986 from all sources.	14. What will be your income before tax for the year ending 31 March 1986? Include income from all sources • Wages, salary • Social Welfare payments (including National Superannuation) • Family Care, Family Benefit • Interest, dividends, rent, commission • Fringe benefits or income in kind • Business or farming income (less expense) • Accident Compensation weekly payments • Bursary, Scholarship • Superannuation 01 Nil or loss 02 $1000 or less per year (Less than $19 per week) 03 $1,001-$2,5000 per year ($19 and less than $48 per week) 04 $2,501-$5,000 per year ($48 and less than $96 per week) 05 $5,001-$7,5000 per year ($96 and less than $144 per week) 06 $7,501-$10,000 per year ($144 and less than $192 per week) 07 $10,001-$12,500 per year ($192 and less than $240 per week) 08 $12,501-$15,000 per year ($240 and less than $288 per week) 09 $15,001-$17,500 per year ($288 and less than $337 per week) 10 $17,501-$20,000 per year ($337 and less than $385 per week) 11 $20,001-$25,000 per year ($385 and less than $481 per week) 12 $25,001-$30,000 per year ($481 and less than $577 per week) 13 $30,001-$35,000 per year ($577 and less than $673 per week) 14 $35,001-$40,000 per year ($673 and less than $769 per week) 15 $45,001-$50,000 per year ($769 and less than $962 per week) 16 $50,001 and over per year ($962 and over per week)

1991	Total income, including income from income support, before tax that a person aged 15 years or over receives from all sources for the year ending 31 March 1991.	15. What will be your income, including income support, before tax for the year ending 31 March 1991? Include income from all sources - Wages, salary, commission - Business or farming income (less expense) - Income Support - Accident Compensation weekly payments - Interest, dividends, rent - Superannuation, pension payments 12 Nil income or loss 13 $2500 or less per year (Less than $48 per week) 14 $2,501-$5,000 per year ($48 and less than $96 per week) 15 $5,001-$7,5000 per year ($96 and less than $144 per week) 16 $7,501-$10,000 per year ($144 and less than $192 per week) 17 $10,001-$15,000 per year ($192 and less than $288 per week) 18 $15,001-$20,000 per year ($288 and less than $385 per week) 19 $20,001-$25,000 per year ($385 and less than $481 per week) 20 $25,001-$30,000 per year ($481 and less than $577 per week) 21 $30,001-$40,000 per year ($577 and less than $769 per week) 22 $45,001-$50,000 per year ($769 and less than $962 per week) 23 $50,001-$70,000 per year ($962 and less than $1,346 per week) 24 $70,001 and over per year ($1,346 and over per week)
1996	Total income, including income from income support, before tax that a person aged 15 years or over receives from all sources for the year ending 31 March 1996. Included is income from: wages,	36. From ALL the sources of income you ticked in question 35, what will the TOTAL income be, that you yourself got before tax or anything else was taken out of it for the 12 months that will end on 31 March 1996? loss zero income $1 -$5,000 per year $5,001-$10,000 per year $10,001-$15,000 per year $15,001-$20,000 per year $20,001-$25,000 per year $25,001-$30,000 per year $30,001-$40,000 per year $40,001-$50,000 per year

	salary, commissions, bonuses paid by employer, self-employment, or business(es) you own and work in, interest, dividends, rent, other investments, ACC regular payments, New Zealand Superannuation, pensions, annuities, unemployment benefit, sickness benefit, invalids benefit, student allowance, other government benefits (including training allowances), government income support payments, or war pensions. Excluded are capital gains, gambling winnings and inheritances.	$50,001-$70,000 per year $70,001-$100,000 per year $100,001 or more

2001	Total income, including income from income support, before tax that a person aged 15 years or over receives from all sources for the year ending 31 March 2001.	26. From all the sources of income you marked in question 25, what will the total income be, that you yourself got before tax or anything else was taken out of it for the 12 months that will end on 31 March 2001? loss zero income $1 -$5,000 $5,001-$10,000 $10,001-$15,000 $15,001-$20,000 $20,001-$25,000 $25,001-$30,000 $30,001-$40,000 $40,001-$50,000 $50,001-$70,000 $70,001-$100,000 $100,001 or more
2006	Information on total personal income received is collected from individuals in the 2006 Census. It represents the before-tax income for the respondent in the 12 months ending 31 March 2006.	31. From all the sources of income you marked in question 30, what will the total income be: that you yourself got before tax or anything was taken out of it in the 12 months that will end on 31 March 2006 loss zero income $1 -$5,000 $5,001-$10,000 $10,001-$15,000 $15,001-$20,000 $20,001-$25,000 $25,001-$30,000 $30,001-$35,000 $35,001-$40,000 $40,001-$50,000 $50,001-$70,000 $70,001-$100,000 $100,001 or more

2013	Total personal income received is the before-tax income of a person in the 12 months ended 31 March 2013. The information is collected as income bands rather than in actual dollars.	31. From all the sources of income you marked in question 30, what will the total income be: that you yourself got before tax or anything was taken out of it in the 12 months that will end on 31 March 2013 loss zero income $1 -$5,000 $5,001-$10,000 $10,001-$15,000 $15,001-$20,000 $20,001-$25,000 $25,001-$30,000 $30,001-$35,000 $35,001-$40,000 $40,001-$50,000 $50,001-$60,000 $60,001-$70,000 $70,001-$100,000 $100,001-$150,000 $150,001 or more

Table A.6.2: Non-response rate in each census from 1986 to 2013

Census	1981	1986	1991	1996	2001	2006	2013
Non-response rate	8.7%	5.5%	5.3%	9.3%	11.5%	10.2%	9.7%

Note: Statistics New Zealand comparison of income information from the 2013 Census with administrative data from the Integrated Data Infrastructure (IDI) shows concludes that the census under-reports income. For individuals where a valid income band is available in both Census and the IDI data sources, 41 percent (1,020,200) have the same income band in both census and IDI tax data, and 75 percent are within one band. Of the 3,125,100 usually resident individuals aged 15+ in the linked Census-IDI dataset, income information is available for 2,484,300 (80 percent) in both census and IDI.

Appendix – Co-authorship Forms

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Co-Authorship Form

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Please indicate the chapter/section/pages of this thesis that are extracted from a co-authored work and give the title and publication details or details of submission of the co-authored work.

Chapter 2 : Alimi, O., Maré, D.C. & Poot, J. (2016).
Income inequality in New Zealand regions. In: P. Spoonley (Eds.), *Rebooting the regions: Why low or zero growth needn't mean the end of prosperity (*pp. 177-212). Auckland, New Zealand: Massey University Press.

Nature of contribution by PhD candidate	Conceptualising the study, empirical analysis, and writing of first draft
Extent of contribution by PhD candidate (%)	75%

CO-AUTHORS

Name	Nature of Contribution
Dave Maré	Guidance, critical feedback, and help with data (15%)
Jacques Poot	Guidance, critical feedback, and help with first draft (10%)

Certification by Co-Authors

The undersigned hereby certify that:

- the above statement correctly reflects the nature and extent of the PhD candidate's contribution to this work, and the nature of the contribution of each of the co-authors; and

Name	Signature	Date
Dave Maré		25/10/18
Jacques Poot		22/10/2018

July 2015

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Chapter 3 : Alimi, O., Maré, D. C., & Poot, J. (2018).
More pensioners, less income inequality? The impact of changing age composition on inequality in big cities and elsewhere. In U. Blien, K. Kourtit, P. Nijkamp & R. Stough (Eds.), *Modelling aging and migration effects on spatial labor markets*. Springer. doi:10.1007/978-3-319-68563-2

Nature of contribution by PhD candidate	Conceptualising the study, empirical analysis, and writing of first draft
Extent of contribution by PhD candidate (%)	80%

CO-AUTHORS

Name	Nature of Contribution
Dave Maré	Guidance and critical feedback (10%)
Jacques Poot	Guidance and critical feedback (10%)

Certification by Co-Authors

The undersigned hereby certify that:

- the above statement correctly reflects the nature and extent of the PhD candidate's contribution to this work, and the nature of the contribution of each of the co-authors; and

Name	Signature	Date
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Chapter 4: Alimi, O., Maré, D. C., & Poot, J. (2018). *International migration and the distribution of income in New Zealand metropolitan and non-metropolitan areas*. IZA Discussion Paper. Bonn: IZA Institute of Labour Economics

Nature of contribution by PhD candidate	Conceptualising the study, empirical analysis, and writing of first draft
Extent of contribution by PhD candidate (%)	75%

CO-AUTHORS

Name	Nature of Contribution
Dave Maré	Guidance, critical feedback and help with the design of methodology - 15%
Jacques Poot	Guidance and critical feedback - 10%

Certification by Co-Authors

The undersigned hereby certify that:

- the above statement correctly reflects the nature and extent of the PhD candidate's contribution to this work, and the nature of the contribution of each of the co-authors; and

Name	Signature	Date
Dave Maré		25/10/18
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Chapter 5 : Alimi, O., Maré, D. C., & Poot, J. (2018). *Who partners up? Educational Assortative Matching and the Distribution of Income in New Zealand.* (Working Paper: 18-13.) Wellington, New Zealand: Motu Economic and Public Policy Research.

Nature of contribution by PhD candidate	Conceptualising the study, empirical analysis, and writing of first draft
Extent of contribution by PhD candidate (%)	90

CO-AUTHORS

Name	Nature of Contribution
Dave Maré	Guidance and critical feedback (5%)
Jacques Poot	Guidance and critical feedback (5%)

Certification by Co-Authors

The undersigned hereby certify that:

- the above statement correctly reflects the nature and extent of the PhD candidate's contribution to this work, and the nature of the contribution of each of the co-authors; and

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Jacques Poot		22/10/2018
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