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Temporal and regional variation in intergenerational income mobility in New Zealand*

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Abstract

This paper documents variation in intergenerational income mobility (IIM) over time and between different regions of New Zealand. Our sample is a cohort of males born between 1963 and 1982 that reached adulthood over a period spanning the policy reforms of the 1980s. We show that the intergenerational elasticity of income (IGE) measure of IIM is higher for men born later in the sample, suggesting that IIM has decreased over the period of rising income inequality following the reforms. To more closely examine the statistical association between income inequality and IIM, we exploit spatiotemporal variation in IGE estimates and Gini coefficients to show that growing up in regions or periods in which there is higher income inequality is associated with lower IIM. Although these results do not imply causality, they are consistent with an international literature that establishes a statistical association between income inequality and IIM.

Keywords: Intergenerational Income Mobility, Intergenerational Elasticity of Income, Income Inequality.

JEL Classification Codes: J62, D31, D63

*Disclaimer: The results in this paper are not official statistics. They have been created for research purposes from the Integrated Data Infrastructure (IDI), managed by Statistics New Zealand. The opinions, findings, recommendations, and conclusions expressed in this paper are those of the author(s), not Statistics NZ, Ministry of Business, Innovation and Employment. Access to the anonymised data used in this study was provided by Statistics NZ under the security and confidentiality provisions of the Statistics Act 1975. Only people authorised by the Statistics Act 1975 are allowed to see data about a particular person, household, business, or organisation, and the results in this paper have been confidentialised to protect these groups from identification and to keep their data safe. Careful consideration has been given to the privacy, security, and confidentiality issues associated with using administrative and survey data in the IDI. Further details can be found in the Privacy impact assessment for the Integrated Data Infrastructure available from www.stats.govt.nz. We thank the Public Policy Institute for providing Datalab access.

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1 Introduction

Equality of opportunity is the normative proposition that individual effort should play a significant role in determining a person's life outcomes (Chetty et al., 2014; OECD, 2018; Deutscher and Mazumder, 2023a). A natural corollary of the proposition is that socioeconomic status of a person's family or neighborhood during childhood should play an insubstantial role in affecting later-life outcomes. Measures of the extent to which a people's economic status is dependent on that of their parents have consequently received substantial attention from empirical researchers over the past few decades (Corak, 2006; Dahl and DeLeire, 2008; Chetty et al., 2014; Corak et al., 2014; Deutscher and Mazumder, 2020). A low level of dependence is indicative of high levels of intergenerational income mobility (IIM) (or, equivalently, a low level of intergenerational income persistence) since it implies that people's incomes in adulthood are only loosely related to those of their parents.

Increasingly this research has pivoted towards using spatial variation to illuminate the underlying processes and policies that influence IIM. Income inequality, education, residential segregation by race and social capital (in terms of social networks and community involvement) have been identified as determinants of intergenerational income persistence in US and Australian studies (Chetty et al., 2014; Connolly et al., 2019; OECD, 2018; Deutscher and Mazumder, 2020), while cross country studies have also documented a link between intergenerational income persistence and income inequality (Corak, 2013). Although such patterns do not imply causation (Durlauf and Seshadri, 2018), they nonetheless assist our understanding of the potential processes and policies that enhance or undermine IIM, and can be used to guide further research efforts. Recent research has also documented changes in IIM over time, showing that it increased in the immediate post-war era in many European countries (OECD, 2018), and decreased in the US subsequent to the economic reforms of the 1980s (Aaronson and Mazumder, 2008; Hilger, 2015; Davis and Mazumder, 2024).

Although a handful of studies have focused on measuring IIM in New Zealand (Andrews and Leigh, 2009; Gibbons, 2010; Iusitini, 2022; Brown, 2022), as yet there is no research documenting variation in these measures, either between regions or across time. This paper fills this gap by estimating measures of IIM for successive cohorts and across different regions. Temporal variation is particularly interesting in the New Zealand (NZ) context, as the country enacted a set of far-reaching and pervasive structural reforms over a very short time period in the mid-1980s, described as "one of the most notable episodes of liberalization that history has to offer" (Henderson, 1995). Although many studies attribute a subsequent rise in income inequality to the reforms (Martin, 1998; O'Dea, 2000; Podder and Chatterjee, 2002), whether IIM was affected has not yet been examined. Our by-cohort-and-region measures can be used for this purpose.

Our measure of intergenerational income persistence is the widely used intergenerational elasticity of income (IGE), which is based on the correlation between income of children in adulthood and that of their parents (Jantti and Jenkins, 2015; Mitnik and Grusky, 2020; Deutscher and Mazumder, 2023a). It thereby measures the persistence of incomes across successive generations of families. Income is measured at the prime earning age of both generations, typically at or around forty years of age for men. A low IGE value indicates that children's income in adulthood is weakly correlated with that of their parents, and is a sign of high mobility within a society (Deutscher and Mazumder, 2023a). It is one of the more widely used measures of intergenerational mobility. While a handful of studies have constructed a national IGE estimate for the whole of the country (Andrews and Leigh, 2009; Gibbons, 2010; Brown, 2022; Iusitini, 2022), as yet, estimates of regional IGEs, as well as IGEs over successive cohorts, are lacking for New Zealand. Building upon previous empirical research, our analysis provides estimates of the IGE over time and across different regions of the country.

Our empirical work proceeds in several steps. First, we provide an overall national IGE estimate based on our full sample of men born between 1963 and 1982. The IGE estimate is 0.2819 (95% CI: 0.2567, 0.3071) in our preferred empirical specification, which is close to a recent estimate of 0.29 provided by OECD (2018) based on Gibbons (2010), but somewhat larger than other recent estimates that rely on smaller sample sizes. Nonetheless, these estimates sit below the OECD average, and characterizes New Zealand as the sixth most mobile nation among 32 OECD countries (OECD, 2018), although cross-country comparisons must be received with caution due to differences in data coverage and measurement methods between countries (Jantti and Jenkins, 2015; OECD, 2018). Our larger sample size also enables us to produce regional estimates of the IGE, which reveal substantial variation in the IIM across different geographic areas of the country. Among the six largest metropolitan areas (Auckland, Hamilton, Tauranga, Wellington, Christchurch, and Dunedin), four exhibit the largest IGE estimates. Dunedin has the largest IGE (estimate: 0.3953, 95% CI: 0.2712, 0.5194), followed by Hamilton City (estimate: 0.3871, 95% CI: 0.2483, 0.5259) and Wellington City (estimate: 0.3824, 95% CI: 0.2876, 0.4772), which covers the CBD and central suburbs of the greater Wellington metropolitan area. The Auckland City Council Territorial Area, encompassing the central isthmus and CBD of the Auckland metropolitan area, also has a comparatively large estimate of 0.3763 (95% CI: 0.2751, 0.4776).

We then consider how IIM may have changed over time. We decompose the sample into cohorts born within successive five-year periods, showing that our preferred IGE estimate has increased from 0.2503 for men born between 1963 and 1967 (95% CI: 0.1761, 0.3245), to 0.2835 for men born between 1978 and 1982 (95% CI: 0.2409, 0.3260. This decline in IIM coincides with a period of rising income inequality that followed the structural policy reforms of the 1980s. However, despite the large sample size, the increase in IGE is not statistically significant in our preferred empirical specification. To investigate the potential relationship between IIM and income inequality in New Zealand, we construct both regional IGE estimates and Gini coefficients for each cohort in our sample, exploiting spatiotemporal variation to identify a statistical association between these measures of IIM and income inequality. Regression results show that growing up in regions or periods of higher income inequality are associated with lower levels of intergenerational mobility later in life, a result that is consistent with patterns observed in the U.S. and other developed countries such as Canada and Australia (Chetty et al., 2014; OECD, 2018; Connolly et al., 2019; Deutscher and Mazumder, 2020). Point estimates from our preferred empirical specification indicate that a 0.1 increase in the Gini coefficient is associated with a statistically significant 0.0910 increase in the IGE coefficient. However, the explanatory power of the Gini coefficient is low, accounting for less that ten percent of the variation in IGE.

This paper makes several contributions to the extant literature. First, it updates and provides an estimate of the national IGE for New Zealand using a sample that is substantially larger than those used in other studies. Second, and as a consequence of this larger sample, we are able to provide estimates of the IGE for different regions and different time periods. The latter enables us to show

how the national IGE has increased over time – specifically, over a period of structural reforms that precipitated an increase in income inequality. Third, by constructing regional Gini coefficients over successive birth-year cohorts, we are able to document a positive statistical correlation between income inequality and intergenerational income persistence in New Zealand. While our results do not imply causation, the association between the two measures is nonetheless of interest. We hope that our work motivates further investigations into the causes and consequences of the apparent decline in IIM in New Zealand.

The remaining sections are organized as follows. The second section provides a description of the IGE concept and describes our approach to ameliorating its associated measurement pathologies. Section three describes the history of New Zealand's economic reforms. Section four provides a summary of the data employed. Section five presents empirical strategies and results. Section six concludes with a discussion of the results.

2 Intergenerational elasticity of income

The intergenerational elasticity of income (IGE) is a commonly used measure of IIM that is based on the strength of statistical association between an individual's income and that of their parent(s) (Gouskova et al., 2010). A high IGE indicates a strong association between people's incomes and those of their parents, which corresponds to greater intergenerational income persistence, or, equivalently, less intergenerational income mobility (Jantti and Jenkins, 2015).

The conventional IGE estimate is obtained from fitting a linear regression model to a sample of individual-level incomes. We use father-son pairs, as men's earnings have been used most frequently in the literature (Mitnik and Grusky, 2020):

$$ln\left(y_i^S\right) = \alpha_0 + \beta ln(y_i^F) + \varepsilon_i \tag{2.1}$$

where i indexes father-son pairs, y_i^S is the son's (adult) income, and y_i^F is the father's income. The parameter β reflects the association in income between the father and son.

The remainder of this section describes the common pathologies that can bias IGE estimates, and approaches used to eliminate or mitigate such biases.

2.1 Common pathologies when measuring IGE

In this subsection we outline common pathologies of IGE measurement and "best practice" solutions identified by the extant literature.

2.1.1 Measurement error and attenuation bias

Data constraints make it difficult to obtain accurate measures of individual incomes. Measurement error in the father's income generates attenuation bias in the OLS estimate of the IGE, thereby potentially leading us to erroneously conclude that mobility is higher than it actually is (Solon, 2017).

Measurement error can be reduced by averaging reported income over several periods (Solon, 1992; Zimmerman, 1992). Empirically, averaging leads to economically significant increases in the estimated IGE (Mazumder, 2015), which accords with a reduction in measurement error in the explanatory variable. Averaging over a wide time interval can mitigate attenuation bias when there is serial dependence in measurement error (Mazumder, 2005). Gregg et al. (2017) show that attenuation bias can be substantially reduced when parental income values are averaged across less-serially dependent (i.e., temporally distant) years.

Random measurement error in the dependent variable (son's income) does not generate bias. It does, however, inflate the the standard errors of the IGE estimates, and thus it is advisable to take multi-year averages to gain more precise estimates. However, Nybom and Stuhler (2016b) present evidence that changes to the son's averaging window can generate systematic biases in the IGE estimate, which could be explained by non-random measurement error in the son's income that is correlated with the explanatory variable. Averaging the son's income can thus help mitigate this bias.

To reduce attenuation bias in our study, a minimum of two census years is used to measure the father's income. Censuses in NZ are typically five years apart. Where possible, we will also take multi-year averages for measuring the son's income, following the recommendation by Nybom and Stuhler (2016b).

2.1.2 Life-cycle bias

Changes in an individual's earnings over their working lifespan can also cause measurement error (Jenkins, 1987). Ideally, the lifetime income of fathers and sons should be used to estimate the IGE. Due to data constraints, in practice researchers have used early career income for sons and later career incomes for fathers (Mazumder, 2015; Nybom and Stuhler, 2016a). Using early career income for sons underestimates their lifetime income and creates a downward bias in IGE estimates (Haider and Solon, 2006). On the other hand, taking income measurements from much later in their career will overstate the IGE measure (Haider and Solon, 2006; Grawe, 2006). See Nybom and Stuhler (2016b) for a detailed econometric analysis of the effects of life-cycle bias on IGE estimates.

Because wage increases diminish over a working lifetime, there exists an age at which a person's annual income best approximates their annuitised lifetime income or 'permanent income'. Although this age varies between individuals, it is typically between early thirties to mid-forties for men. Brenner (2010) finds the optimal age to measure the son's income is somewhere between 30 and 40 for men born between 1939 and 1944 in Germany. In the US, Haider and Solon Haider and Solon (2006) find that it is between the early 30s to mid-40s for men born between 1931 to 1933, while Mazumder (2018) finds the optimal age is 37 for men born between 1952 and 1958. In Canada, Chen et al. (2017) find the optimal age is between the late 30s and early 40s for men born between 1963 and 1966.

We also take steps to reduce life-cycle bias. Following Haider and Solon (2006) and Grawe (2006), we use a specific age range for both fathers and sons. To our knowledge, no research has been carried out to determine the optimal age to measure income in New Zealand. Therefore we will adopt the same approach used by OECD (2018) and use 40 as the optimal age. Following Mazumder

(2015), this means we will conduct a multi-year average of income centred at a mid-point age of approximately 40.

In addition, polynomials of the parent's and the child's age can be included as explanatory variables in the regression to control for age differences between observations in the sample that might otherwise bias estimates due to differences in earnings over the life-cycle (Nilsen et al., 2008). We include a quadratic polynomial in the son's age in our regressions as an additional precaution. However, following guidance provided by Mitnik et al. (2015) and Mitnik and Grusky (2020), we do not include the father's age as a control. Mitnik et al. (2015) point out that "the age at which parents have their children is not exogenous to income, and parental age may affect their children's life chances [...] controlling for parental age is inconsistent with the objective of measuring the gross association between parents' and children's income."

2.1.3 Model misspecification

More recently, mobility researchers have argued that regression models such as (2.1) are misspecified (Mitnik et al., 2015; Mazumder, 2018; Mitnik and Grusky, 2020; Mitnik, 2020). The population regression function (PRF) implied by (2.1) above is

$$E(ln\,Y\,|\,x) = \beta_0 + \beta_1 ln\,x \tag{2.2}$$

This literature argues that the regression function is misspecified because the parameter β_1 is the percent increase in the *geometric mean* of the son's income given a unit percentage increase in the father's income. Mitnik and Grusky Mitnik and Grusky (2020) argue that mobility scholars have incorrectly interpreted the sample estimate $\hat{\beta}_1$ as the arithmetic mean, and have assumed that it is constant across different levels of the father's income.

To address this issue, Mitnik et al. (2015) propose using a Poisson Pseudo Maximum Likelihood (PPML) estimator to estimate the following population regression function:

$$ln\,E(Y|x) = \beta_0 + \beta_1 ln\,x \tag{2.3}$$

such that $\beta_1 = \frac{d\,ln\,E(Y|x)}{d\,ln\,x}$, and thus the estimate now represents the percentage differential in the son's expected income given a marginal increase in the long-run income of the father. Although the conventional Poisson estimator is designed to model count data, the Poisson Pseudo Maximum Likelihood estimator can accommodate continuous variables (Shepherd, 2016).

The PPML estimator has many other desirable properties (Santos Silva and Tenreyro, 2011). Unlike OLS estimates of (2.1), the estimator can accommodate zero income values (Santos Silva and Tenreyro, 2011; Shepherd, 2016; Mitnik and Grusky, 2020; Schreiber, 2022), which are frequently encountered when fitting IGE regressions to individual incomes. Zero incomes are addressed by either omitting those observations from the estimation sample, which can generate sample selection bias since these individuals are more likely to have low incomes (Mitnik and Grusky, 2020) and downward bias in the IGE estimate (Mitnik et al., 2015), or replacing zero incomes with an arbitrarily selected low income figure (e.g. $1 or $1000), which can also bias OLS estimates because the estimator is highly sensitive to outliers (Gibbons, 2010; Chetty et al., 2014; Mazumder, 2015). Adopting PPML circumvents these problems altogether. PPML is also consistent and robust to heteroskedasticity in the error term (Schreiber, 2022).

Due to these benefits, our preferred empirical specifications in this paper are based on the PPML estimator. However, we also report OLS estimates for comparability to the previous empirical work.

3 Institutional background: The 1980s structural reforms

This section briefly describes the structural reforms so that the reader unfamiliar with this period may better understand the changing political and economic environment, and the possible consequences of these reforms on intergenerational mobility. In particular, we focus on education, employment and welfare policies which might have feasibly impacted income inequality and IIM. Our goal is only to provide a summary of the scale and scope of the reforms – we do not attribute any particular empirical finding to any specific reform.

Beginning in 1984, New Zealand experienced significant shifts in political, economic and social policy paradigms (Scott, 1996). The vast majority of these reforms occurred under the centre-left (Labour Party) government (1984-1990), although the following centre-right (National Party) government implemented further welfare and labour reforms. These reforms were enacted in response to a prolonged deterioration in economic conditions and increasing government debt. New Zealand's GNP per capita fell from fifth in the world to twentieth in the 1980s (Evans et al., 1996; Scott, 1996). By 1982, annual inflation was 15% and the fiscal deficit reached 9 percent of GDP (Scott, 1996). New Zealand was facing a currency crisis, and the country's credit rating fell from AAA to AA as international confidence in New Zealand's economy weakened (Scott, 1996).

The structural reforms affected all sectors of the economy, and included the liberalisation of financial markets, welfare and tax policy reform, privatization of state-owned enterprises, and the deregulation of international trade, labour markets, and various industries (Evans et al., 1996). Many of these policies are likely to have impacted inequality and social mobility. The top marginal tax rate was reduced from 66% to 33% (Stephens, 1993) and a regressive goods and services tax (GST) was introduced. Welfare payments were significantly reduced in 1991, when unemployment peaked at 11.2%. Universal payments, such as family benefits were abolished, and child support and housing services for low-income families became more targeted (Vowles et al., 2017). Corporatisation focused state trading departments on achieving profitability, rather than a broad range of ill-defined social goals (Evans et al., 1996), resulting in massive redundancies as these trading departments became state-owned enterprises (Bridgman and Greenaway-McGrevy, 2016). Such structural reforms to promote efficiency led to large reductions in staff numbers in sectors of the economy that the government had previously used to transfer rents to low-skilled workers (Bridgman and Greenaway-McGrevy, 2021). Meanwhile the Employment Contracts Act of 1991 eroded union bargaining power. These labour market changes plausibly reduced wages and impaired job security as much of the workforce transitioned from secure state-provided or union-protected employment to the vicissitudes of a newly liberalised job market. The education sector was also reformed. The Education Act in 1989 abolished free tertiary education and bursaries that covered fees and living costs were replaced with means-tested student allowances (Te Ara, 2022). At the primary and secondary levels, regional boards were abolished (Scott, 1996), and a greater emphasis was placed on parental choice and involvement, competition between schools, and school autonomy. Gordon and Whitty (1997) argue that these reforms enabled "self-perpetuating oligarchies" as schools, now governed by parental boards of trustees, could determine their own enrollment requirements, thereby discouraging diversity. Gordon (2003) argues that deregulating the education system created a disproportionate demand for specific schools, resulting in an exodus of students from the "unpopular", "low-decile", "market-loser" schools which consequently faced reductions in funding as enrollments dropped. Although targeted funding to schools in poorer regions was enacted to reverse this trend, this effort was kept at a minimal level, and a widening gap in learning became more evident between high and low achievers during this period (Gordon, 2003).

These structural reforms precipitated a rapid and permanent impact on income inequality over the 1980s to 1990s. Hyslop and Maré (2001) construct household Gini coefficients using the Household Economic Survey (HES), showing that it increased from 0.347 in 1983-86 to 0.398 in 1995-98. Martin (1998) also constructs household Gini coefficients from census data, showing that it increased from 0.3108 in 1976 to 0.3325 in 1986, reaching 0.4017 by 1996. O'Dea (2000) documents rapid changes in New Zealand's income distribution between 1983-86 and 1995-98 that are consistent with a general increase in inequality. Podder and Chatterjee (2002) show that the shifts in the income distribution over this period were primarily due to changes in the distribution of wages, salary and self-employment, rather than other sources of income. Thus, while the economic reforms are widely believed to have minimised a potentially prolonged recession (Evans et al., 1996; Scott, 1996), they are also widely believed to have generated a large and permanent increase in income inequality. Motivated by the well-documented link between income inequality and IIM in other countries, we will explore whether IIM declined over this period in which income inequality rose.

4 Data description

This section provides descriptions of the datasets and methods used to construct the key variables used.

4.1 Data source and sample

Our data are obtained from the New Zealand Longitudinal Census (NZLC), which is assembled and maintained by Statistics New Zealand (Statistics New Zealand, 2024a,b). Censuses are conducted every five years in New Zealand, and the NZLC links individuals who have answered consecutive censuses over time. Currently, the NZLC covers eight waves of census responses from 1981 to 2018.[1]

Our sample consists of men born between 1963 and 1982 who consequently reached the age of 18 between 1981 and 2000. It therefore spans the period before and after the structural reforms of interest. Specifically, we select men aged 14 to 18 in each of the census years 1981, 1986, 1991 or 1996, shown in Table 4.1.[2] For men born between these years to be included in the sample, we must have an income observation for both them and their fathers. The process for obtaining permanent income measures for fathers and sons is described below.

[1]The 2011 census was delayed until 2013 due to the 2011 Christchurch earthquakes.
[2]Please refer to Appendix A.1 for a detailed description of the data cleaning process.

Permanent incomes for sons are derived by using the same multi-year average method developed by Mazumder (2015). The average is calculated across a range of annual income observations that is centred at a specific mid-point age. Because the census collects information about individuals every five years, it is infeasible to keep the mid-point of this age range fixed at a single value without substantially limiting the sample size.[3] We target a mid-point age of forty for both fathers and sons, but allow up to three years either side of forty.[4]

Table 4.1 tells us whether a son born between 1963 and 1982 can be included in our sample, depending on which censuses he answered. It tabulates the age of sons born in each birth year at the time of each census between 1981 and 2018. In order to be included in the sample, a son must have answered the censuses corresponding to the boldfaced ages. For example, a man born in 1963 must have answered both the 2001 and 2006 censuses to be included in the sample. His mid-point age between these two censuses was approximately 40.5 years. Individuals with missing income values for these specific census years are not used. Bracketed age ranges represent additional census years that can be used if these values are reported in the NZLC. However, we maintain a symmetric window around the mid-point of 40.5 years of age when calculating the average. For example, if a man born in 1963 reported an annual income for each census year between 1991 and 2013, but not 2018, then his income in 1996, 2001, 2006 and 2013 are averaged. Note that cohorts 1, 2 and 3 have a minimum of two census years to calculate a proxy value for sons' permanent income. As discussed above, we average reported income over at least two census years, which are spaced five years apart, in order to reduce measurement error. However, for cohort 4, only a single year is feasible due to data constraints.

Each of these men are linked to their fathers via census records. To estimate the father's income at the target age of forty, we average his reported income across a minimum of two census years. As discussed above, this is done to mitigate classical measurement error and associated attenuation bias in the IGE estimates. Together with the targeted mid-point age of 40 years (plus or minus 3 years), and the fact that the earliest available census is from 1981, this requirement restricts the earliest birth year for fathers to 1942. Given the latest available census is from 2018, it also means the latest birth year for fathers is 1964.

Table 4.2 tells us whether a father born between the years of 1942 and 1964 is included in the sample. In order to be included in the sample, a father must have answered the censuses corresponding to the ages appearing in bold. Thus, to be included in the sample, a father born in 1951 must have answered the 1986, 1991 and 1996 censuses, at which he would have been 35, 40, and 45 years of age, respectively. His mid-point age over this fifteen year period would be 40. Bracketed age ranges correspond to additional census years that can be used if annual incomes are recorded in the NZLC. However, we maintain a symmetric age range around the reported age mid-point. Thus, if a father born in 1951 also answered the 1981 and 2001 censuses, these income values would also be used in the average.

In order to examine how the IGE has changed over the time span of interest, we decompose the sample into four cohorts spanning five-year intervals of birth-years; men born between 1963-67 are

[3]An exception is the 7 year gap between the 2006 to 2013 censuses due to the Christchurch earthquake in 2011.

[4]Due to data availability restrictions, the mid-point age for the cohort born in 1982 is 36. Robustness checks for removing cohorts born in 1981 and 1982 are provided later in section 5.

"cohort 1", 1968-72 are "cohort 2", 1973-77 are "cohort 3" and 1978-1982 are "cohort 4". Cohort 1 were therefore between 14 and 18 years of age in 1981, three years before the reforms began in 1984. We can therefore plausibly conclude that these individuals completed their secondary education prior to the reform period. Cohort two are fourteen to eighteen in 1986, when many of the market liberalisation reforms have been implemented, and tax and state owned enterprise reform was just beginning. We group cohorts 1 and 2 together as "pre-reform" group. Cohort four, born between 1978 and 1982, spends the majority of their education and family upbringing in the post-reform era. We group cohorts 3 and 4 together as a "post-reform" group.

4.1.1 Income measure

Although the census includes information on incomes, direct measures of income are not collected.[5] Incomes are instead categorised by respondents into 12 to 13 bands (or ranges), including a band for zero income, and another band for a loss. We assign the respondent the median income of their reported income band,[6] except for respondents recording a loss, which we re-code to zero income. For cohorts 3 and 4, sons' income measurements come exclusively from the 2018 census, and therefore these cohorts include individuals with a zero income measure. In contrast, because their income measure is averaged across multiple census years, there are no cases of zero-income sons in cohorts 1 and 2. Incomes are deflated to March 2022 equivalent dollars using the CPI, following standard convention (Deutscher and Mazumder, 2020).

Table 4.3 presents descriptive statistics of our sample of father-son pairs[7]. We have 14,412 father-son observations in total. The average income of sons is $74,293 (in 2022-equivalent $) and $65,688 for fathers.

[5]The census collects information on individuals' "total personal income", measured as gross (before tax) annual income received from all sources for the 12 months ended March 31 of the census year.

[6]Statistics New Zealand report median incomes by band for each census in our sample except for the 1981 census. We instead use the mid-point of the bands for 1981.

[7]Siblings were given a unique identifiers to allow for clustering of standard errors within families when running regression models in section 5. Please note that the sibling count in the sample does not equal the sum of siblings within cohorts since sibling can span different cohorts.

Table 4.1: Age of sons in census years

Cohort	Birth year	Census Year								Mid-point age
		1981	1986	1991	1996	2001	2006	2013	2018	
1	1963	18	23	⟦28	33	**38**	**43**	50	55⟧	40.5
	1964	17	22	⟦27	32	**37**	**42**	49	54⟧	39.5
	1965	16	21	⟦26	31	**36**	**41**	48	53⟧	38.5
	1966	15	20	⟦25	30	**35**	**40**	47	52⟧	37.5
	1967	14	19	24	⟦29	**34**	**39**	**46**	51⟧	40
2	1968	13	18	23	⟦28	**33**	**38**	**45**	50⟧	39
	1969	12	17	22	27	⟦32	**37**	**44**	49⟧	40.5
	1970	11	16	21	26	⟦31	**36**	**43**	48⟧	39.5
	1971	10	15	20	25	⟦30	**35**	**42**	47⟧	38.5
	1972	9	14	19	24	⟦29	**34**	**41**	46⟧	37.5
3	1973	8	13	18	23	28	**33**	**40**	**45**	39
	1974	7	12	17	22	27	**32**	**39**	**44**	38
	1975	6	11	16	21	26	**31**	**38**	**43**	37
	1976	5	10	15	20	25	30	**37**	**42**	39.5
	1977	4	9	14	19	24	29	**36**	**41**	38.5
4	1978	3	8	13	18	23	28	35	**40**	40
	1979	2	7	12	17	22	27	34	**39**	39
	1980	1	6	11	16	21	26	33	**38**	38
	1981	0	5	10	15	20	25	32	**37**	37
	1982	n/a	4	9	14	19	24	31	**36**	36

Notes: The Table reports the approximate age of men born between 1963 and 1982 at the time of each census between 1981 and 2018. In order to be included in the sample, census respondents must have reported income values in the censuses corresponding to tabulated ages in boldface font. For example, a son born in 1963 must have answered both the 2001 and 2006 censuses to be included in the sample. The reported mid-point age is the middle of this range. Bracketed age ranges represent additional census years that can be used in a symmetric range centred at the mid-point if these values are reported in the NZLC. For example, if a son born in 1963 reported income values for each census between 1991 and 2013, but not 2018, then his income values in 1996, 2001, 2006 and 2013 will be averaged to compute his permanent income.

Table 4.2: Age of fathers in census years

Birth year	Census years								Mid-point
	1981	1986	1991	1996	2001	2006	2013	2018	age
1942	**39**	**44**	49	54	59	64	71	76	41.5
1943	**38**	**43**	48	53	58	63	70	75	40.5
1944	**37**	**42**	47	52	57	62	69	74	39.5
1945	**36**	**41**	**46**	51	56	61	68	73	41
1946	**35**	**40**	**45**	50	55	60	67	72	40
1947	**34**	**39**	**44**	49	54	59	66	71	39
1948	⟦33	**38**	**43**	48⟧	53	58	65	70	40.5
1949	⟦32	**37**	**42**	47⟧	52	57	64	69	39.5
1950	⟦31	**36**	**41**	**46**	51⟧	56	63	68	41
1951	⟦30	**35**	**40**	**45**	50⟧	55	62	67	40
1952	⟦29	**34**	**39**	**44**	49⟧	54	61	66	39
1953	⟦28	33	**38**	**43**	48	53⟧	60	65	40.5
1954	⟦27	32	**37**	**42**	47	52⟧	59	64	39.5
1955	⟦26	31	**36**	**41**	**46**	51	58⟧	63	41
1956	⟦25	30	**35**	**40**	**45**	50	57⟧	62	40
1957	⟦24	29	**34**	**39**	**44**	49	56⟧	61	39
1958	⟦23	28	33	**38**	**43**	48	55	60⟧	40.5
1959	⟦22	27	32	**37**	**42**	47	54	59⟧	39.5
1960	21	⟦26	31	**36**	**41**	**46**	53	58⟧	41
1961	20	⟦25	30	**35**	**40**	**45**	52	57⟧	40
1962	19	⟦24	29	**34**	**39**	**44**	51	56⟧	39
1963	18	23	⟦28	33	**38**	**43**	50	55⟧	40.5
1964	17	22	⟦27	32	**37**	**42**	49	54⟧	39.5

Notes: The Table reports the approximate age of men born between 1942 and 1964 at the time of each census between 1981 and 2018. In order to be included in the sample, census respondents must have reported income values in the censuses corresponding to tabulated ages in boldface font. For example, a father born in 1942 must have answered both the 1981 and 1986 censuses to be included in the sample. The reported mid-point age is the middle of this range. Bracketed age ranges represent additional census years that can be used in a symmetric range centred at the mid-point if these values are reported in the NZLC. For example, if a father born in 1953 reported income values for each census between 1981 and 2001, but not 2006, then his income values in 1986, 1991, 1996 and 2001 will be averaged to compute his permanent income.

Table 4.3: Individual income descriptive statistics

Generation and cohort		Sample size	Income								Siblings count
			mean	st dev	5^{th}%	95^{th}%	min	max	median	\$0 inc	
Sons	All	14, 412	74, 293	43, 726	16, 732	162, 825	0	224, 684	68, 480	119	1, 722
	Cohorts 1 & 2	4, 275	72, 266	36, 380	25, 807	152, 486	1, 494	208, 968	64, 804	–	384
	Cohorts 3 & 4	10, 140	75, 125	46, 452	13, 200	179, 242	0	224, 684	68, 537	119	981
	Cohort 1	1, 080	69, 691	34, 633	25, 734	149, 211	1, 494	205, 040	62, 536	–	63
	Cohort 2	3, 195	73, 137	36, 916	25, 807	155, 392	2, 605	208, 968	65, 696	–	192
	Cohort 3	4, 416	75, 160	42, 651	18, 165	174, 860	0	223, 842	66, 496	6	246
	Cohort 4	5, 724	75, 099	49, 188	13, 200	224, 684	0	224, 684	68, 537	113	327
Fathers	All	13, 524	65, 688	28, 862	30, 100	121, 155	757	246, 203	60, 104	–	–
	Cohorts 1 & 2	3, 981	66, 265	29, 080	31, 712	119, 076	4, 841	246, 203	60, 258	–	–
	Cohorts 3 & 4	9, 543	65, 448	28, 769	29, 632	122, 042	757	246, 203	59, 816	–	–
	Cohort 1	1, 002	65, 830	29, 529	30, 428	118, 963	9, 811	246, 203	59, 642	–	–
	Cohort 2	2, 979	66, 411	28, 932	31, 762	119, 076	4, 841	246, 203	60, 377	–	–
	Cohort 3	4, 113	65, 604	28, 156	30, 522	119, 076	996	246, 203	60, 017	–	–
	Cohort 4	5, 427	65, 366	29, 228	28, 732	124, 506	757	246, 203	59, 665	–	–

Notes: Random rounding to the base 3 (RR3) has been applied to all count values per Statistics New Zealand's requirement to release the data. Thus the mean values are recalculated using the rounded value. \$0 inc represents number of individuals reporting \$0 income. Siblings count represents the number of sons from the same family for the corresponding cohort.

4.1.2 Data limitations

Although the NZLC is currently the best available dataset for studies that require (i) repeated observations of census data on individuals over time, and (ii) linking across different generations, it does have several drawbacks. There is no unique identifiers across different censuses. Therefore, the linking process is dependent on responses to some of the key questions from the census (Didham et al., 2014). For example, sex, birth date, ethnicity, and usual residence information are some of the key determining variables that allow the identification of the same individuals across censuses . Didham et al. (2014) note that the linkage rate depends on the accuracy of the responses given by respondents. For example, the census includes a question confirming whether the respondent is currently located in the same residential address as five years ago (in the previous census). If the response does not match his/her residential history, then this individual would not be linked.

Another concern in using the NZLC data is that individuals who have skipped answering one of the censuses would be excluded in the linked population sample (Didham et al., 2014). The linking process in the NZLC is based on tracking individuals using their response in the latest census and working backwards to find their responses to previous censuses. If a person answered all of the earlier censuses except for one, then the linking process would stop at the point of the missing census, and their responses to earlier censuses would not be linked. This restriction means that the linked population sample includes an over-representation of those who are less likely to migrate or travel overseas. The linking rate between consecutive censuses is, on average, approximately around 70%–75%. There are variations in the linkage rate among different ethnic groups; Māori and Pasifika have a lower linkage rate of around 60%, whereas Asian ethnic groups have a higher linking rate of 65% (Didham et al., 2014).

The IGE could be biased if there are systematic differences between the over- and under-represented groups. One of the empirical approaches that can be used to check the degree of bias in the estimate is by using weights that account for systematic over- or under-representation of socioeconomic and ethnic groups in the sample. Singhal (2015) developed a weighting technique based on characteristics of individuals whose linking has been successful to the previous census against those who were not able to be linked.[8] Using a logistic function, Singhal (2015) calculates the probability of being linked conditional on observable characteristics, and constructs sample weights based on these probabilities. These weights can be applied to each of the individuals. If individuals are members of groups that are under-represented, then a higher weight would be applied to their responses to account for non-linkage. We use these weights as a robustness check to examine whether sample selection is biasing our findings. These can be found in Appendix B.3.

4.2 Geographic boundaries

Spatial variation in IIM between different geographic regions is a key focus of our analysis. This subsection describes how we construct geographical regions that are suitable for this purpose. Regions that are too small will suffer from a lack of data to construct accurate estimates of the IGE and other measures.

[8] Those who were not able to be linked, also known as the "residual population", excludes immigrants who moved to New Zealand between the two censuses.

There are five standard geographical units used in New Zealand prior to 2013; Meshblocks (MB), Area Units (AU), Territorial Authorities (TA), Regional Councils (RC), and Aggregated Regional Councils (Grimes et al., 2006). Larger geographic units are comprised of smaller geographic units. Regions that are too large (such as RCs) result in less spatial variation to identify correlations of interest. MBs or AUs are too small to have a sample size sufficiently large to measure concepts with sufficient accuracy.[9] We therefore use TAs as the basis for our work.

We adopt the 74 territorial authorities (TA) used for the 1996 census (Statistics New Zealand, 2024c), amalgamating the less populous, contiguous areas to ensure that there is sufficient observations to estimate an IGE for each resultant region. For example, Far North, Whangārei, and Kaipara are merged; the northern Canterbury regions excluding Christchurch are grouped together; likewise for the southern Canterbury regions. Our groupings are based on District Health Boards (DHB) boundaries, which each have at least one secondary level public hospital (King et al., 2002). Some DHB regions with tertiary service hospitals, like Auckland City, Hamilton City, Wellington City, Christchurch City and Dunedin City, are considered separately. Additionally, regions with insufficient sample size of father-son pairs are grouped together. Henceforth we use "regions" to refer to this modified set. The notes to Figure 5.1 provide a list of the regions and their constituent TAs. We have 22 regions in total.

5 Empirical results

In this section, we present our empirical models and results. We begin by providing a national IGE measure based on the sample of men born between 1963 and 1982. Based on this preliminary analysis, we select a preferred empirical strategy for estimating the IGE. We also decompose the sample to document regional variation in the IGE. In the second subsection, we document temporal changes in IIM by estimating an IGE for each of our four cohorts, showing that the IGE measure has generally increased over time. In the third subsection, we investigate whether spatiotemporal variation in the IGE between different regions and cohorts are associated with spatiotemporal variation in the Gini measure of income inequality.

5.1 National IGE

We measure IGE using both OLS and PPML estimators. OLS is based on the following specification:

$$ln\left(y_i^S\right) = \alpha_0 + \beta ln(y_i^F) + \lambda_1 age_S + \lambda_2 age_S^2 + \varepsilon_i \tag{5.1}$$

where y_i^S is the son's income, y_i^F is the father's income, and age_S is the age of the son.[10] The model specification for using the PPML estimator is as above, but uses the level of son's income (not the log) as the dependent variable:

$$y_i^S = \alpha_0 + \beta ln(y_i^F) + \lambda_1 age_S + \lambda_2 age_S^2 + \varepsilon_i \tag{5.2}$$

[9]Meshblocks capture only 30 to 60 dwellings per unit, while Area Units capture approximately 3000 to 5000 people (Grimes et al., 2006).

[10]We use the mid-point age of the son based on their birth year as tabulated in Table 4.1. Estimates of the regression without age controls are provided as a robustness check.

Individuals reporting \$0 income presents a problem for the log-log specification when using the OLS estimator. Therefore, we consider both (i) proxying \$0 income as \$1, and (ii) excluding observations with zero income, when running the OLS specification. For the PPML estimator, no proxy has been used as it can accommodate zeros in the dependent variable.

Table 5.1 presents the estimates of the IGE. The OLS estimator is quite sensitive to how zero incomes are treated, with a substantially higher IGE estimate when \$0 is replaced with \$1. When individuals with \$0 income are removed, both OLS and PPML estimates are similar, differing by approximately 0.01. The confidence intervals are also narrower relative to the OLS estimator with \$1 proxied income. PPML estimates are similar regardless of whether \$0 incomes are included or excluded. Including controls has a negligible effect on the IGE estimate.

Our preferred empirical method is based on PPML, includes age controls, and includes zero income observations. This yields a national IGE estimate of 0.28 (2 d.p.).

We conduct a battery of additional robustness checks on our estimates, including the use of weights to address possible selection bias due to linkage issues in the NZLC data, and to test the sensitivity of the estimate using a different timespan of men born between 1965 and 1980. These results are presented in Appendix B.1. The estimates are robust to these alternative specifications, lying within the 95% CI of the estimates presented here.

Our estimate is higher than some of the previous estimates for New Zealand that lie between 0.22 and 0.25 (Andrews and Leigh, 2009; Gibbons, 2010; Iusitini, 2022). Andrews and Leigh (2009) analyse data from an international survey of sixteen countries including New Zealand and obtain an IGE estimate of approximately 0.25 based on a relatively small sample of sons aged 25 to 54 in 1999 ($n < 300$). Similarly, using the Dunedin Longitudinal Study, Gibbons (2010) obtains an estimate of 0.29 based on males born between 1972 and 73 (n=393).[11] More recently, Iusitini (2022) uses the 1981-2013 New Zealand Longitudinal Census (NZLC) to obtain IGE estimates between 0.22 and 0.25 for a sample of males born between 1967 to 1979 (n = 4617).[12][13]

Why is our estimate higher than that of Andrews and Leigh (2009) and Iusitini (2022)? These differences could be due to several differences in methodology. First, our study has a much larger sample size (n = 14,412) compared to the previous three studies in New Zealand, which have a sample size between approximately 300 to 4,617. Our sample also spans a longer time span of birth years. Finally, our empirical strategy addresses possible sources of measurement error, namely

[11] Gibbons obtains a smaller estimate of 0.253 when the sample is restricted to sons still living in New Zealand when their adult incomes were measured (n = 289).

[12] Iusitini (2022) obtains an estimate of 0.25 when zero incomes are replaced with \$0.01. The 0.22 estimate is obtained \$0 incomes are removed from the sample or when the PPML estimator is used.

[13] Brown (2022) estimates rank-rank measures of IIM based on a sample of 93,900 children born between 1985/6 to 1987/8. This is a vastly larger sample than ours or that of Andrews and Leigh (2009), Gibbons (2010) or Iusitini (2022). Brown (2022) matches biological parents to children through Department of Internal Affairs birth records, and uses Inland Revenue Department data to measure incomes, which are only available from 2000 onwards. Unfortunately we cannot adopt the same sampling method as Brown (2022) without introducing some of the potential sources of bias discussed in section 2.1. As discussed above, we measure income of fathers and sons centred at age 40 to minimise life-cycle bias and to ensure there is no mismatch in the age at which fathers' and sons' incomes are measured. We also use longitudinal census data and match fathers to sons to more accurately measure the actual financial resources available to a child throughout their upbringing, which is best represented by the income of the parent(s) with whom the child resides (Mazumder, 2005; Gregg et al., 2017), and we focus exclusively on father-son pairs to circumvent measurement issues stemming from secular trends in women's labour force participation and financial empowerment (Chen et al., 2017). We also require personal income from prior to 2000 in order to construct IGE estimates from earlier time periods in New Zealand's history, and the IRD dataset does not have income from the periods of interest.

life-cycle and attenuation bias. As discussed earlier, not accounting for these forms of measurement error result in IGE estimates that are downward-biased.

Our preferred IGE estimate of 0.28 is in the middle of the range of estimates for other OECD countries, and is similar to estimates for Sweden, Germany, Turkey and Greece (see Figure 4.8, OECD, 2018). Interestingly, our IGE estimate is substantially lower than the estimate for Australia, which is New Zealand's nearest neighbour and shares a similar culture, historical development, and political institutions, but has higher GDP per capita.

Table 5.1: IGE estimates for men born between 1963 and 1982

Estimator type	$0 income proxy	Model specification	Estimate	Standard error
OLS	$0 included	incl. age controls	**0.3065** (0.2568, 0.3562)	0.0254
		excl. age controls	**0.3092** (0.2593, 0.3591)	0.0255
	$0 excluded	incl. age controls	**0.2721** (0.2436, 0.3005)	0.0145
		excl. age controls	**0.2719** (0.2434, 0.3004)	0.0145
PPML	$0 included	incl. age controls	**0.2819** (0.2567, 0.3071)	0.0129
		excl. age controls	**0.2813** (0.2561, 0.3065)	0.0129
	$0 excluded	incl. age controls	**0.2787** (0.2537, 0.3036)	0.0127
		excl. age controls	**0.2778** (0.2529, 0.3027)	0.0127

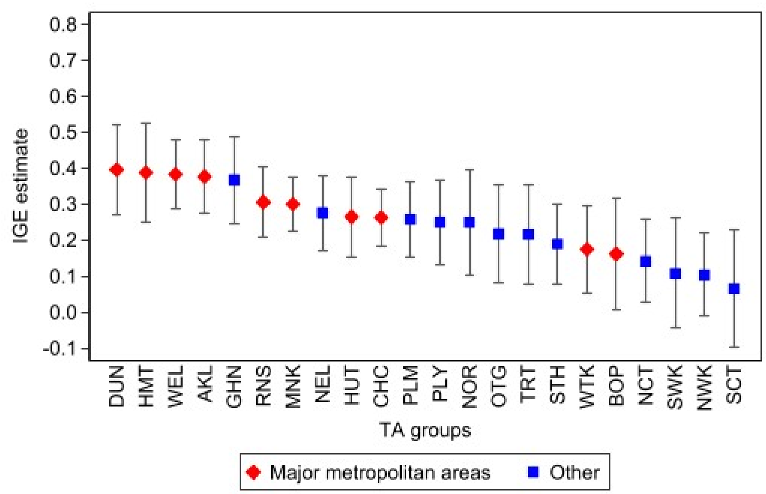
Note: $0 are proxied as $1 when using the OLS estimator. However, this proxy is not used for the PPML estimator since it can accommodate $0 in the dependent variable. 95% confidence intervals are included in the parentheses. Controls are a quadratic polynomial in the son's age. Standard errors are clustered at the family level.

5.2 Regional variation in IGE

Next we investigate regional variation in IGE estimates by decomposing the sample into our 22 regions, based on sons' reported place of residence during ages 14-18. Figure 5.1 displays IGE estimates for each region, ordered from highest to lowest. Reported estimates are based on our preferred empirical method of PPML, including $0 incomes in the sample, and including son age controls. These are also tabulated in Table B.3 in Appendix B.1. Red diamonds represent regions that comprise part of or else contain one of the "major" metropolitan areas of New Zealand: Auckland, Hamilton, Tauranga, Wellington, Christchurch and Dunedin. ("BOP" contains both the Tauranga and Bay of Plenty TAs because the Tauranga TA has a low population count early in the sample period.)

Regional estimates of the IGE range from 0.0652 to 0.3953, indicating that there is substantial variation in IIM between regions in New Zealand. Dunedin (DUN) exhibits the most intergenerational income persistence, while Timaru, Mackenzie, and Waimate (SCT) exhibit the least. Notably, the major metro areas tend to have higher IGE estimates compared to other regions. Lower mobility in metropolitan areas is consistent with results for the US from Chetty et al. (2014). However, it is broadly inconsistent with Canadian results from Corak (2020), who finds that mobility tends to be higher in metropolitan areas, and Australian results from Deutscher and Mazumder (2020), who find that mobility is lower in the outback regions of Australia, which are vast, sparsely populated areas. It is important to note that there is substantial variation in the confidence intervals around the estimates, due to the reduced sample sizes involved.

Figure 5.1: IGE estimates by region for men born between 1963 and 1982



Notes: Regions (Grouped Territorial Authorities): AKL: Auckland City; BOP: Tauranga, Whakatāne, Kaweru, Ōpōtiki, Western Bay; CHC: Christchurch City; DUN: Dunedin; GHN: Gisborne, Wairoa, Hastings, Napier City, Central Hawkes Bay; HMT: Hamilton City; HUT: Upper Hutt, Lower Hutt; MNK: Manukau City, Papakura, Franklin; NCT: Kaikōura, Hurunui, Waimakariri, Banks Peninsula, Selwyn, Ashburton; NEL: Tasman, Nelson City, Malborough, Buller, Grey, Westland; NOR: Far North, Whangārei, Kaipara; NWK: Thames-Coromandel, Hauraki, Waikato, Matamata-Piako; OTG: Waitaki, Central Otago, Clutha; PLM: Manawatū, Palmerston City, Tararua, Horowhenua, Masterton, Carterton, South Wairarapa; PLY: New Plymouth, Stratford, South Taranaki, Wanganui, Rangitīkei; RNS: Rodney; North Shore City; SCT: Timaru, Mackenzie, Waimate; STH: Queenstown-Lakes, Southland, Gore, Invercargill City; SWK: Waipa, Ōtorohanga, South Waikato, Waitomo, Ruapehu; TRT: Taupō, Rotorua; WEL: Kāpiti Coast, Porirua, Wellington City; WTK: Waitākere City.

5.3 Temporal variation in IGE

In this section we document temporal variation in national IGE estimates.

We begin by presenting estimates for each of the four cohorts in Table 5.2. For all estimation methods, there is a general upward trend in the IGE estimates over time, indicating a reduction in IIM. There is a considerable increase between cohort 2 (born between 1968-72) and cohort 3 (born between 1973-77), followed by a slight fall from cohort 3 to cohort 4 (born between 1978-82) (except for the OLS estimate with the $1 proxy for zero income values). Our preferred PPML approach, which includes $0 incomes and son's age controls, yields an estimate of 0.2503 for cohort 1; 0.2571 for cohort 2; 0.3034 for cohort 3; and 0.2835 for cohort 4.[14] The $0 imputation again has a considerable effect on OLS estimates. This is most evident for cohort 4, which has an OLS IGE estimate of 0.3659 when $0 incomes are included, and 0.2764 when they are excluded.

There is substantial sampling variation in the point estimate for each cohort, as illustrated by the wide confidence intervals, which generally overlap. In order to formally test whether there are been a statistically significant change in the IGE coefficient over time, we nest estimation of the IGE coefficient for each cohort within the same regression model and use dummy indicators for each cohort. The point estimates of the IGE coefficients are therefore identical to those obtained from the individual cohort regressions. However, because the coefficients are nested within the same model, we can formally test whether the changes are statistically significant via pair-wise Wald tests of equivalence in coefficients. The regression model is presented in Appendix B.2.

Wald tests reveal that there is a statistically significant difference between the earlier and later cohorts for the OLS estimator with $0 incomes included in the sample. Specifically, there is a statistically significant difference between the estimated IGEs of cohort 1 (1963-67) and cohort 4 (1978-82) and between cohort 2 (1968-72) and cohort 4 at the 5% level (the two-tailed p-values are 0.0386 and 0.0333, respectively). This can occur because the Wald test evaluates differences between the point estimates themselves, while confidence intervals account for the uncertainty around each estimate: The overlap of confidence intervals does not necessarily rule out statistically significant differences in the point estimates. We do not find a statistically significant difference between the estimates based on the preferred PPML estimator.

[14] These trends are robust to changes in cohort classifications. PPML estimates for four different four-year intervals (1965-68, 1969-72, 1973-76 and 1977-80) reveal similar trends. Results available upon request.

Table 5.2: IGE estimates by cohort

Cohort	Estimator	Specification	Estimate	Standard error
1	OLS	-	**0.2279**	0.0388
(born 1963-67)			$(0.1518, 0.3040)$	
	PPML	-	**0.2503**	0.0379
			$(0.1761, 0.3245)$	
2	OLS	-	**0.2388**	0.0248
(born 1968-72)			$(0.1901, 0.2875)$	
	PPML	-	**0.2571**	0.0251
			$(0.2080, 0.3063)$	
3	OLS	\$0 included	**0.2804**	0.0302
(born 1973-77)			$(0.2212, 0.3396)$	
		\$0 excluded	**0.2962**	0.0258
			$(0.2457, 0.3468)$	
	PPML	\$0 included	**0.3034**	0.0215
			$(0.2612, 0.3456)$	
		\$0 excluded	**0.3051**	0.0215
			$(0.2630, 0.3472)$	
4	OLS	\$0 included	**0.3659**	0.0539
(born 1978-82)			$(0.2602, 0.4715)$	
		\$0 excluded	**0.2764**	0.0245
			$(0.2283, 0.3245)$	
	PPML	\$0 included	**0.2835**	0.0217
			$(0.2409, 0.3260)$	
		\$0 excluded	**0.2747**	0.0212
			$(0.2330, 0.3163)$	

Notes: \$0 are proxied as \$1 for the OLS estimator. Son's age controls included in all regressions. 95% confidence intervals in parentheses. Standard errors are clustered at the family level.

Next, we examine cohorts growing up in the pre- and post-reform periods. We define the pre-reform cohort as men born between 1963 and 1972. These boys reached the age of 18 by 1990 or earlier, and thus the majority of their educational and developmental period occurred prior to the structural reforms. The post-reform cohort is men born between 1973 and 1982. These men reached the age of 18 in 1991 or later.

Results are presented in Table 5.3. As described in Section 4.1, only cohorts 3 and 4 include individuals reporting zero income. Therefore, both methods of using a \$1 proxy and excluding those reporting zero income will be presented. We use both the OLS and PPML estimators.

Our preferred measure is PPML (including \$0 incomes), which increases from 0.2568 to 0.2918. But whichever method is selected, point estimates of the IGE are larger for the post-reform cohort, regardless of whether \$0 income values are included or excluded. This suggests that IIM has decreased over a period spanning the structural reforms of the 1980s.

To test whether there is a statistically significant increase in the IGE, we employ the same procedure as described above, nesting the pre- and post- reform group within the same regression specification.

For the OLS estimators, we can reject the null that the IGE coefficients are equal at the five percent level when $0 incomes are included (two-tailed p-value = 0.0222) and at the ten percent level when $0 incomes are excluded (two-tailed p-value = 0.0950). For the latter specification, a one-tailed test of the null of no increase against the alternative of an *increase* can be therefore rejected at the five percent level. As previously for the by-cohort regression, there is no statistical evidence of a significant increase when PPML is used to estimate the IGE.

Table 5.3: IGE estimates for pre- and post-reform periods

Estimator	Pre-Reform (men born 1963-72)		Post-Reform (men born 1973-82)			
			$0 income incl.		$0 income excl.	
	Estimate	Standard error	Estimate	Standard error	Estimate	Standard error
OLS	**0.2370**	0.0212	**0.3296**	0.0341	**0.2850**	0.0184
	(0.1954, 0.2787)		(0.2628, 0.3964)		(0.2489, 0.3210)	
PPML	**0.2568**	0.0214	**0.2918**	0.0157	**0.2875**	0.0155
	(0.2149, 0.2987)		(0.2610, 0.3227)		(0.2571, 0.3179)	

Notes: $0 are proxied as $1 when using the OLS estimator. However, this proxy is not used for the PPML estimator since it can accommodate $0 in the dependent variable. 95% confidence intervals are included in parentheses. Standard errors are clustered at the family level.

5.4 Relationship between IIM and income inequality

In this subsection we examine whether there is a correlation between IIM and income inequality. First, we construct estimates of the Gini coefficient by-cohort-and-region. Then, using by-cohort-and-region IGE estimates, we analyze how much of the spatiotemporal variation in the IGE can be explained by variation in the Gini measure of income inequality.

5.4.1 Gini coefficients

We estimate Gini coefficients for each cohort and region using census data from the 1981, 1986, 1991 and 1996 censuses. This period spans the structural reforms of the 1980s and the well-documented increase in income inequality after the reforms. We construct Gini coefficients based on male incomes as reported in the census in order to ensure that the measures of inequality are less affected by the increase in female labour force participation over the sample period. 1981 is the earliest year available in the longitudinal census data. Refer to the Appendix A.1 for further details on the methodology.[15] As shown in Martin (1998), Gini coefficients based on individual male incomes rose over the reform period, mirroring the rise in the Gini based on household incomes.[16]

Changes in regional income inequality between the 1980s to the mid-1990s using Gini coefficients have been documented in the literature (Martin, 2000; Alimi, O. et al., 2016; Alimi, 2019). This research consistently finds that there was a small decline in regional income inequality between 1981 and 1986, followed by a much larger and sustained rise between 1986 and the mid-1990s.

We create Gini coefficients for our 22 regions.[17] These are reported in Table B.2 in the Appendix.[18] A noteworthy finding is that the majority of regions exhibiting a significant rise in the Gini coefficient between 1981 and 1996 include the six largest metropolitan areas (Auckland, Hamilton, Tauranga, Wellington, Christchurch, and Dunedin). Compared to other regions, Wellington and Auckland exhibited sizeable increases of 0.152 and 0.102, respectively.

5.4.2 Regression results

The results presented in the preceding sections show that that there has been a general increase in estimated IGEs over a period when Gini coefficients were increasing. In this final subsection we investigate whether there is a statistically significant correlation between IGE and the Gini coefficients. To do so, we exploit spatiotemporal variation in the IGE coefficients by estimating a separate IGE for each of the four cohorts and each of the 22 regions ($n = 88$). Then, to explore whether there is a statistical correlation between the IGE and the Gini, we run a simple pooled

[15] Individual income values in the longitudinal census are banded and therefore the highest income bracket for each census year is open-ended which makes it difficult to calculate income inequality at the regional level. To address this, we adopt a mean-constrained integration over brackets (MCIB) approach. The MCIB method performs more accurately than other estimators such as the robust Pareto midpoint estimator (RPME). Like RPME, the MCIB method is based on the assumption that income within the top bracket follows a Pareto distribution, but MCIB produces a more accurate estimate of the Pareto shape parameter as it uses underlying count data rather than the midpoint (Jargowsky and Wheeler, 2018).

[16] Their estimate of the Gini based on male incomes was 0.398 in 1981, 0.373 in 1986, 0.436 in 1991, and reached 0.476 by 1996 (Martin, 1998).

[17] Previous work on regional income inequality in New Zealand is based on 16 regions (Karagedikli et al., 2000; Alimi, 2019). We use a slightly finer geographic resolution in order to provide additional cross-sectional variation in our panel regressions.

[18] Please refer to Appendix A.2 for additional information on how the Gini coefficient has been calculated.

regression of the by-cohort-and-region IGEs on the Gini coefficients:[19]

$$IGE_{j,g} = \alpha + \beta G_{j,g} + \varepsilon_{j,g} \tag{5.3}$$

where $IGE_{j,g}$ denotes the IGE estimate of region j and cohort g, α is the intercept, and $G_{j,g}$ is the Gini of region j and cohort g. We use the Gini obtained from the 1981 census for cohort 1 (men born 1963-67), the 1986 census for cohort 2 (men born 1968-72), 1991 census for cohort 3 (men born 1973-77), and 1996 census for cohort 4 (men born 1978-82). The measure of income inequality is taken when the sons are teenagers, between 14 and 18 years of age, as they are completing their secondary education. As discussed above, we cannot, unfortunately, attain an estimate of the Gini across the entire span of their upbringing, since it is difficult to attain Gini estimates prior to 1981. Importantly, however, the period does span the significant increase in income inequality between 1986 and 1996, thereby offering substantial variation with which to identify any potential correlation between the IGEs and the Ginis.

Table B.3 in the Appendix B.1 presents the individual estimates of the IGEs for each cohort and each region. The samples that are used to estimate the IGE for each cohort and region are notably much smaller than those used to obtain estimates for the different cohorts (at the national level) or the different regions (across all four cohorts), and consequently this estimation error is likely to have a substantial impact of the precision of our estimate of β. However, because the IGEs are the dependent variables in our regression, this form of measurement error will inflate the standard errors of our estimated coefficients, thereby increasing the probability of type II error (i.e. acceptance of the null hypothesis of no relationship between IGE and the Gini). In addition, in one model specification, we weight the regressions by the (square root of the) number of observations used to construct the IGEs, which results in a down-weighting of IGE estimates with large standard errors. This approach is equivalent to correcting for heteroskedasticity due to estimation error via a generalized least squares transformation. In all specifications, standard errors are clustered at the region level to allow for serial dependence and heteroskedasticity.

Table 5.4 below exhibits the results. The coefficient on the Gini coefficient is positive and statistically significant in both the weighted and unweighted specifications, indicating that there is a strong statistical association between the IGE measure of IIM and the Gini measure of income inequality. The estimated coefficient in the weighted regression is 0.910, indicating that a 0.1 increase in the Gini is associated with a 0.0910 increase in the IGE coefficient. There is strong evidence that areas and time periods where there is more income inequality generally have lower levels of IIM. We note, however, that this is a statistical correlation, and does not imply causality. We also note that the explanatory power of the Gini coefficient is low, accounting for less than ten percent of the variation in the IGE. The positive correlation between the Gini coefficient and IGE within New Zealand is consistent with intertemporal and within-country versions of the "Great Gatsby Curve" established in other countries, such as the US (Durlauf and Seshadri, 2018), Canada (Corak, 2020), and Australia (Deutscher and Mazumder, 2023b).

[19]We do not consider specifications that include parameterised heterogeneity, such as cross-sectional or period fixed effects, as these parameters control for unobserved confounders and our goal is not to establish causality, but whether there is a positive statistical correlation between the Gini and the IGE.

Table 5.4: Panel regression of IGE on Gini coefficient

	Weighted		Unweighted	
	Coefficient on Gini	R^2	Coefficient on Gini	R^2
Estimate	**0.910*****	0.098	**0.906*** **	0.064
Clustered standard errors	0.264		0.301	
Pr>|t|	0.002		0.007	

Notes: Results from running a panel regression of IGE on Gini coefficients. "Weighted" indicates the regression has been weighted by the sample size used to construct the IGE coefficient. Standard errors are clustered at the region level. Values are rounded to the nearest 3 d.p. ***p < 0.01; **p < 0.05; *p < 0.1

6 Conclusion

This study contributes to the empirical literature on intergenerational income mobility in New Zealand by providing estimates of the IGE for a sample of men born between 1963 and 1982 using the latest NZLC data (at the time of writing). This cohort reached adulthood over a period that spans rapid and pervasive structural reforms that began in the mid-1980s. While these reforms are widely believed to have precipitated a rapid and permanent rise in income inequality (Martin, 1998; O'Dea, 2000; Podder and Chatterjee, 2002), their effects on mobility have, as yet, remained unexplored. We show that IGE estimates are higher for men born later in the sample, indicating that there has been a reduction in mobility that coincides with the reforms and the rise income inequality. However, the increase is not statistically significant in our preferred empirical specification. Exploiting spatiotemporal variation in the IGE, we show that growing up in areas or periods of higher income inequality is associated with lower mobility, suggesting that the rise in income inequality commonly associated with these reforms coincided with a reduction mobility.

We conclude by noting that our results are based on one measure of mobility that summarises the entire income distribution. More recent work in IIM allows the relationship between the earnings of parents and children to vary between different quantiles of the parents' income distribution (Brown, 2022; Kenedi and Sirugue, 2023; Deutscher and Mazumder, 2020; Alesina et al., 2018). These methods consequently require large datasets to allow greater modelling flexibility. In this paper, we have constructed the largest feasible dataset subject to data availability constraints over the time period of interest while also maintaining "best practice" measurement of outcomes to enable an enhanced geographic and cohort resolution to examine regional and temporal variation in mobility. However, future research could use this dataset to allow the relationship between father's and son's incomes to vary by income quantile. In addition, as time passes and additional data are collected, regional measures of mobility for more recently born cohorts could be estimated based on vastly larger datasets that maintain best practice sampling methods to minimise known pathologies of the IGE.

7 References

Aaronson, D. and Mazumder, B. (2008). Intergenerational economic mobility in the United States, 1940 to 2000. *Journal of Human Resources*, 43(1):139–172.

Alesina, A., Stantcheva, S., and Teso, E. (2018). Intergenerational mobility and preferences for redistribution. *American Economic Review*, 108(2):521–554.

Alimi, O. (2019). *Inequality within and between New Zealand urban areas.* PhD thesis, University of Waikato.

Alimi, O., Maré, D. C., and Poot, J. (2016). Income inequality in New Zealand regions. In Spoonley, P., editor, *Rebooting the regions: Why low or zerogrowth needn't mean the end of prosperity*, pages 177–212. Massey University Press.

Andrews, D. and Leigh, A. (2009). More inequality, less social mobility. *Applied Economics Letters*, 16(15):1489–1492.

Brenner, J. (2010). Life-cycle variations in the association between current and lifetime earnings: Evidence for German natives and guest workers. *Labour Economics*, 17(2):392–406.

Bridgman, B. and Greenaway-McGrevy, R. (2016). The fall (and rise) of labour share in New Zealand. *New Zealand Economic Papers*, 52(2):109–130.

Bridgman, B. and Greenaway-McGrevy, R. (2021). Public enterprise and the rise and fall of labor share. *Economic Inquiry*, 60(1):320–350.

Brown, S. (2022). Intergenerational income mobility in New Zealand. *Policy Quarterly*, 18(3):24–30.

Chen, W.-H., Ostrovsky, Y., and Piraino, P. (2017). Lifecycle variation, errors-in-variables bias and nonlinearities in intergenerational income transmission: New evidence from Canada. *Labour Economics*, 44:1–12.

Chetty, R., Hendren, N., Kline, P., and Saez, E. (2014). Where is the land of opportunity? The geography of intergenerational mobility in the United States. *The Quarterly Journal of Economics*, 129(4):1553–1623.

Connolly, M., Corak, M., and Haeck, C. (2019). Intergenerational mobility between and within canada and the united states. *Journal of Labor Economics*, 37(S2):S595–S641.

Corak, M. (2006). Do poor children become poor adults? Lessons from a cross-country comparison of generational earnings mobility. In *Dynamics of Inequality and Poverty*, pages 143–188. Emerald.

Corak, M. (2013). Income inequality, equality of opportunity, and intergenerational mobility. *Journal of Economic Perspectives*, 27(3):79–102.

Corak, M. (2020). The Canadian geography of intergenerational income mobility. *The Economic Journal*, 130(631):2134–2174.

Corak, M., Lindquist, M. J., and Mazumder, B. (2014). A comparison of upward and downward intergenerational mobility in Canada, Sweden and the United States. *Labour Economics*, 30:185–200.

Dahl, M. and DeLeire, T. (2008). The association between children's earnings and fathers' lifetime earnings: Estimates using administrative data. resreport, Institute for Research on Poverty.

Davis, J. M. and Mazumder, B. (2024). The decline in intergenerational mobility after 1980. *Review of Economics and Statistics*, pages 1–47.

Derby, N. (2003). Derivation of the gini index. Technical report, Department of Biostatistics and Statistics, University of Washington.

Deutscher, N. and Mazumder, B. (2020). Intergenerational mobility across Australia and the stability of regional estimates. *Labour Economics*, 66:101861.

Deutscher, N. and Mazumder, B. (2023a). Measuring intergenerational income mobility: A synthesis of approaches. *Journal of Economic Literature*, 61(3):988–1036.

Deutscher, N. and Mazumder, B. (2023b). Measuring intergenerational income mobility: A synthesis of approaches. *Journal of Economic Literature*, 61(3):988–1036.

Didham, R., Nissen, K., and Dobson, W. (2014). Linking censuses: New Zealand longitudinal census 1981-2006. Technical report.

Durlauf, S. and Seshadri, A. (2018). Understanding the Great Gatsby Curve. *NBER Macroeconomics Annual*, 32(1):333 – 393.

Evans, L., Grimes, A., Wilkinson, B., and Teece, D. (1996). Economic reform in New Zealand 1984-95: The pursuit of efficiency. *Journal of Economic Literature*, 34(4):1856–1902.

Gibbons, M. (2010). Income and occupational intergenerational mobility in New Zealand. techreport WP (10/06), The Treasury.

Gordon, L. (2003). School choice and the social market in New Zealand: Education reform in an era of increasing inequality. *International Studies in Sociology of Education*, 13(1):17–34.

Gordon, L. and Whitty, G. (1997). Giving the 'hidden hand' a helping hand? The rhetoric and reality of neoliberal education reform in England and New Zealand. *Comparative Education*, 33(3):453–467.

Gouskova, E., Chiteji, N., and Stafford, F. (2010). Estimating the intergenerational persistence of lifetime earnings with life course matching: Evidence from the PSID. *Labour Economics*, 17(3):592–597.

Grawe, N. D. (2006). Lifecycle bias in estimates of intergenerational earnings persistence. *Labour Economics*, 13(5):551–570.

Gregg, P., Jonsson, J. O., Macmillan, L., and Mood, C. (2017). The role of education for intergenerational income mobility: A comparison of the United States, Great Britain, and Sweden. *Social Forces*, 96(1):121–152.

Grimes, A., Maré, D. C., and Morten, M. (2006). Defining areas: Linking geographic data in New Zealand. Working Papers 06-07.

Haider, S. and Solon, G. (2006). Life-cycle variation in the association between current and lifetime earnings. *American Economic Review*, 96(4):1308–1320.

Henderson, D. (1995). The revival of economic liberalism: Australia in an international perspective. *The Australian Economic Review*, 28(1):59–85.

Hilger, N. G. (2015). The great escape: Intergenerational mobility in the United States since 1940. NBER Working Papers 21217, National Bureau of Economic Research, Inc.

Hyslop, D. and Maré, D. (2001). Understanding changes in the distribution of household incomes in new zealand between 1983-86 and 1995-98. New Zealand Treasury Working Paper 01/21, Wellington.

Iusitini, L. (2022). *Intergenerational income mobility in New Zealand.* PhD thesis, Auckland University of Technology.

Jantti, M. and Jenkins, S. P. (2015). Income mobility. In Atkinson, A. B. and Bourguignon, F., editors, *Handbook of income distribution*, volume 2 of *Handbook of Income Distribution*, pages 807–935. Elsevier.

Jargowsky, P. A. and Wheeler, C. A. (2018). Estimating income statistics from grouped data: Mean-constrained integration over brackets. *Sociological Methodology*, 48(1):337–374.

Jenkins, S. (1987). Snapshots versus movies: 'Lifecycle biases' and the estimation of intergenerational earnings inheritance. *European Economic Review*, 31(5):1149–1158.

Karagedikli, O., Maré, D. C., and Poot, J. (2000). Disparities and despair: Changes in regional income distributions in New Zealand 1981-96. *Australasian Journal of Regional Studies*, 6(3).

Kenedi, G. and Sirugue, L. (2023). Intergenerational income mobility in France: A comparative and geographic analysis. *Journal of Public Economics*, 226:104974.

King, R., Skelly, C., and Borman, B. (2002). Atlas of New Zealand's District Health Boards. Technical report, Ministry of Health.

Martin, B. (1998). *Incomes of individuals and families in New Zealand, 1951 to 1996.* PhD thesis, University of Waikato.

Martin, B. (2000). Sub-national income differentials, 1986 - 1996. Technical report, University of Waikato.

Mazumder, B. (2005). Fortunate sons: New estimates of intergenerational mobility in the United States using social security earnings data. *The Review of Economics and Statistics*, 87(2):235–255.

Mazumder, B. (2015). Estimating the intergenerational elasticity and rank association in the US: Overcoming the current limitations of tax data. FRB of Chicago Working Paper 2015-04, Federal Reserve Bank of Chicago. Last revised: 4 September 2015, 56 pages. Available at SSRN: https://ssrn.com/abstract=1234567.

Mazumder, B. (2018). Intergenerational mobility in the United States: What we have learned from the PSID. *The ANNALS of the American Academy of Political and Social Science*, 680(1):213–234.

Mitnik, P. A. (2020). Intergenerational income elasticities, instrumental variable estimation, and bracketing strategies. *Sociological Methodology*, 50(1):1–46.

Mitnik, P. A., Bryant, V., Weber, M., and Grusky, D. B. (2015). New estimates of intergenerational economic mobility using administrative data. Technical report.

Mitnik, P. A. and Grusky, D. B. (2020). The intergenerational elasticity of what? The case for redefining the workhorse measure of economic mobility. *Sociological Methodology*, 50(1):47–95.

Nilsen, , Vaage, K., Aakvik, A., and Jacobsen, K. (2008). Estimates of intergenerational elasticities based on lifetime earnings. *SSRN Electronic Journal*.

Nybom, M. and Stuhler, J. (2016a). Biases in standard measures of intergenerational income dependence. *Journal of Human Resources*, 52(3):800–825.

Nybom, M. and Stuhler, J. (2016b). Heterogeneous income profiles and lifecycle bias in intergenerational mobility estimation. *The Journal of Human Resources*, 51(1):239–268.

O'Dea, D. (2000). The changes in New Zealand's income distribution. Treasury Working Paper Series 00/13.

OECD (2018). A broken social elevator? How to promote social mobility. Technical report, OECD Publishing, Paris.

Podder, N. and Chatterjee, S. (2002). Sharing the national cake in post reform New Zealand: Income inequality trends in terms of income sources. *Journal of Public Economics*, 86(1):1–27.

Santos Silva, J. and Tenreyro, S. (2011). Further simulation evidence on the performance of the poisson pseudo-maximum likelihood estimator. *Economics Letters*, 112(2):220–222.

Schreiber, S. (2022). A practical approach to estimating sector-level substitution elasticities with PPML. Economics Working Paper Series 2022-03-A, U.S. International Trade Commission, 500 E Street SW, Washington, DC 20436.

Scott, G. C. (1996). *Government Reform in New Zealand*. International Monetary Fund, USA.

Shepherd, B. (2016). The gravity model of international trade: A user guide. Manual and training material, United Nations, Bangkok. Asia-Pacific Research and Training Network on Trade (ARTNeT), UN ESCAP, United Nations Development Programme (UNDP).

Siegel, J. S. and Swanson, D. A. (2004). *The methods and materials of demography, Second Edition*. Academic Press.

Singhal, R. (2015). Adjusting for linkage bias in the New Zealand longitudinal census. Summer scholarship report, Department of Statistics, University of Auckland, Auckland, New Zealand.

Solon, G. (1992). Intergenerational income mobility in the United States. *The American Economic Review*, 82(3):393–408.

Solon, G. (2017). Intergenerational transmission of income inequality: What do we know? *Focus*, 33(2):3–5.

Statistics New Zealand (2024a). IDI census 2013. https://datainfoplus.stats.govt.nz/Item/nz.govt.stats/571d9fc4-ffb2-4422-b10d-ee5f05eec2ce/28. Accessed: 2024-03-02.

Statistics New Zealand (2024b). Integrated Data Infrastructure. https://www.stats.govt.nz/integrated-data/integrated-data-infrastructure. Accessed: 2024-03-02.

Statistics New Zealand (2024c). Territorial Authority 1995. https://cdm20045.contentdm.oclc.org/digital/collection/p20045coll18/id/427/rec/161.

Stephens, R. (1993). Radical tax reform in New Zealand. *Fiscal Studies*, 14(3):45–63.

Te Ara (2022). Tertiary sector reform from the 1980s. https://teara.govt.nz/en/tertiary-education/page-4.

Vowles, J., Coffe, H., and Curtin, J. (2017). *The fall and rise of inequality in New Zealand*, pages 25–48. ANU Press.

Zimmerman, D. J. (1992). Regression toward mediocrity in economic stature. *The American Economic Review*, 82(3):409–429.

A Methodology

A.1 Data cleaning process

We identify men born between 1942 and 1964 (sample size = 1,356,534). Of these, we identify men with parents' role code in the census with no missing income values for the required mean-centred age (sample = 264,069). From these men we identify those with sons born between 1963 and 1982. We find sons in cohort 1 by using the child_code in 1981, whose birth year is between 1963 and 1967 (inclusive), who have the same family number with the fathers in 1981, who do not have missing TA values for 1981, and who do not have missing later-life income observations. The same process is followed for cohorts 2 through 4, using the 1986, 1991 and 1996 censuses, respectively. This yields $14,412$ father-son pairs.

A.2 Gini coefficients

The standard Gini coefficient is: $G = 1 - \sum_{i=0}^{k-1} (Y_{i+1} + Y_i)(X_{i+1} - X_i)$, where X_i represents the cumulative proportion of incomes and Y_i represents the cumulative proportion of the population with the income level (Derby, 2003; Siegel and Swanson, 2004). To calculate the Gini we use male income data from NZLC for each of the census years 1981, 1986, 1991 and 1996. As these values are in bands with the top band open-ended , we fit a Pareto distribution to the top end of the distribution using a mean-constrained integration over brackets (MCIB) approach (Jargowsky and Wheeler, 2018).

B Additional results

B.1 Additional tables and figures

Table B.1: IGE estimates in the pre- and post-reform periods for different samples

Estimator	Birth years of sons in sample	Pre-Reform Estimate	Pre-Reform s.e.	Post-Reform Estimate ($0 income incl.)	Post-Reform s.e.	Post-Reform Estimate ($0 income excl.)	Post-Reform s.e.
OLS	1963-82	0.2370	0.0212	0.3296	0.0341	0.2850	0.0184
		(0.1954, 0.2787)		(0.2628, 0.3964)		(0.2489, 0.3210)	
	1965-80	0.2324	0.0219	0.2991	0.0363	0.2730	0.0209
		(0.1895, 0.2752)		(0.2279, 0.3702)		(0.2319, 0.3140)	
PPML	1963-82	0.2568	0.0214	0.2918	0.0157	0.2875	0.0155
		(0.2149, 0.2987)		(0.2610, 0.3227)		(0.2571, 0.3179)	
	1965-80	0.2546	0.0221	0.2895	0.0183	0.2870	0.0181
		(0.2114, 0.2979)		(0.2537, 0.3253)		(0.2516, 0.3224)	

Notes: $0 are proxied as $1 for the OLS estimator. 95% confidence intervals are included in parentheses. Son's age controls included in all regressions. Standard errors are clustered at the family level.

Table B.2: Regional Gini coefficients in census years, 1981 to 1996

Region	1981	1986	1991	1996	change: 1996 to 1981
NOR	0.401	0.346	0.408	0.414	0.013
RNS	0.348	0.334	0.426	0.466	0.118
WTK	0.305	0.303	0.382	0.405	0.100
AKL	0.379	0.345	0.446	0.481	0.102
MNK	0.329	0.326	0.417	0.444	0.115
NWK	0.402	0.332	0.389	0.403	0.001
HMT	0.335	0.326	0.405	0.437	0.102
SWK	0.389	0.333	0.409	0.416	0.027
BOP	0.380	0.334	0.423	0.452	0.072
GHN	0.373	0.315	0.381	0.391	0.018
TRT	0.348	0.317	0.394	0.406	0.058
PLY	0.360	0.321	0.393	0.407	0.047
PLM	0.373	0.334	0.397	0.399	0.026
WEL	0.335	0.336	0.445	0.487	0.152
HUT	0.307	0.311	0.405	0.438	0.131
NEL	0.350	0.316	0.371	0.375	0.025
NCT	0.399	0.328	0.367	0.385	−0.014
CHC	0.343	0.325	0.400	0.417	0.074
SCT	0.357	0.318	0.372	0.361	0.004
OTG	0.403	0.325	0.373	0.357	−0.046
DUN	0.350	0.340	0.414	0.424	0.074
STH	0.387	0.313	0.371	0.401	0.014

Notes: Regions (Grouped Territorial Authorities): AKL: Auckland City; BOP: Tauranga, Whakatāne, Kaweru, Ōpōtiki, Western Bay; CHC: Christchurch City; DUN: Dunedin; GHN: Gisborne, Wairoa, Hastings, Napier City, Central Hawkes Bay; HMT: Hamilton City; HUT: Upper Hutt, Lower Hutt; MNK: Manukau City, Papakura, Franklin; NCT: Kaikōura, Hurunui, Waimakariri, Banks Peninsula, Selwyn, Ashburton; NEL: Tasman, Nelson City, Malborough, Buller, Grey, Westland; NOR: Far North, Whangārei, Kaipara; NWK: Thames-Coromandel, Hauraki, Waikato, Matamata-Piako; OTG: Waitaki, Central Otago, Clutha; PLM: Manawatū, Palmerston City, Tararua, Horowhenua, Masterton, Carterton, South Wairarapa; PLY: New Plymouth, Stratford, South Taranaki, Wanganui, Rangitīkei; RNS: Rodney; North Shore City; SCT: Timaru, Mackenzie, Waimate; STH: Queenstown-Lakes, Southland, Gore, Invercargill City; SWK: Waipa, Ōtorohanga, South Waikato, Waitomo, Ruapehu; TRT: Taupō, Rotorua; WEL: Kāpiti Coast, Porirua, Wellington City; WTK: Waitākere City.

Table B.3: Regional IGE estimates

Region	Cohort 1 (born 1963-67)			Cohort 2 (born 1968-72)			Cohort 3 (born 1973-77)			Cohort 4 (born 1978-82)			All (born 1963-82)		
	estimate	s.e.	count	estimate	s.e.	count	estimate	s.e.	count	estimate	s.e.	count	estimate	s.e.	count
NOR	0.5372	0.27	21	0.1248	0.11	87	0.3370	0.11	129	0.2239	0.13	159	0.2488	0.08	396
RNS	0.1823	0.12	60	0.1075	0.15	162	0.2878	0.07	273	0.3917	0.07	378	0.3051	0.05	870
WTK	0.1002	0.23	45	0.3122	0.10	144	0.3022	0.14	189	−0.0126	0.08	225	0.1736	0.06	603
AKL	0.2293	0.15	51	0.3365	0.10	144	0.3545	0.09	207	0.4291	0.08	342	0.3763	0.05	744
MNK	0.1961	0.16	87	0.3245	0.07	267	0.2724	0.06	384	0.3362	0.07	504	0.2994	0.04	1,242
NWK	0.4200	0.16	33	0.0641	0.15	81	0.0661	0.07	123	0.1160	0.11	183	0.1036	0.06	417
HMT	0.3428	0.24	36	0.0633	0.14	87	0.1961	0.10	144	0.6336	0.13	168	0.3871	0.07	435
SWK	0.2545	0.14	33	0.1931	0.17	90	0.2070	0.11	135	−0.0890	0.15	168	0.1077	0.08	423
BOP	−0.0907	0.22	39	0.2576	0.09	120	0.3079	0.12	144	0.0949	0.12	195	0.1612	0.08	495
GHN	0.3347	0.14	57	0.2229	0.09	171	0.2899	0.10	219	0.4355	0.11	264	0.3673	0.06	708
TRT	0.4079	0.12	30	0.1541	0.19	57	0.2551	0.15	102	0.1830	0.10	117	0.2153	0.07	312
PLY	−0.4843	0.12	54	0.1500	0.10	183	0.1521	0.11	258	0.4384	0.09	360	0.2492	0.06	858
PLM	0.2486	0.14	72	0.2158	0.12	192	0.3028	0.09	291	0.2233	0.09	342	0.2571	0.05	897
WEL	0.1942	0.17	57	0.4464	0.12	150	0.3340	0.09	303	0.4152	0.07	381	0.3824	0.05	894
HUT	0.2497	0.16	51	0.2520	0.11	195	0.2826	0.11	231	0.2485	0.09	312	0.2638	0.06	786
NEL	0.2444	0.19	54	0.2684	0.07	171	0.2215	0.12	189	0.3236	0.08	291	0.2758	0.05	705
NCT	0.0640	0.19	33	0.1835	0.11	117	0.1568	0.10	150	0.0729	0.09	195	0.1413	0.06	495
CHC	0.3499	0.13	114	0.2239	0.09	315	0.4008	0.07	405	0.1369	0.07	474	0.2623	0.04	1,311
SCT	−0.0947	0.39	30	0.1238	0.11	93	−0.0238	0.09	96	0.0690	0.17	126	0.0652	0.08	348
OTG	0.3329	0.13	27	0.1995	0.11	96	0.1956	0.17	93	0.2305	0.10	96	0.2172	0.07	309
DUN	0.2754	0.14	42	0.3732	0.11	141	0.4521	0.09	144	0.3896	0.11	201	0.3953	0.06	528
STH	0.3250	0.13	48	0.1402	0.10	135	0.2826	0.09	204	0.0671	0.11	240	0.1884	0.06	630

Notes: Regions (Grouped Territorial Authorities): AKL: Auckland City; BOP: Tauranga, Whakatāne, Kaweru, Ōpōtiki, Western Bay; CHC: Christchurch City; DUN: Dunedin; GHN: Gisborne, Wairoa, Hastings, Napier City, Central Hawkes Bay; HMT: Hamilton City; HUT: Upper Hutt, Lower Hutt; MNK: Manukau City, Papakura, Franklin; NCT: Kaikōura, Hurunui, Waimakariri, Banks Peninsula, Selwyn, Ashburton; NEL: Tasman, Nelson City, Malborough, Buller, Grey, Westland; NOR: Far North, Whangārei, Kaipara; NWK: Thames-Coromandel, Hauraki, Waikato, Matamata-Piako; OTG: Waitaki, Central Otago, Clutha; PLM: Manawatū, Palmerston City, Tararua, Horowhenua, Masterton, Carterton, South Wairarapa; PLY: New Plymouth, Stratford, South Taranaki, Wanganui, Rangitīkei; RNS: Rodney; North Shore City; SCT: Timaru, Mackenzie, Waimate; STH: Queenstown-Lakes, Southland, Gore, Invercargill City; SWK: Waipa, Ōtorohanga, South Waikato, Waitomo, Ruapehu; TRT: Taupō, Rotorua; WEL: Kāpiti Coast, Porirua, Wellington City; WTK: Waitākere City.

B.2 Wald test for differences in cohort IGEs

We nest all cohorts within the same regression and test for statistical significance in the differences in the point estimates of each cohort's IGE coefficient. Suppose that there are G different groups in total (so $G = 4$ for the cohort regressions and $G = 2$ for the pre- and post-reform group regressions). For the OLS estimator, the regression equation is

$$ln\left(y_i^S\right) = \sum\nolimits_{g=1}^{G} \gamma_g D_g + \sum\nolimits_{g=1}^{G} \beta_g ln(y_i^F) D_g + \sum\nolimits_{g=1}^{G} \lambda_g age_S D_g + \sum\nolimits_{g=1}^{G} \kappa_g age_S^2 D_g + \varepsilon_i \quad \text{(B.1)}$$

while for the PPML estimator, we have

$$y_i^S = \sum\nolimits_{g=1}^{G} \gamma_g D_g + \sum\nolimits_{g=1}^{G} \beta_g ln(y_i^F) D_g + \sum\nolimits_{g=1}^{G} \lambda_g age_S D_g + \sum\nolimits_{g=1}^{G} \kappa_g age_S^2 D_g + \varepsilon_i \quad \text{(B.2)}$$

where D_g is a an indicator equal to one if individual i is a member of group $g = 1, ..., G$. Thus β_g is the IGE coefficient of group g. The p-value on the null hypothesis that $\beta_g = \beta_h$ for all $h = 1, 2, 3, 4$ and $h \neq g$ is less than 0.01 for both PPML and OLS, regardless of whether \$0 income are excluded or included.

B.3 IGE estimates using NZLC sample weights

Tables in this subsection present national IGE estimates when sampling weights are used to adjust for linkage bias in the NZLC linked dataset.

Table B.4: National IGE estimate with NZLC sampling weights

Men born 1963–82					Men born 1965–80***				
Estimator type	$0 income proxied	Model specification	Estimate	se	Estimator type	$0 income proxied	Model specification	Estimate	se
OLS	$0 included	incl. age controls	0.3251	0.0284	OLS	$0 included	incl. age controls	0.2923	0.0278
			(0.2694, 0.3807)					(0.2378, 0.3467)	
		excl. age controls	0.3279	0.0285			excl. age controls	0.2917	0.0278
			(0.2720, 0.3837)					(0.2373, 0.3461)	
	$0 excluded	incl. age controls	0.2797	0.0156		$0 excluded	incl. age controls	0.2655	0.0169
			(0.2491, 0.3103)					(0.2324, 0.2987)	
		excl. age controls	0.2794	0.0157			excl. age controls	0.2642	0.0169
			(0.2487, 0.3101)					(0.2312, 0.2973)	
PPML	$0 included	incl. age controls	0.2883	0.0133	PPML	$0 included	incl. age controls	0.2825	0.0148
			(0.2622, 0.3145)					(0.2536, 0.3114)	
		excl. age controls	0.2876	0.0133			excl. age controls	0.2813	0.0148
			(0.2614, 0.3137)					(0.2524, 0.3103)	
	$0 excluded	incl. age controls	0.2841	0.0132		$0 excluded	incl. age controls	0.2801	0.0146
			(0.2583, 0.3099)					(0.2513, 0.3088)	
		excl. age controls	0.2830	0.0132			excl. age controls	0.2788	0.0146
			(0.2572, 0.3089)					(0.2501, 0.3075)	

Notes: $0 are proxied as $1 for the OLS estimator. 95% confidence intervals are included in parentheses. se = standard error. Controls are a quadratic polynomial in the son's age. Standard errors are clustered at the family level.

Table B.5: IGE estimate with NZLC sampling weights for different cohorts

Cohort	Estimator	Specification	Estimate	Standard error
1	OLS	-	0.2344	0.0405
(1963-67)			(0.1550, 0.3139)	
	PPML	-	0.2534	0.0381
			(0.1787, 0.3282)	
2	OLS	-	0.2438	0.0257
(1968-72)			(0.1934, 0.2942)	
	PPML	-	0.2627	0.0254
			(0.2129, 0.3124)	
3	OLS	\$0 income incl	0.2911	0.0322
(1973-77)			(0.2280, 0.3543)	
		\$0 income excl	0.3078	0.0285
			(0.2519, 0.3637)	
	PPML	\$0 income incl	0.3128	0.0220
			(0.2696, 0.3559)	
		\$0 income excl	0.3145	0.0220
			(0.2715, 0.3576)	
4	OLS	\$0 income incl	0.3904	0.0581
(1978-82)			(0.2766, 0.5042)	
		\$0 income excl	0.2805	0.0256
			(0.2303, 0.3308)	
	PPML	\$0 income incl	0.2874	0.0224
			(0.2435, 0.3312)	
		\$0 income excl	0.2767	0.0218
			(0.2339, 0.3195)	

Notes: \$0 are proxied as \$1 for the OLS estimator. Please note that only cohort 3 and 4 include sons with \$0 income values. 95% confidence intervals are included in parentheses. Son's age controls included in all regressions. Standard errors are clustered at the family level.

Table B.6: IGE estimates for pre- and post- reform periods and with NZLC sampling weights

Estimator	Pre-Reform		Post-Reform			
	Estimate	s.e.	\$0 income incl.	s.e.	\$0 income excl.	s.e.
OLS	0.2429	0.0220	0.3494	0.0373	0.2918	0.0197
	(0.1997, 0.2860)		(0.2762, 0.4226)		(0.2532, 0.3303)	
PPML	0.2622	0.0217	0.2977	0.0163	0.2921	0.0160
	(0.2197, 0.3046)		(0.2658, 0.3295)		(0.2608, 0.3235)	

Notes: \$0 are proxied as \$1 for the OLS estimator. 95% confidence intervals are included in parentheses. Son's age controls included in all regressions. Standard errors are clustered at the family level.