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POLICY, DEMOGRAPHY, AND MARKET INCOME VOLATILITY: WHAT SHAPED INCOME DISTRIBUTION AND INEQUALITY IN AUSTRALIA BETWEEN 2002 AND 2016?

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Isolating the impact of policy, demographic shifts, and market volatility on changes in income inequality is of great interest to policymakers. However, such estimation can be difficult due to the complex interactions and evolutions in the social and economic environment. Through an extended decomposition framework, this paper estimates the effect of four main components (policy, demography, market income and other factors) on the year-over-year changes in income inequality in Australia between 2002 and 2016. This was a period marked by substantial policy, population, and economic shifts due to factors such as the mining boom, the global financial crisis and increasing immigration. The framework also incorporates a flexible non-parametric market income model which captures demand-side shock better than a standard parametric model. Our results suggest that market income was the primary driver of income inequality for all segments of the income distribution in Australia over the past 15 years. Policy factors, moreover, have had the largest net impact on reducing inequality overall, especially for lower income earners.

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1. Introduction

Policymakers are often interested in understanding the contribution of policy, demographic shifts, and market income volatility on changes in income distribution, given that social inequality has been shown to have an impact on growth and social cohesion, both in the short and long run (Wilkinson and Pickett, 2009). However, such estimation is often difficult due to the complex interactions and evolutions in the social and economic environment. By extending the decomposition framework suggested by Bourguignon *et al.* (2008), Bargain and Callan (2010), Biewen and Juhasz (2012), Bargain *et al.* (2015) and Sologon *et al.* (2018), we explore the year-on-year changes in the Australian income distribution over 15 years and identify what drives changes in income inequality. These potential

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drivers include not only policy reforms in the tax and transfer system but also fluctuations in market income (wage and non-wage), variations in employment, occupation and industry, and shifts in demography and household composition.

Australia has experienced some significant externally driven shocks, such as the mining boom and the global financial crisis, over the past decade. Demographically, population ageing, together with an increasing number of migrants, adds a complex mixture to the study of the income distribution over time. Throughout the past decade in Australia, growing attention in both public discourse and the academic literature has been paid to income inequality (Johnson and Wilkins, 2004; Atkinson and Leigh, 2007; Wilkins, 2014, 2015) as well as to the role of tax and transfer reforms in mitigating inequality (Creedy and Hérault, 2015; Hérault and Azpitarte, 2015, 2016). Despite this growing interest, however, few empirical papers exist in Australia systemically examining the drivers of income inequality over time.

Earlier studies on Australia's income inequality tend to focus solely on the period before and during the global financial crisis in 2007–09. For instance, Hérault and Azpitarte (2015) examine the trends in the redistributive impact of the tax-benefit system in Australia between 1994 and 2009, while Hérault and Azpitarte (2016) investigate the role of tax-transfer policy reforms on income inequality over the 1999–2008 period and Creedy and Hérault (2015) study the period from 2000 to 2006. Our study adds to the understanding of the primary factors driving changes in income inequality in Australia between 2002 and 2016, covering both the pre- and post-crisis phases. It introduces several methodological refinements, described below, including the use of a non-parametric approach to generate the counterfactual annual income distribution and a more accurate policy effect assessment using annual data.

As suggested by the mixed results from European decomposition studies, the role of tax-transfer policy reforms may change during and after the financial crisis in 2007–09. For example, recent findings in Europe on the decomposition of changes in the income distribution following the global financial crisis illustrate that, across 27 European Union (EU) countries, the key drivers influencing inequality were changes in market income and population characteristics, with an inequality-increasing effect, while tax and transfer policies more often reduced inequality (e.g. Paulus and Tasseva, 2017). Similar findings of the inequality-buffer effects of tax-transfer systems have also been found among OECD countries (Jenkins *et al.*, 2011) and in various European economies (Brewer *et al.*, 2012; Matsaganis and Leventi, 2014; Sologon *et al.*, 2018). However, Bargain *et al.* (2017) found mixed outcomes when investigating the role of tax-benefit policies in income distribution variations in four European countries during and after the Great Recession (2008–13). They observe that during the first stage (2008–10), the policy reaction helped stabilize or reduce inequality and poverty in France, the U.K., and Ireland but pushed up poverty rates in Germany when combined with market income changes. Variations in market income (e.g. job losses or wage cuts) also increased France's income inequality and poverty rate. By the later stage of the crisis (2010–13), poverty lessened in France thanks to subsequent policy reforms but rose in Ireland and varied for different subgroups in the U.K. and Germany due to regressive tax policy and slow increases in social benefits among the poorest groups.

Compared to the decomposition framework used in the earlier literature examining income inequality, this paper represents one of the few attempts to capture year-on-year changes in income inequality, with the two-factor decomposition of United States income inequality by Bargain *et al.* (2015) being the only exception to our knowledge. Most existing studies investigate each factor's contribution to inequality changes between two single points in time: the beginning and the end of the period (Bargain and Callan, 2010; Bargain, 2012a, 2012b; Bargain *et al.*, 2017 for European countries; Creedy and Hérault, 2015, Hérault and Azpitarte, 2015, 2016 for Australia). The findings of these earlier studies, as a result, tend to be sensitive to the years selected and might underestimate or overestimate the performance of each factor for the whole period. Exploring the evolution of each factor's contribution to inequality can mitigate these issues, enabling more appropriate assessment of the role of tax and transfer policies.

In addition, the detailed information on the annual income distribution shift allows us to nest a non-parametric income model, as opposed to the standard wage model used in the previous literature. The volatility of the market income return in our decomposition model is assumed to be driven by external shocks rather than the gradual change in characteristics of the population. Non-parametric models relax the stringent assumptions imposed in a linear wage model and align better with the economic change in the period we study, where significant external demand shocks, such as changes in international demand for mining commodities and the global financial crisis, are observed. The year-on-year decomposition allows us to capture the shifts caused by the external shocks at a refined granularity.

Finally, the existing literature on the decomposition of income distribution often tends not to provide the standard errors of the estimates, which are useful for assessing the robustness of the findings. Two exceptions are Bargain and Callan (2010) and Paulus and Tasseva (2017) who provided standard errors in decompositions with one explicitly modelled component (tax policy). When including components beyond deterministic tax policy simulation in a more complex decomposition, the statistical uncertainties of the simulation parameters need to be considered in the decomposition, especially when the parameters are estimated from a survey. To fully capture the impact of the sampling design, we use the replicate weights available in the Household, Income and Labour Dynamics in Australia (HILDA) dataset and estimate the standard errors of both 1-year and cumulative contributions of each component to income inequality.

To capture a complete picture of the income distribution change, we examine the impact of the policy response on not only the Gini index but also the relative income ratio at different sections of the income distribution (P95/P75, P75/P50, P50/P25, P25/P5). The reason for including this analysis is that the overall Gini index may not adequately reflect the intricate patterns and the policy interactions occurring at the different segments of the income distribution.

The remainder of the paper is structured as follows. Section 2 overviews the policy and economic background in Australia over the period 2002–16. Sections 3 and 4 describe the decomposition method and dataset, respectively. These are followed by a presentation of the results in Section 5 and a robustness test using an alternative indexation assumption in Section 6. The last section concludes.

2. Australian Economic and Policy Background

The demographic, economic, and policy landscape in Australia experienced some major changes in the period we examine in this paper. Demographically, Australia faces an ageing population. Despite the relatively large number of young immigrants, the median age of the population was 37.2 years in 2016, compared with 35.7 years in 2001 (Australian Bureau of Statistics, 2017). Over one in seven people in Australia were aged 65 and over in 2017, with many of these older people receiving the public age pension, which is the single largest item of government social welfare spending. The age pension serves as social assistance in Australia, available to anyone above the age threshold meeting the income and asset test criteria.

The Australian social security system relies heavily on means-tested benefits and less on social insurance schemes (Harding *et al.*, 2009) and is considered as one of the most effective and efficient redistributive tax-transfer systems in the world (Whiteford, 2006). Among the OECD countries, Australia has one of the lowest levels of tax and social expenditures (Whiteford, 2017). Over the last two decades, the welfare system has seen major reforms aimed at reducing welfare dependency and promoting self-reliance through paid work (see Online Appendix A for more details). Australia is often described as a liberal welfare regime with a strong emphasis on welfare provision through market mechanisms (Hérault and Azpitarte, 2015). While income tax experienced multiple changes throughout the period of this study, the largest indirect tax in Australia, the goods and services tax (GST, equivalent to VAT in many other countries) remained unchanged through the period of this study since its introduction in 2000. This fortunately allows us to produce a cleaner estimate of the impact of direct tax and welfare policy changes on the income distribution for the period of the study.

In terms of economic development, Australia enjoyed relatively stable growth over the period being examined in our analysis, except for a dip in growth during the 2007–2009 global financial crisis. The mining industry has played a major role in recent economic growth in Australia, as natural resources are significant sources of the country's export earnings (Sahoo *et al.*, 2014). According to Rahman and Mamun (2016), energy exports explained 31 percent of total commodity exports in Australia in 2013–14, making Australia the world's eighth largest energy producer. The reliance on the global market means that the Australian domestic economy likely fluctuates in line with the variations in exports to its main trade partners.

Figure 1 shows that Australia's economy continued to grow from the early 2000s until before the worst period of the global financial crisis in 2007–2009. It then quickly recovered but had slowed down again by 2014. These trends were likely to have been associated with the China-driven mining boom period and the fluctuations in the Chinese economy. Downes, Hanslow, and Tulip (2014) estimate that the China-driven mining boom had increased real per capita household disposable income for Australians by 13 percent in the decade preceding 2013 and raised real wages by six percent while lowering the unemployment rate by about 1.25 percentage points. However, the boom period ended by 2014, when Chinese economic growth slowed. Associated with a significant decline in mineral prices, this resulted in lowered growth rates in Australia between 2014 and 2016.

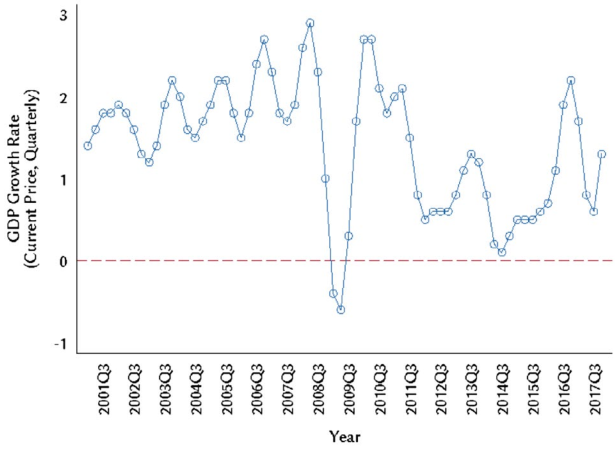

Figure 1. GDP Quarterly Growth Rate in Current Price (Trend) Between 2001 and 2017
Source: Australian Bureau of Statistics Data Catelogue 5206.0–Australian National Accounts: National Income, Expenditure and Product.

The complex landscape across all three of the major dimensions of the socio-economic environment and their interactions means that any point estimates of policy effects must be highly contextual. Therefore, it is essential to capture the complex dynamics of the demographic and economic environment when isolating the contribution of policies on income distribution.

3. Methodology

3.1. *Decomposition Framework*

We adopt a decomposition framework broadly resembling the approaches used by Bourguignon *et al.* (2008), Bargain and Callan (2010), Biewen and Juhasz (2012) and Sologon *et al.* (2018), with an extension of semi-parametric demographic profile adjustments and a non-parametric market income simulation model. In addition, following Bargain *et al.* (2015), we decompose the inequality changes on a year-by-year basis, in contrast to the earlier literature where a selection of two relatively distant time points was used. This allows us to capture better the dynamics of both the different components and the major financial and economic shocks that occurred over the period.

The decomposition separates the contribution of each factor to overall inequality by comparing the income distributions in counterfactuals, where marginal changes in each of the examined components are introduced. The counterfactuals are generated through an approach that combines micro-econometric modelling with microsimulation techniques. This approach extends the ubiquitous Oaxaca-Blinder decomposition by accounting for the entire distribution rather than focusing on the mean value. Although the approach cannot claim to identify causal effects, it provides a basis for understanding the complexities inherent in the interactions between tax-benefit rules, market income distributions and the main drivers (namely labor market structures, income processes and demographic profiles) in determining the changes in the distribution of household disposable income.

We decompose year-over-year changes in the inequality measures (I) into four components:

- Changes in the tax and welfare policies (p)
- Changes in the demographic structure of the population (d)
- Changes in the market income distribution (y)
- Other changes in the data (a), for example, joint distribution between all other variables

Formally, we can describe the difference in the inequality measures between time $t+1$ and time t as.

$$
\begin{aligned}
\Delta I_{t,t+1}(p,d,y,a) &= I\left(p_{t+1},d_{t+1},y_{t+1},a_{t+1}\right) - I\left(p_t,d_t,y_t,a_t\right)\\
&= \underbrace{I\left(p_{t+1},d_{t+1},y_{t+1},a_{t+1}\right) - I\left(p_{t\to t+1},d_{t+1},y_{t+1},a_{t+1}\right)}_{\text{Policy Effect}}\\
&\quad + \underbrace{I\left(p_{t\to t+1},d_{t+1},y_{t+1},a_{t+1}\right) - I\left(p_{t\to t+1},d_t,y_{t+1},a_{t+1}\right)}_{\text{Demographic Effect}}\\
&\quad + \underbrace{I\left(p_{t\to t+1},d_t,y_{t+1},a_{t+1}\right) - I\left(p_t,d_t,y_t,a_{t+1}\right)}_{\text{Market Effect}}\\
&\quad + \underbrace{I\left(p_t,d_t,y_t,a_{t+1}\right) - I\left(p_t,d_t,y_t,a_t\right)}_{\text{Residual Effect}}
\end{aligned} \tag{1}
$$

where the subscript denotes the time period ($t,\ t+1$) for which the component is derived. In the case of the policy effect, subscript $t\to t+1$ indicates the policy setting if the policy at time t were to be implemented at time $t+1$. This policy setting usually differs from p_t, as certain aspects of the policies may need to be adjusted based on indexation or other pre-determined course of change, which may affect some or all policy parameters. In the market effect component, the income variable y_t and y_{t+1} are not from the same year. Therefore, the estimation of $I(\cdot)$ also includes the normalization via $p_{t\to t+1}$ in order to control for the part of the policies that are endongous to the income change. The framework in equation (1) can be applied to all income distribution measures I, including, but not limited to, the Gini index. For comparability reasons, we focus on the Gini index as the overall inequality measure and use P95/P75, P75/P50, P50/P25 and P25/P5 to analyze the changes in income inequality in different segments of the income distribution. The use of more than one measurement will offer a more complete picture of the changes in income distribution. The component a is not explicitly modelled. Instead, it reflects the difference between the observed datasets conditional on the other three components. Therefore, changes in a means the changes in the base dataset in empirical estimations.

By separating the contributions from each of the four components described above, we will be able to analyze the extent of changes in inequality driven by the identified components over time. The estimation uses information from both the observed data and the detailed tax and transfer policy information incorporated in the simulation process. The additionally injected policy information can be used to better distil the policy impact compared with the alternative decomposition approaches such as the Oaxaca-Blinder method (Blinder, 1973; Oaxaca, 1973) and variance decomposition techniques, where the identification solely relies on the observed data which contains a mixture of policy and interaction effects.

It is worth noting that it is possible to rewrite the equation depending on the order in which variables are introduced, and this may lead to different results. The variation reflects the inherent non-linear nature of the interactions of these components, including the behavioral shifts that are correlated with any of the components. This is also known as the path dependency issue (Shorrocks, 1982). To obtain a stable result, we use the popular Shorrocks-Shapley decomposition technique by averaging each factor's contributions from all possible decomposition paths.[1] The standard errors of the decomposition are estimated using the 45 replicate weights included in the dataset, which capture the complex sampling design of the data. In addition, as all equations are re-estimated with a different set of weights, the statistical uncertainties in the estimation process are also reflected in the final estimates.

The analytical framework is built based on the ability to estimate $I\left(p_t, d_t, y_t, a_t\right)$, which relies on three important methodological components: a tax benefit model that can accurately simulate taxation and welfare policies; a semi-parametric model which introduces marginal changes in demography in the dataset; and a combination of both semi- and non-parametric models to capture labor structure and market income changes. We now discuss these methodological components in detail.

3.2. *Demographic Model*

We use the semi-parametric method from DiNardo *et al.* (1996) to simulate the effect of demographic shifts on the population. The method is easy to implement and allows better control of the covariates included in the demographic components compared with using the longitudinally linked weights, which may be influenced by other factors. To mimic the demographic structure at time $t+1$ on the population data from time t, we modify the weight of each observation at time t with an estimated adjustment ratio. Specifically, the weight of an individual i from data t can be updated to mimic the population demographic structure at time $t+1$ by

$$w_{i,t\to t+1} = w_{i,t}\frac{\Pr\left(X_{i,t}|t+1\right)}{\Pr\left(X_{i,t}|t\right)} = w_{i,t}\frac{\Pr\left(t+1|X_{i,t}\right)}{\Pr\left(t|X_{i,t}\right)}\gamma_{t,t+1} \tag{2}$$

where

$$\gamma_{t,t+1} = \frac{\Pr(t)}{\Pr(t+1)}$$

[1]Four factors are included in the decomposition with values from either $t+1$ or t, resulting in 2^4 unique states of the income distribution.

$X_{i,t}$ is a vector containing the observed demographic attributes that reflect the gradual changes in the population's demographic structure. This includes gender, age, marital status and income unit size. In addition, we also introduce age squared and interactions between age and marital status to allow a flexible specification of the demographic evolution. The prior of the adjustment ratio, $\gamma_{t,t+1}$ is the unconditional probability of observing the individuals from a different period. It is equal to $\frac{\Pr(t)}{\Pr(t+1)}$, which is simply the relative ratio of the population. The conditional probability $\Pr(t|X)$ is estimated using a standard probit model.

3.3. *Income Model*

There are two steps involved in the simulation of the counterfactual household income profiles, which capture both the labor market structure changes and the shifts in labor and capital returns. The first step adjusts the industrial and occupational distribution, and the second step adjusts wages and other incomes.

The weighting of the individuals is updated in the same fashion as the demographic model (equation (2)) to adjust for the changes in the occupational, industrial and employment structures. This model semi-parametrically adjusts the weights in the dataset so that the labor market structure resembles the targeted distribution. The variables used in the reweighting process include industries, occupations and the number of working hours (grouped) interacted with gender to mimic the conditional distribution of the main labor characteristics.

In the second step, we derive the income rank function $\Lambda(\cdot)$ of income source k under the observed market structure and income levels. Mathematically, the income of an individual i at time t can be expressed via this non-parametric function, where

$$y_{i,k,t} = \Lambda_{k,t}\left(r_{i,k,w_{it}}\right) \tag{3}$$

and where $r_{i,k,w_{it}}$ is the observed income rank of individual i in the income category k, which could be wage, business or investment income, at time t. The rank parameter ranges between zero and one and is only computed for those with non-zero income in the category. The estimation is weight-adjusted to reflect the observation's position in the total population.

Once the underlying employment structure has been adjusted, we can recalculate the individual ranks based on the changes in weights and the counterfactual income at time $t+1$ under the market structure at time t which can be simulated as

$$y^{*}_{i,k,t+1} = \Lambda_{k,t+1}\left(r_{i,k,w_{i,t\rightarrow t+1}}\right) \tag{4}$$

If a simulated ranking falls between two observed rankings, the earnings are linearly extrapolated using the two nearest values. As $\Lambda(\cdot)$ is non-parametrically derived, we do not need to impose any distributional assumption, and it captures both the changes in the wage distribution and heterogeneous changes to wage levels at different income segments simultaneously. In addition, the retaining of the rank orders means that the joint distribution of all income sources is preserved through the rank positions. Other income items, such as foreign transfers and incidental income, are assumed to be constant in real terms in our analysis. One limitation of this approach is the absence of the re-ranking effect in the income model, although its impact on our final conclusions is likely to be limited as the overall income distribution is always constrained. As re-ranking is not explicitly included in the income model, its effects, similar to all factors not modeled in this decomposition, are captured by the residual term and the interactions between components.

This approach differs from some existing literature such as Bourguignon *et al.* (2008) and Sologon *et al.* (2018), where each of the employment-related variables is parametrically estimated using logistic, log-linear or Singh-Maddala models based on the Ordinary Least Squares or Maximum Likelihood techniques. The underlying assumption under the parametric model approach is that market income is mostly driven by the observed supply-side changes (e.g. education), echoing human capital theory. In the non-parametric approach we adopt, the overall wage distribution is assumed to be determined by the observed changes in the market structure and the jobs available, which has a closer link to the demand shift.

Both the traditional parametric approach and the non-parametric approach have their merits. In this paper, we prefer to use the non-parametric specification as the economic fluctuations in Australia over the selected period were mostly driven by external forces. These fluctuations include rises and falls in the demand for mining commodities by China and the global financial crisis which originated in the U.S. In addition, the short-term fluctuations in investment returns and business outcomes are arguably more driven by the market demand change than human capital during this period. The non-parametric income model also allows us to deploy a consistent modelling framework for all income sources without imposing structural assumptions on the earning equations, which often contain a sizeable component that cannot be explained by the observed characteristics.

3.4. *Tax and Transfer Policy Model*

The decomposition framework requires disposable incomes to be re-estimated under each counterfactual scenario, given the changes in household characteristics and policies. We use an Australian tax-transfer model (STINMOD+) to numerically calculate household disposable income based on the corresponding tax and social transfer rules. STINMOD+ comprehensively covers all personal taxation and federally administered welfare payments and replicates the implementation of the social security system in real life, incorporating elements such as income and asset testing (Li, 2019). The model covers tax and transfer policy parameters from 2001 to the present, which enables us to estimate disposable income accurately using the same model over time.

The Australian welfare system, as noted earlier, is highly means-tested, and the majority of the eligible conditions do not depend on previous contributions or complex employment history. This characteristic is utilized in our model to estimate disposable incomes accurately. STINMOD+ simulates almost all government welfare payments, except for benefits given in exceptional circumstances, which constitute less than 1 percent of the total welfare payment expenditure. The model includes a behavioral component where households seek to maximize their disposable income should they have a choice between two or more welfare options. Multiple welfare eligibilities tend to be rare due to designed policy principles but may happen occasionally.

In contrast to some other countries, the take-up rate of welfare benefits in Australia is generally considered high despite the extensive use of means-testing. It has been suggested that the stigma of means-tested benefits in Australia may, on average, be low because they target a relatively large proportion of the population (Mood, 2006). We, therefore, assume full take-up in this paper. Empirically, simulating the benefits on the assumption of full take-up provides policy costings and coverage that are comparable with administrative figures. In addition, adopting this approach, the accuracy rate (i.e. the number of correctly simulated eligibilities as a proportion of the total population) for the largest government benefits, using HILDA data as the comparison, exceeds 90 percent.[2] Overall, the tax-benefit model shows a high degree of consistency with both survey and administrative data sources.

When transplanting policies in the decomposition, certain combinations may lead to discrepancies between the policy year and the year when the market income distribution is derived. Such differences may lead to biased policy effect estimation, as the policy in year t may not be intended to be applied in a different year. Therefore, to simulate the counterfactual policy $p_{t\to t+1}$, a range of tax thresholds and benefit levels should also be uprated with the legislated indexation method.[3] The indexation method itself may have implications for income distribution. Sutherland *et al.* (2008) have previously explored this issue in the United Kingdom. As the official uprating method of policies is relatively complex in Australia,[4] we instead approximate the effect of implementing $p_{t\to t+1}$ using p_t on an income distribution y by adjusting the average income so that the indexed thresholds and benefit levels can remain at their relative positions in the income distribution. Mathematically, this approximation can be expressed as

$$I\left(p_{t\to t+1}, d, y_{t+1}, a\right) \approx I\left(p_t, d, \tau_{t+1\to t} y_{t+1}, a\right) \tag{5}$$

[2]When comparing our results with those reported in the surveys, the accuracy rates (proportion of correctly simulated eligibilities) are very high: 97 percent for Family Tax Benefit (FTB A & B), 90 percent for the age pension, 95 percent for parenting payment and 88 percent for other allowances in all waves of HILDA. In terms of identifying beneficiaries, the true positive rate (the proportion of actual beneficiaries that are correctly identified) is 92 percent for pension beneficiaries, and 90 percent and 92 percent for those receiving FTB A and FTB B, respectively.

[3]It should be noted that the choice of the indexation is an analytical one to make two counterfactuals comparable. One possible approach could be strictly following the legitimation as this could be a plausible counterfactual should no new change in the tax policy occurs. At the same time, there are also concerns whether the different price levels should be taken into account for the estimation. Fortunately in our case, the difference between the actual legislation change and the price change is relatively small. We therefore consider using the CPI to discount future year income in order to simulate the effects of no changes in tax policies. AWE indexation is also used as a robustness check.

[4]Most welfare payments in Australia are indexed. A range of different methods are used. These include indexation based on the consumer price index (CPI) (e.g. FTB and unemployment benefit), indexation based on growth in average weekly earnings (AWE) (e.g. pensions), and other methods to adjust the values of tax and transfer payments quarterly.

where $\tau_{t+1\rightarrow t}$ is the discount factor to scale down the income y_{t+1} so that it can match with the intended tax benefit policy p_t which is designed for income y_t. As our final distributional measures are independent of the scale of the income, a proportional change in all income does not affect the Gini index. We use CPI as the primary uprating factor, as it can be considered as a median value of all indexation approaches used by the government. We also use the AWE series, which is usually higher than CPI, as a test of the sensitivity of the results to the indexation assumptions. The approach of discounting income by the wage growth rate also resembles what has been proposed by Callan, Coleman, and Walsh (2006) and Bargain (2012a) as a "distributionally neutral" measure which gives a different interpretation of policy effect. The policy effect with the AWE discount factor can be considered as the effect of policy change beyond catching up with income growth, while CPI-based results reflect changes both in the policy itself and the pre-determined policy trajectory.

3.5. *Limitations*

Although our decomposition framework provides a practical approach to distilling the complex effects of policy, demographic, and market income changes on income distribution, it does have some limitations. Most notably, we do not explicitly model the behavioral responses to policy changes, except for the behavioral response to benefit choices in the STINMOD+ model. These exclusions include, but are not limited to, changes in decisions about labor supply, fertility, education, consumption, savings, and household formation and dissolution. The inherent non-linear transformation of the income distribution means that such effects are likely to be allocated across all components, including the residual terms (Biewen, 2014).

Not specific to this paper, the behavioral response is often excluded in income distribution decomposition exercises. Where behavioral responses are incorporated, attempts are generally limited to modelling labor supply responses (see Bargain, 2012a; Hérault and Azpitarte, 2016; Sologon *et al*. 2018). Papers that include labor supply response tend to decompose changes between two points in time that are relatively far from each other, where sufficient policy variations can be introduced. In our case, however, we focus on the year-over-year effect, which means the policy changes tend to be incremental and the labor supply response, as a result, tends to be moderate. In addition, incorporating a behavioral model from the supply side, such as the standard labor supply model, means that some strong assumptions would need to be made about human behavior, and structural adjustment in the event of an external shock. These extra assumptions could further bias our estimates compared with our chosen approach. Given that the shocks to market income are likely greater than the ones introduced by the policy structure under the incremental nature of reforms, demand-side factors are likely to dominate the limited supply-side responses during the period we are studying. As a result, the absence of the cross-sectional supply-side models would be unlikely to pose any major change to the general conclusions in our estimation.

4. Data

This paper draws data from a nationally representative survey, the Household, Income, and Labour Dynamics in Australia (HILDA) survey. HILDA is a longitudinal survey conducted annually since 2001, with 19,914 individuals and 7,682 households included in the first wave. It records a wide range of socio-economic characteristics, including detailed individual employment and income characteristics that are required to estimate potential welfare eligibility and tax payments (Wooden *et al*., 2002).

This paper uses waves 2 to 16 of HILDA, which correspond to the years 2002 to 2016, to examine the redistribution effects of tax and transfer policies. The first wave of HILDA is used to construct the lag variables which are required to estimate tax liability and benefit payments accurately. We group income into four categories: wages and salaries, business income, investment income, and other income. The first three are considered as market income.

Disposable income is equivalized with the OECD-modified scale,[5] consistent with the methodology used by the Australian Bureau of Statistics. Although the income variables, the primary variables used from HILDA, do not contain missing values, some variables, such as household asset value, were only collected once in every four waves. Some imputations are therefore required. Generally, we use contextual information (e.g. age) to infer the value of the variable. If this is inconclusive, we use the nearest observed value for the same individual for discrete variables and linear interpolation for the continuous variables. For example, in the case of the household asset variable, which is observed only in waves 2, 6, 10, and 14, we use a linear interpolation technique to impute the missing values. For the occasional missing value in the working hours variable, we assign the working hours based on the reported employment status. For the study load, we assume that all individuals aged between 5 years and under 15 years are studying at school if the study load is not reported. Table 1 describes the extent of imputation. It should be noted that our imputations do not alter age and private income, which are the primary determinants of benefit payments in Australia. As the imputed variables constitute only a small part of the sample (1.5 percent), and they play only a minor role in tax and transfer policy, the use of imputation is unlikely to have any significant impact on the results.

Table 2 provides some key demographic descriptive variables for the sample. All estimates are adjusted with population weights. The ageing of the Australian population is evident: the average age of the population has increased from just under 36 to 37 and a half during the 15 years of the survey. At the same time, the proportion of the population in domestic partnerships has more or less been stable, with only a marginal increase from 47.8 percent in 2002 to 48.0 percent in 2016. The average age of single people has also increased slightly over the period. There are also slight

[5]The OECD-modified scale assigns a value of 1 to the first adult in the household, 0.5 to the second and each subsequent person aged 15 and over and 0.3 to each child aged 14 or under.

TABLE 1
Imputation Statistics of the Estimation Sample

Total number of enumerated persons in HILDA (Wave 2–16)	40,746
Total number of observations in HILDA	317,738
Proportion of imputed working hours	4.3%
Proportion of imputed study load	24%
Proportion of imputed salary sacrifice for superannuation	3%
Proportion of imputed salary sacrifice for non-superannuation	5%
Proportion of imputed household asset values	70%
Proportion of imputed values among all STINMOD + input variables	1.5%

TABLE 2
Population Characteristics, 2002–2016

Year	Average Age	Partnered (%)	Average Age of Singles	Income Unit Size	Number of Dependent Children
2002	35.93	47.81	40.47	2.77	1.08
2003	36.07	47.95	40.20	2.78	1.09
2004	36.28	47.73	40.25	2.75	1.07
2005	36.47	48.31	40.36	2.75	1.07
2006	36.57	48.27	40.71	2.76	1.07
2007	36.68	48.01	41.06	2.74	1.06
2008	36.76	48.58	40.99	2.73	1.04
2009	36.82	48.15	40.78	2.74	1.05
2010	36.92	48.26	41.15	2.73	1.04
2011	37.10	47.94	41.13	2.74	1.06
2012	37.17	48.17	41.35	2.74	1.05
2013	37.22	48.02	41.47	2.75	1.06
2014	37.35	48.35	41.51	2.77	1.08
2015	37.47	47.51	41.68	2.74	1.06
2016	37.59	48.02	41.48	2.74	1.05

drops in the average size of an income unit,[6] and the average number of dependent children over time. Demographically, we are looking at a population that got older and had slightly smaller families over the course of the 2002 to 2016 period.

Table 3 describes the changes in the employment and the income of the population. The first two columns report the changes in average working hours among those who work. There is a slight reduction in the average working hours for men, but not much change for women. Columns three to five report the average fortnightly income, conditional on a non-zero value. The average values for wage and business income have increased by 70~90 percent through the period, while average investment income has more than doubled during the same period despite some fluctuations during the years of the global financial crisis. Among the adult population in Australia, there is an increasing proportion receiving wage income while a decreasing share of the population has business and investment income. Given that business and investment income are much more unequally distributed than wage income, the changes in the income composition over the period will contribute to the overall change in the income distribution.

[6]An income unit is a tax unit in Australia, which consists of a maximum of two partnered adults and their dependent children (if any) for those in a partnership, and one adult and his or her dependent children for singles. Most households in Australia contain only one income unit.

TABLE 3
Employment and Income Characteristics, 2002–2016

Year	Male Working Hours	Female Working Hours	Average Wage	Average Business Income	Average Investment Income	(%) Has Wage	(%) Has Business Income	(%) Has Investment Income
2002	42.9	31.3	1,360.2	764.2	145.8	62.1	8.1	42.3
2003	42.4	31.2	1,393.6	719.2	149.9	62.1	8.5	41.4
2004	42.0	31.1	1,444.3	758.1	184.2	62.2	8.6	40.7
2005	42.1	31.2	1,520.8	845.2	207.6	63.5	8.5	41.0
2006	41.9	31.5	1,619.4	852.8	260.0	64.2	8.1	41.8
2007	41.9	31.7	1,747.8	866.5	238.7	64.9	7.6	42.9
2008	41.9	31.5	1,832.6	903.0	270.0	65.3	7.3	41.5
2009	41.4	31.4	1,887.7	950.7	259.2	65.3	7.6	41.7
2010	41.1	31.5	1,975.7	1,032.5	234.3	65.6	7.6	42.0
2011	40.6	31.2	2,036.4	1,211.4	247.6	64.8	7.5	41.8
2012	40.5	31.4	2,112.8	1,171.5	265.2	65.0	7.4	41.4
2013	40.2	31.2	2,210.8	1,282.5	273.3	64.5	7.2	41.3
2014	40.2	31.1	2,241.1	1,363.0	298.9	64.4	6.6	41.3
2015	40.2	31.2	2,296.2	1,491.9	309.9	64.6	6.6	39.1
2016	39.9	31.4	2,346.3	1,408.0	310.4	64.2	6.7	37.4

Notes: Columns 2 to 6 are fortnightly estimates conditional on non-zero values. Columns 7 to 9 are estimates for the adult population only.

5. Results

5.1. *Overall Inequality Trends*

Table 4 reports the inequality trends in Australia both in terms of the Gini index and the four different percentile ratios of the income distribution. As presented, the Gini coefficients for both gross income and disposable income have been relatively stable since 2002, although fluctuations are observed throughout the period, especially in the years immediately after the global financial crisis. The difference between the lowest and the highest Gini is 0.03 for gross income and 0.02 for disposable income. Most of the fluctuations in the Gini can be observed between 2003 and 2008, which covers the period of the global financial crisis and the periods immediately preceding it.

Looking at the relative income ratio across the different segments of the income distribution, the gradual change in the income components affects different segments of the income distribution differently. The lower income part of the distribution has experienced an increase in inequality, as reflected in the P25/P5 results, in the years prior to the financial crisis, before being restored to its original level in 2010. The richer part of the income distribution (P95/P75), shows a small increase in the income gap despite a dip during the financial crisis period.

Our results about income inequality are generally consistent with others' estimates derived using HILDA, such as those presented in Wilkins (2014) and Wilkins (2015). Trends and patterns are comparable with earlier literature and also the disposable income Gini index published by the Australian Bureau of Statistics based on the Survey of Income and Housing (Australian Bureau of Statistics, 2016).

TABLE 4
Income Inequality in Australia, 2002–16

Year	Gini (Gross)	Gini (disp.)	P95/P75	P75/P50	P50/P25	P25/P5
2002	0.475	0.330	1.685	1.444	1.497	1.571
	(0.007)	(0.008)	(0.038)	(0.014)	(0.017)	(0.020)
2003	0.477	0.332	1.692	1.426	1.509	1.560
	(0.008)	(0.008)	(0.030)	(0.023)	(0.021)	(0.022)
2004	0.459	0.314	1.683	1.407	1.493	1.572
	(0.006)	(0.005)	(0.027)	(0.024)	(0.024)	(0.012)
2005	0.455	0.313	1.670	1.389	1.494	1.591
	(0.007)	(0.007)	(0.035)	(0.018)	(0.018)	(0.034)
2006	0.462	0.329	1.685	1.423	1.433	1.650
	(0.007)	(0.008)	(0.030)	(0.018)	(0.018)	(0.036)
2007	0.459	0.332	1.708	1.395	1.500	1.724
	(0.009)	(0.008)	(0.023)	(0.019)	(0.032)	(0.033)
2008	0.448	0.323	1.705	1.428	1.447	1.689
	(0.007)	(0.007)	(0.054)	(0.017)	(0.026)	(0.044)
2009	0.448	0.320	1.672	1.404	1.486	1.750
	(0.006)	(0.005)	(0.025)	(0.020)	(0.032)	(0.040)
2010	0.451	0.316	1.659	1.400	1.470	1.556
	(0.006)	(0.005)	(0.040)	(0.026)	(0.017)	(0.030)
2011	0.454	0.319	1.707	1.439	1.450	1.515
	(0.006)	(0.005)	(0.029)	(0.010)	(0.011)	(0.020)
2012	0.452	0.321	1.683	1.436	1.453	1.520
	(0.006)	(0.007)	(0.037)	(0.018)	(0.026)	(0.046)
2013	0.455	0.319	1.678	1.443	1.449	1.594
	(0.007)	(0.005)	(0.049)	(0.015)	(0.017)	(0.079)
2014	0.457	0.319	1.683	1.430	1.466	1.498
	(0.006)	(0.005)	(0.036)	(0.022)	(0.016)	(0.047)
2015	0.453	0.314	1.684	1.427	1.442	1.454
	(0.006)	(0.006)	(0.030)	(0.013)	(0.014)	(0.031)
2016	0.456	0.322	1.700	1.415	1.422	1.557
	(0.007)	(0.007)	(0.036)	(0.019)	(0.018)	(0.030)

Notes: Standard errors in parentheses. 45 sets of replicate weights used in the estimation.

5.2. *Decomposition Results*

Table 5 reports the overall change in the Gini index compared to the previous year (column 10), the single contribution of each component to this change (columns 2–5) and the cumulative contribution of these components (columns 6–9). The policy contribution (columns 2 and 6) reflects how tax and welfare policy change affects the income distribution in Australia. The estimates of the standard errors are shown in parentheses in the table for both single year contributions and the cumulative contributions since 2002. Figure 2 visualizes each component's contributions over time.

Results from Table 5 suggests that the policy effect appears to be a large contributor to the overall changes in the income distribution between 2002 and 2016, especially outside the financial crisis period of 2006 to 2009. Generally, changes in the tax and transfer policy system in Australia reduce overall income inequality, except for the 2006–07 financial year when a large tax cut was implemented. Specifically, the income tax cut policy implemented since 2004 under the conservative Coalition government (1996–2007) had an adverse impact on overall income inequality by providing income tax relief for higher income earners. The threshold for the highest marginal income tax rate was increased from $70,000 in 2004–05

TABLE 5

Component Contribution to Changes in Gini (Percentage Point, Income Adjusted by CPI)

	Single Year Contribution				Cumulative Contribution From 2002				
Year	Policy	Demography	Market	Residual	Policy	Demography	Market	Residual	ΔGini (Single Year)
2002–03	−0.16	0.06	0.40	−0.12	−0.16	0.06	0.40	−0.12	0.18
	(0.01)	(0.02)	(0.31)	(0.76)	(0.01)	(0.02)	(0.31)	(0.76)	(0.79)
2003–04	−0.14	−0.00	−0.65	−1.01	−0.29	0.05	−0.25	−1.13	−1.80
	(0.01)	(0.02)	(0.37)	(0.57)	(0.01)	(0.03)	(0.27)	(0.84)	(0.73)
2004–05	−0.32	0.04	0.26	−0.10	−0.62	0.09	0.01	−1.23	−0.13
	(0.01)	(0.02)	(0.29)	(0.58)	(0.02)	(0.03)	(0.33)	(0.91)	(0.63)
2005–06	0.14	−0.01	0.64	0.86	−0.48	0.09	0.65	−0.37	1.63
	(0.01)	(0.02)	(0.38)	(0.73)	(0.02)	(0.03)	(0.41)	(1.02)	(0.79)
2006–07	0.45	−0.01	1.04	−1.23	−0.03	0.08	1.68	−1.60	0.25
	(0.05)	(0.03)	(0.66)	(0.75)	(0.05)	(0.03)	(0.63)	(0.90)	(0.90)
2007–08	0.01	0.02	−1.21	0.29	−0.02	0.10	0.47	−1.31	−0.89
	(0.02)	(0.02)	(0.64)	(0.70)	(0.06)	(0.03)	(0.39)	(0.93)	(0.81)
2008–09	−0.45	−0.01	0.31	−0.16	−0.47	0.09	0.79	−1.47	−0.31
	(0.01)	(0.02)	(0.26)	(0.64)	(0.06)	(0.04)	(0.41)	(0.88)	(0.67)
2009–10	−0.32	0.01	0.45	−0.49	−0.79	0.10	1.23	−1.96	−0.36
	(0.02)	(0.02)	(0.25)	(0.49)	(0.06)	(0.04)	(0.38)	(0.91)	(0.54)
2010–11	−0.08	0.02	0.13	0.25	−0.87	0.12	1.36	−1.71	0.32
	(0.01)	(0.02)	(0.37)	(0.54)	(0.06)	(0.04)	(0.51)	(0.83)	(0.62)
2011–12	−0.14	−0.00	−0.26	0.54	−1.01	0.11	1.10	−1.16	0.14
	(0.02)	(0.02)	(0.26)	(0.59)	(0.06)	(0.05)	(0.46)	(0.91)	(0.61)
2012–13	−0.25	0.03	0.51	−0.44	−1.26	0.15	1.61	−1.61	−0.15
	(0.02)	(0.03)	(0.21)	(0.54)	(0.07)	(0.05)	(0.54)	(0.80)	(0.64)
2013–14	−0.12	−0.02	−0.07	0.16	−1.38	0.12	1.54	−1.45	−0.05
	(0.02)	(0.02)	(0.23)	(0.44)	(0.07)	(0.05)	(0.48)	(0.86)	(0.53)
2014–15	−0.31	0.00	−0.13	−0.02	−1.69	0.13	1.42	−1.47	−0.45
	(0.02)	(0.02)	(0.21)	(0.53)	(0.07)	(0.05)	(0.51)	(0.84)	(0.52)
2015–16	0.03	0.01	0.01	0.76	−1.66	0.13	1.42	−0.71	0.80
	(0.01)	(0.03)	(0.18)	(0.78)	(0.08)	(0.05)	(0.52)	(0.97)	(0.82)

Notes: Standard errors in parentheses. Official CPI series (Australian Bureau of Statistics, 2018a) used for the indexation. 45 sets of replicate weights used in the estimation.

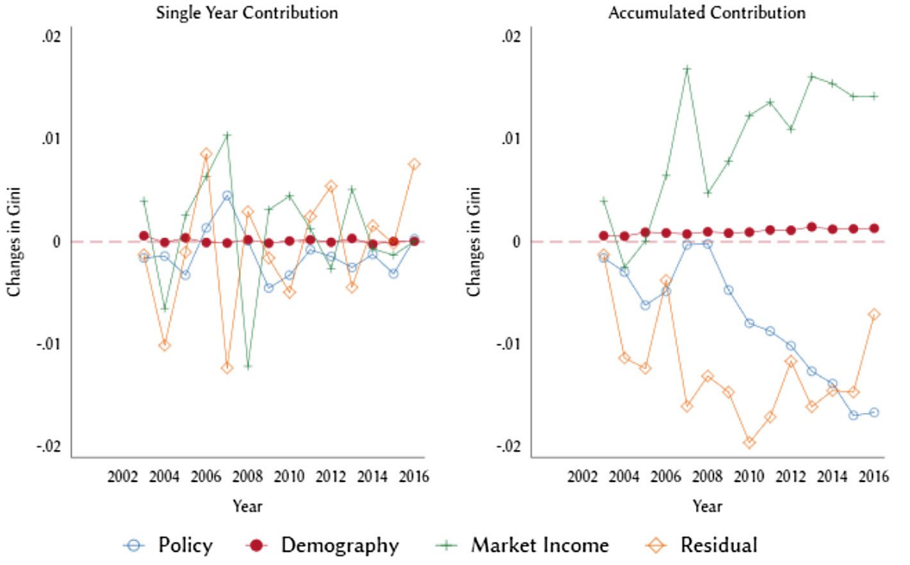

Figure 2. Decomposition of Gini changes Between 2002 and 2015 in Australia

to $150,000 in 2006–07. In contrast, the age pension reforms since 2009 (with a pension increase of $1,689 per year for singles and $527.28 per year combined for couples on the full rate) under the Labor government (2007–13) brought more benefits for low-income pensioners, and to some extent decreasing the income inequality. The effects of these major policy changes, including the ones discussed in the Online Appendix A, are well captured by our model as reported in Table 5 and Figure 2. As expected, the standard errors of the policy component were low, considering that the policy effect estimation involves applying two sets of deterministic policy rules to the same individuals (i.e. paired samples) while estimating other components (e.g. market income, demography) requires transplanting the distribution to different observations (i.e. unpaired samples).

As demonstrated by our results in Table 5, decomposition using two points of time far apart from each other sometimes cannot capture the real impact of specific policy reforms, and the conclusion could change if the start or end year of the period of interest changes. For example, while policy change contributes to a reduction of income inequality between 2002 and 2006, moving the end year to 2007 reduces the overall effect to nearly zero due to a major tax cut in 2006–07. This again highlights the importance of the year-on-year decomposition for an accurate policy impact assessment. In comparing our results with those reported in previous literature, it is important to consider the time period of each study. We find our results consistent with Creedy and Hérault's (2015) finding that income inequality was reduced due to tax policy change between 2000 and 2005. The absence of any major tax reform between 2000 and 2002 makes these results broadly comparable with ours. However, results from studies such as Hérault and Azpitarte (2016), where the period of study starts from 1999 with an additional tax reform included, would not be directly comparable with our study, given our starting year is 2002.

Demographic factors play a minor role in income inequality during the period of study. As shown in the early descriptive summaries (Table 2), the average age of the population is one of the factors that experienced a steady change over time among the key covariates controlled in the demographic variables. Other demographic variables are relatively stable, which explains the absence of major fluctuations in the contribution of the demographic component. Theoretically, ageing is likely to lead to greater income inequality as the within-cohort earning inequality tends to rise as the cohort gets older and the differences in human capital accumulation increase for the majority of the working population (Deaton and Paxson, 1997). Its effect, however, is relatively limited based on the overall population Gini measure in Australia, with only a net 0.001 gain in the Gini throughout the period that can be attributed to demographic change alone.

Market income induced inequality change is volatile before and during the global financial crisis, as shown in Figure 2. The most substantial impact of the market income change is observed between 2006 and 2008, the years around the financial crisis. The shifts in market income increased the Gini by more than 0.010 in 2006–2007, the year leading up to the crisis period. However, the increase was offset in the year after with a decline of more than 0.012 in 2007–2008. The decline in income inequality was largely due to the sudden drop in investment returns, which effectively lowered the net income for the middle and high end of the income distribution, which holds investment assets. While the single year contribution of the market factor may not be statistically significant due to the short time period and the absence of the strong assumptions in the decomposition model, the standard errors of the cumulative contribution estimates take into account the correlation over time and can better reflect the impact of market changes that span across several years. Between 2002 and 2016, the market factor is the largest contributor to changes in income inequality; it significantly increased the Gini in Australia and has generally acted to increase income inequality since the end of the financial crisis.

The residuals of the decomposition, which reflect the behavioral change and other non-modelled effects, shifts in unobserved characteristics and the non-linearity of the decomposition, also play a role in shaping inequality. The contribution from the residuals is larger when the absolute contributions from other factors are substantial. This may be due to a more aggressive behavioral adjustment when a significant policy or market shock is introduced.

Throughout the whole period of study, a 0.017 reduction in the Gini can be attributed to the cumulative policy change and 0.001 to demographic change. Market income pushes income inequality higher, raising the Gini measure by 0.014. The cumulative effect of the residuals accounts for around 0.007 of the total change in the Gini. In terms of the sum of the absolute annual impact,[7] the market income factor is the largest contributor to income inequality change during the period studied.

Besides the Gini results, Figures 3 and 4 present further insights into the effects of the four contributing factors on the income distribution by examining the changes occurring at different income levels. These figures demonstrate substantial

[7]This can be calculated by summing up the absolute value of the annual contribution as reported in the first column of the Table 5.

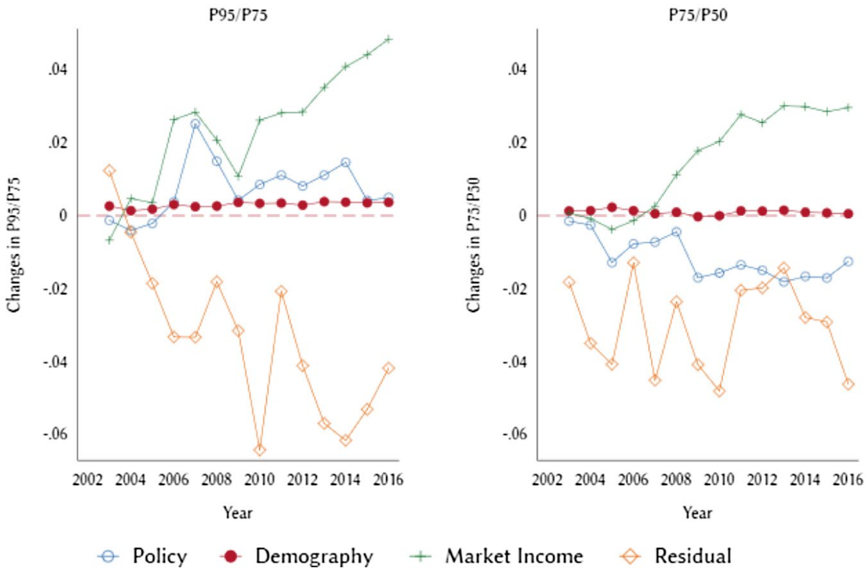

Figure 3. Decomposition of P95/P75 and P75/P50 Ratio Between 2002 and 2015 in Australia (Cumulative)

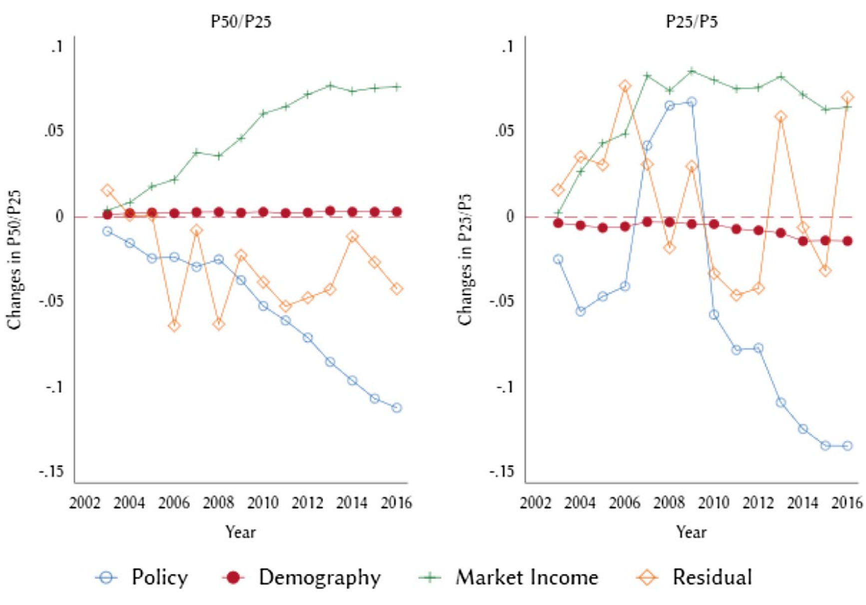

Figure 4. Decomposition of the P50/P25 and P25/P5 Ratio Between 2002 and 2015 in Australia (Cumulative)

heterogeneities in the effects of policy, demographic ageing and market income at different parts of the income distribution. The estimates and the standard errors used in the figures are reported in Online Appendix B.

Market income tends to be the primary driver pushing inequality higher for all parts of the income distribution. The average cumulative effect of the market income change also appears to be the largest for the lower end of the income distribution compared with its impact on the other segments of the population. We see a small decline in market income contribution for P25/P5 in the years since the financial crisis. For other segments of the income spectrum, we can see the cumulative contribution of market income increases from 2009 onwards.

Policy reforms has the most heterogeneous effects on income distribution, depending on the relative position in this spectrum. While policy reform tends to reduce income inequality overall, this is not the case for the upper quartile, where policy reforms increase income inequality. Much of this impact can be attributed to the various tax cuts offered to the higher income group during the 2006–2007 financial year under the Coalition government. This particular tax reform also has the largest effects on the lower end of the income distribution, increasing income inequality in this poorest part of the population during this period. In contrast, there was a sharp decline in the income inequality of this segment in 2010. This decline was largely due to the increased rate of the age pension under the Labor government, which, as previously noted, is the single largest welfare payment in Australia. Retirees receiving the age pension tend to be in the bottom quartile of the income distribution given the income test constraints of the benefit. In addition, the policy effect plays an apparently positive role in the lower half of the income distribution in the years following the financial crisis. This may reflect the income distribution's sensitivity to the level of benefit payments in a highly means-tested welfare system. Policy changes had much less effect on the other segments of the income distribution.

It should be noted that the standard errors for the percentile income ratio (P95/75/50/25/5) contribution estimates is higher than the estimates for the Gini, both in absolute and relative terms. It should be considered, however, that these estimates are contributions in absolute terms, and also capture the uncertainties in the index itself. The percentile income ratio values are calculated based on two percentile values, and thus are more volatile when additional sampling errors are considered. This uncertainty is also reflected by the standard error of the income ratios themselves. However, the patterns from the point estimates are generally clear and consistent with the policy expectations.

Demographic factors seem to matter more in the lower end of the income distribution, where they impose a small downward pressure on inequality—a different direction than the overall Gini results indicated. This is likely due to the existence of the nature of the age pension in Australia, which does not depend on work history or contributions. The benefit is generally tax-free,[8] and the amount is inversely correlated with private income, with a maximum of up to nearly half of average employee earnings post-tax. The absence of any contribution requirement reduces income inequality among retirees, contributing to the compression of the income distribution among the lower income population. For the high-income population, which mostly consists of working individuals, demographic change

[8]A recipient may still need to pay tax if he or she has income other than the age pension.

pushes income inequality upwards slightly in the top quartile over the past decade, consistent with findings in some of the earlier literature, such as Dolls *et al.* (2019).

Residuals also play a non-negligible role compared with the size of the other factors in almost all sections of the income distribution, suggesting interactions and possible behavioral responses due to the changing economic and policy environment. The residual term, which captures the behavioral response and other factors that are not explicitly modelled in this decomposition exercise, is more significant for the more affluent part of the population relative to the contribution of other components, suggesting possibly greater capacity for behavioral adaptations in this population group. Such behavioral adaptations could relate to capacities for income diversification in the event of external shocks, the generation of non-labor income and effective tax management, as well as standard labor supply adjustment, although the labor supply among higher income groups tends to be less elastic than for the average working population (Bargain *et al.*, 2014).

The absence of an explicit labor supply model in our framework could mean that certain secondary effects of the policies are not entirely attributed to the policy component. Earlier literature using Australian data (Hérault and Azpitarte, 2015, 2016) suggests policy effects could be overestimated without a labor supply model. Given that policy changes tend to be gradual in our decomposition exercises, the major contribution patterns from the different components would likely remain unchanged if a standard structural labor supply model was introduced although the uncertainties around the policy contribution estimates might increase.

6. Alternative Policy Indexation Assumption

The tax-transfer system in Australia, including welfare payments, is annually adjusted using a mixture of CPI, AWE and other indices. As we do not directly observe how policies at time t are implemented at time $t+1$ should there be no policy change, we adjust the income of time $t+1$ to time t by CPI so that the income level is comparable with the threshold and the benefit level for which the policies are designed. The adjustment, however, may not always match the actual indexation of welfare policies, given the mixture of indices used, and the fact that AWE is often higher than CPI (see Australian Bureau of Statistics, 2018a, 2018b). Changes in the policy assumptions may also affect the estimations of the other components due to the non-linearity of the decomposition. It is, therefore, important to check the stability of the results with alternative assumptions. In addition, using the AWE uprating factor also leads to a different interpretation of the policy effect, as previously discussed. Instead of capturing the change in the original trajectory of the policies, the policy effect using AWE can be considered as a distributionally neutral version of the policy effects, which is independent of the changes in income growth, as the total income in the distribution remains stable when the policies are transplanted.

Table 6 describes each component's contribution to overall Gini change under a different policy uprating assumption. Among all four components, the overall policy effect shows the largest change, which is unsurprising given that the use of AWE instead of CPI has a direct impact on policy implementation. Numerically, the policy factor shows a weakened effect in reducing inequality, although the

TABLE 6
Single Year Contribution to Changes in Gini Under the Alternative Indexation Assumption (Percentage Point, Income Adjusted by AWE)

Year	Policy	Demography	Market Income	Residual
2002–2003	0.17	0.06	0.40	−0.45
	(0.00)	(0.00)	(0.05)	(0.11)
2003–2004	−0.08	−0.00	−0.65	−1.07
	(0.00)	(0.00)	(0.06)	(0.09)
2004–2005	−0.13	0.04	0.26	−0.29
	(0.00)	(0.00)	(0.04)	(0.09)
2005–2006	0.19	−0.01	0.64	0.80
	(0.00)	(0.00)	(0.06)	(0.11)
2006–2007	0.68	−0.01	1.04	−1.46
	(0.01)	(0.00)	(0.10)	(0.11)
2007–2008	−0.07	0.02	−1.21	0.38
	(0.00)	(0.00)	(0.10)	(0.10)
2008–2009	−0.12	−0.01	0.31	−0.49
	(0.00)	(0.00)	(0.04)	(0.10)
2009–2010	−0.20	0.01	0.45	−0.62
	(0.00)	(0.00)	(0.04)	(0.07)
2010–2011	−0.05	0.02	0.13	0.22
	(0.00)	(0.00)	(0.06)	(0.08)
2011–2012	0.12	−0.00	−0.26	0.28
	(0.00)	(0.00)	(0.04)	(0.09)
2012–2013	−0.16	0.03	0.51	−0.53
	(0.00)	(0.00)	(0.03)	(0.08)
2013–2014	−0.23	−0.02	−0.07	0.26
	(0.00)	(0.00)	(0.03)	(0.07)
2014–2015	−0.31	0.00	−0.13	−0.02
	(0.00)	(0.00)	(0.03)	(0.08)
2015–2016	0.06	0.01	0.01	0.73
	(0.00)	(0.00)	(0.03)	(0.12)

Notes: Standard errors in parentheses. Average weekly earnings series (Australian Bureau of Statistics, 2018b) used for the indexation. 45 sets of replicate weights used in the estimation.

general pattern over time remains stable and is at the same magnitude for different assumptions. The difference between the CPI-based estimates and AWE-based estimates of the policy contribution is about 0.001 per annum for the overall Gini measure and accounts for a small proportion of the total change in a year. The changes in demographic and market income components are even smaller, as expected, because the indexation method only directly affects the policy component, and the fractional differences between CPI and AWE have minimal implications for the estimations of other explicitly modelled components. This suggests the assumptions used to uprate the policy parameter variables have only a minor impact on the overall estimates. In other words, both the pattern and the trend of the policy effect remain stable with and without the distributionally neutral adjustment of the policies. Both series indicate that the reforms implemented in 2006 tend to have the largest impact on income inequality in Australia over the period studied.

The demography and market income components in the alternative assumption model show very similar results to their original contributions as reported in Table 5, indicating these estimates are not sensitive to varying assumptions for certain policies. The results for the residual term largely mirror the changes in the policy factor contribution in the opposite direction.

7. Conclusion

We decompose the changes in inequality in Australia into factors directly related to tax and welfare policy change, shifts in market income, demographic change and the contribution of other factors. In terms of methodology, we extend the counterfactual income distribution decomposition framework used by Bourguignon *et al.* (2008), Bargain and Callan (2010), Biewen and Juhasz (2012), Bargain *et al.* (2015) and Sologon *et al*. (2018) by allowing a more accurate impact assessment through analyzing year-on-year data, incorporating a flexible non-parametric market income model which better captures the demand-side shocks during the global financial crisis compared with a standard parametric model, and deriving the standard errors of the estimates with the replicate weights from the survey. The ability to tease out the differences year-on-year may help policymakers pinpoint what works and what does not in particular social and economic contexts, and may partially mitigate the sensitivity of the results to the selection of the years.

We find that the level of inequality in Australia was more volatile before the financial crisis and has become more stable following that period. The highest level of inequality was observed in 2006–07, when changes in both market income and policies contributed to increased inequality. The financial crisis seemingly reduced income inequality in Australia with a drop of the Gini measure for both gross and disposable income in 2007 and 2008.

Decomposition using annual data between 2002 and 2016 suggests the primary driver of income inequality in Australia over the past decade is market income for all segments of the income distribution. The financial crisis in 2007–08, despite the dramatic drop in stock markets worldwide, only temporarily reduced income inequality for the upper end of the income distribution. The single year contributions from the market component tend to have a degree of uncertainty, although the cumulative contributions are generally significant across most years. Compared with the two-timepoint decomposition in the existing literature, the year-on-year analysis can help to pinpoint the exact policy change responsible for the income distribution shift and paints a more comprehensive picture of the distribution change over time.

During the period we studied, changes in market income are generally associated with increases in income inequality in Australia while policy shifts reduced income inequality, particularly at the lower end of the income distribution. Market income has the greatest impact on income distribution among all modelled factors in terms of the sum of the absolute annual changes in the Gini measure during the period of study. Demographic and household composition changes had a minor impact in compressing the income distribution for the poor, but were associated with a slight increase in the income gap in the top quartile of the income distribution. Overall, policy reform factors have the largest role in reducing overall income inequality throughout the period although this component tends to drive higher inequality for the top end of the income distribution, largely due to a sharp increase in the top tax threshold benefiting the P95 income group the most, and reducing income inequality for the P75 or below groups.

In our analysis, we also noted that the residual term, which reflects the non-linearity of the interactions of the components and some behavioral adjustments, is relatively important for the upper end of the income distribution, suggesting possible behavioral adjustment for the wealthier segment of the population.

The decomposition results are not sensitive to the uprating factor for the analysis. While the numeric values of the policy factor contribution in each year did change somewhat under an alternative indexation assumption, the overall pattern and the relative importance of each significant factor remained largely the same, suggesting our conclusion is robust against an alternative indexation assumption.

Our findings suggest the need to regularly review policies in order to understand the impact of policies in the context of changes in the population and economic environment, due to the complex interactions between economic, demographic and policy factors. This is particularly important if suppressing the growth of income inequality is one of the policy objectives. The year-on-year analysis allows a more accurate allocation of the policy effects, as we can limit the policy changes to what happened in a single year. This is not only useful in identifying policy effects but also necessary when there are significant shocks into the system. For both policy and research purposes, examining the policy effects for the entire distribution reveals much more information than a single inequality index, given policy's highly heterogeneous impact on different income distribution segments over time. Future research may consider further decomposing the policy components so that more targeted policy recommendations can be made.

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Supporting Information

Additional supporting information may be found in the online version of this article at the publisher's web site:

Appendix A: Major Tax-Welfare Policy Reforms in Australia Between 2002 and 2016

Appendix B: Additional Results

Table B.1: Cumulative Contribution to Changes in P25/P5 (Percentage Point, Income Adjusted by CPI)

Table B.2: Cumulative Contribution to Changes in P50/P25 (Percentage Point, Income Adjusted by CPI)

Table B.3: Cumulative Contribution to Changes in P75/P50 (Percentage Point, Income Adjusted by CPI)

Table B.4: Cumulative Contribution to Changes in P95/P75 (Percentage Point, Income Adjusted by CPI)