World Inequality Lab – Working Paper N° 2020/23

Distributional National Accounts (DINA) for Austria, 2004-2016

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October 2020

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This Version: October 2020

Abstract

This paper constructs distributional national accounts for Austria for the period 2004-2016. We enrich survey data with tabulated tax data and make it fully consistent with national accounts data. The comprehensive dataset allows us to analyse the distribution of macroeconomic growth across the income distribution and to explore the evolution of income inequality in pre-tax income over time. Our results suggest that the distribution of growth has changed over time, which had considerable repercussions on inequality. Inequality started to decline at the very beginning of the economic and financial crisis in 2007, however it has increased again after 2012. We further provide novel insights into the evolution of capital income for top income groups and explore redistribution mechanisms that operated in Austria. Government spending was found to play a key role for redistributive effects across the income distribution. In particular, the transfer system redistributes pre-tax income to a large extent. Our results further show that lower educated and younger individuals faced negative growth in pre-tax income over the years, but also considerably benefited from redistribution.

Keywords: Distributional national accounts; Austria; survey data; tax data; income inequality
JEL Classifications: C55, D31, E01

*This research was financially supported by the Chamber of Labour Vienna. The authors would like to thank Michael Ertl, Franziska Disslbacher, Matthias Schnetzer (AK Wien); Predrag Cetkovic, Stefan Humer (INEQ - WU Vienna) and Stefan Ederer (WIFO) for valuable and helpful comments and suggestions. `jestl@wiiw.ac.at`; `emanuel.list@wu.ac.at`.

Contents

1 Introduction

In the recent past, the question of how population groups benefit from economic growth has attracted much attention in politics, academics and the general public. It is widely acknowledged that population groups in many developed countries have participated unevenly in economic growth since the 1980s (see OECD, 2015). Lower income groups have been left behind as compared to higher income groups which increased income inequality within countries.

While the system of national accounts is well developed to measure economic growth and is to a large extent harmonized across countries, it does not record the personal distribution of income. Most of the data to measure income inequality rely, therefore, on survey or tax data which however are related to some limitations. One major shortcoming is that survey and tax data are not fully consistent with macro aggregates coming from the national accounts. There exist gaps in income components between survey as well as tax data and macro aggregates. Tax data primarily report income that is defined by fiscal law which excludes, for instance, tax exemptions. The quality of tax data[1] is further affected by tax avoidance and evasion (see, for example, Zucman, 2014). Moreover, survey data tend to underrepresent the rich and suffer from measurement errors at the tails of the distribution (see, for instance, Angel, Disslbacher, Humer, & Schnetzer, 2019). Both tax and survey data are therefore likely to underestimate inequality.

Recently, novel approaches have been developed on the initiative of the *OECD-Eurostat Expert Group*[2] and the *WID.world project*[3] to link distributional information on income, consumption and wealth to their counterparts in the national accounts. Most prominently, Piketty, Saez, and Zucman (2018) combine national accounts, survey and tax data for the US in order to obtain a long-term series of comprehensive individual income data that are fully consistent with macro aggregates. The constructed distributional national accounts (DINA)[4] data coincide with the American national income. In the meanwhile, Piketty and other prominent scholars have also applied the DINA approach to other countries using a wide range of data sources. Similar to Piketty et al. (2018), Garbinti, Goupille-Lebret, and Piketty (2018) use a rich set of data sources to generate DINA series for France for the period 1900-2014. Even more recently, Blanchet, Chancel, and Gethi (2019) compiled survey and tax data with different qualities for 38 European countries, including Austria, to produce DINA series for 1980-2017. Alvaredo et al. (2020, 2016) have collected and reconciled various approaches to use different data sources to construct DINA series and define state-of-the-art methods in their DINA guidelines.

[1] For a further discussion on limitations of tax data see Clarke and Kopczuk (2017).

[2] *OECD-Eurostat Expert Group on Disparities in a National Accounts framework (EG-DNA).* The Expert Group has its origin in a collaboration between the OECD and Eurostat in 2011 – `https://www.oecd-ilibrary.org/content/paper/2daa921e-en`

[3] `https://wid.world/`

[4] For critical notes on the DINA methodology see, for instance, Auten and Splinter (2018).

In this paper, we construct distributional national accounts for Austria for the period 2004-2016. We use survey data and tax data and combine it with national accounts data. This allows us to distribute the total national income to Austrian residents. We contribute to the literature in several ways. First, to our best knowledge, we provide the first detailed distributional national accounts series for Austria. Second, along with a small number of studies (for example Garbinti et al., 2018; Piketty et al., 2018), we rely on detailed sectoral national accounts data and thus apply a disaggregated approach to construct our series. Third, we discuss the overall impact of using the DINA methodology by comparing the final income distribution with the initial income distribution that comes from the survey data. Fourth, we present a thorough analysis of how the Austrian income distribution has been affected by the global financial and economic crisis.

In detail, throughout our analysis, we address a number of interesting questions. We analyse which population groups have benefited the most from macroeconomic growth and what have been repercussions on income inequality in Austria over time. As the crisis particularly affected the development in the financial sector (see Schürz, Schwaiger, Übeleis, et al., 2009), dynamics in capital income might have changed in the post-crisis period as compared to the pre-crisis period. When capital is concentrated among the society, changes in the return to capital are likely to have substantial implications for inter-personal income inequality (see Milanovic, 2016). Moreover, Austria is characterised by a pronounced welfare state (see Adema, Fron, & Ladaique, 2011) that has operated as an important stabilizer through the crisis (see Famira-Mühlberger & Leoni, 2014). We therefore also investigate the redistribution mechanisms that are in play in Austria. The data allow to draw a comprehensive picture of the redistributive effects, also including transfers in-kind and collective consumption. Finally, we shed light on heterogeneous effects across population subgroups.

The remainder of this paper is as follows. In Section 2 we describe the data and the methodology used in this analysis. In Section 3 we present and discuss the results of our research. Finally, Section 4 concludes.

2 Data & Methodology

In this section we outline income concepts that are typically used in distributional national accounts. In addition, we present our data sources and summarise steps that we needed to take in the data preparation process.

2.1 Income Concepts

Distributional national accounts aim to gather information on the distribution of the net national income and to explore it over time (see Alvaredo et al., 2020). The net national income equals the gross domestic product (GDP) minus capital depreciation, plus net foreign income. In addition to the income of private households, the national income also includes the income of the other domestic sectors (i.e., the nonfinancial corporations, the financial corporations, the general government, and the nonprofit institutions serving households). By applying the DINA concept, the income of all the other sectors is distributed to private households, since all income streams are assumed to benefit households eventually. Our statistical unit of analysis is the population aged 16 years and older. If a household consists of more than one person, the DINA guidelines promote two procedures to allocate income among household members. The *equal-split* approach splits income equally within a household, while the *individual-split* approach attributes income to the respective recipient. In our analysis, we primarily use the equal-split approach. Moreover, the DINA guidelines advocate the use of different income concepts[5]. We distinguish between the two following income concepts[6]:

Pre-tax National Income (PRTNI) is our benchmark income concept. It is the sum of all income flows gained by the individual owner of the factors of production, labour and capital, after taking into account the operation of the pension system as well as unemployment insurance system. Accordingly, pensions and unemployment benefits are included. However, due to data limitations contributions to both systems cannot be considered separately. We therefore deduct the total sum of social contributions (including also contributions to health and accident insurance). Other government transfers and taxes remain unconsidered. The PRTNI is the main concept to study the income distribution before government intervention.

Post-tax National Income (POTNI) adds all other government transfers and deducts all taxes from the PRTNI. Therefore, POTNI includes all social monetary transfers, transfers in-kind and collective consumption. The allocation of all forms of government spending to individuals ensures that the sum of POTNI equals the national income. The DINA guidelines recommend to allocate transfers in-kind and collective consumption proportionally to income, whereby income distribution remains unaffected. We however depart from this approach and allocate transfers in-kind and collective consumption equally by means of a per-capita allocation. Consequently, we expect to find distributional effects that emanate from these government transfer types. Rocha-Akis et al. (2019) provide insight into the distribution of transfers in-kind in Austria and base the allocation on detailed micro information from survey data. In the light of their findings, the per-capita allocation approach seems to be more accurate.

2.2 Data

To conduct our analysis, we use data from three main sources. Data on national accounts are taken from the non-financial sector accounts (ESA 2010) provided by Eurostat which are principally based

[5] An overview of the income concepts is provided in the Appendix.

[6] Importantly, both income concepts add up to the national income.

on data from National Statistical Institutions (NSI). Most importantly, these data further involve breakdowns by essential variables on the level of institutional sectors, such as private households, both financial and non-financial corporations and the governmental sector. Essentially, our analysis relies on the variables at this sectoral level.

To bring in information at the micro level, we utilise the cross-sectional data from the European Survey on Income and Living Conditions (EU-SILC). This dataset constitutes an ex-post harmonized household survey which is conducted by national statistical institutions in the European Union and is available from Eurostat. It provides detailed information about various income components and expenses at both, the individual and household level. In general, the data cover the population older than 16 years. In order to ensure the representativeness of the data, we take into account weights in our calculations. All income components are deflated to prices in 2010 using the GDP deflator from Eurostat.

Using survey data allows us to gather information about the income distribution. In survey data, the rich however tend to underreport their income which results in biased results when analysing distributional concerns. Importantly, there has been a methodological change in the data processing process of EU-SILC for Austria in 2008 (Jäntti, Törmälehto, & Marlier, 2013; Statistics Austria, 2014). From 2008 onwards, respondents' information on wages, unemployment benefits and old-age pensions are merged to the corresponding variables in their tax statements and are corrected accordingly. This allows to limit the measurement errors in these variables which is of particular concern at the top of the income distribution (see Angel et al., 2019). However, information on other income components, for example self-employment income, still relies on the respondents' information from survey data. Moreover, the data correction has not been applied in the period 2004-2007 and the underrepresentation of the rich is not taken into account in the total time period. In accordance with the DINA guidelines, we use tax data to correct top incomes in survey data. Specifically, we employ tabulated tax statistics from Statistics Austria and apply generalised pareto imputation methods to correct for top incomes. The data preparation process is discussed in more detail in the next section.

2.3 Data Preparation

2.3.1 Taxes and Social Security Contributions

The SILC dataset does not supply disaggregated data on taxes and social security contributions, which were paid to governmental bodies. It contains only the sum of those levies but not separately for taxes and social contributions. We therefore simulate taxes and social security contributions using EUROMOD, a tax-benefit microsimulation model for the European Union. For this exercise, we use the national SILC data for the respective years, since only these data sets provide the variables that are required for using EUROMOD. After conducting simulations via EUROMOD, we extract the simulated taxes and contributions separately for each person in the national SILC micro files. As concerns taxes, we distinguish between the taxation of labour income and capital income. In general, the reference income for taxes and contributions constitutes the taxable income, composed of labour and capital income. Labour income covers employees' salaries, self-employment income, public pensions and rental income while capital income includes income from different financial investments. Overall, we distinguish between simulated labour and capital income taxes, and social security contributions as well as employers' contributions. In a further step, we calculate tax and contribution ratios for each observation, where taxes refer to labour income and capital income respectively, while employees' social security contributions and employers' contributions only refer to labour income. Finally, we check the tax and social security contribution rates for outliers. In general, especially the lower part of the income distribution is characterized by more significant fluctuations in the rates. We trim a small number of observations such that all rates lie between 1 and -1. To provide tax and social contribution rates that can be applied to our dataset as well, we sort individuals by taxable income and generate average rates for each percentile. All percentiles' rates up to the highest percentile with a zero mean tax and contribution rate (below the 20^{th} percentile) are set to zero to mitigate random noise at the lower tail of the taxable income distribution. In order to decrease the impact of small fluctuations across adjacent percentiles, we smooth all rates along the taxable income distribution using smoothing splines. Since the policy regimes for the years from 2003 to 2005 are not available in EUROMOD, we extrapolate the contribution rates from 2006 back to these years. For illustration purposes, Figure A.4 in the Appendix plots average simulated tax and contribution ratios by percentile for 2016. For the first two years, there are also no data available for imputed rents and we therefore impute the data for these years using the deflated imputed rents from 2006.

2.3.2 Tax Data Calibration

As already discussed above, in 2012 Statistics Austria started to adjust the SILC data with register data for certain income concepts like wages, pensions and unemployment benefits and revised the data back until 2008 (Jäntti et al., 2013; Statistics Austria, 2014). However, self-employment income or rental income is not adjusted and furthermore the linking of individuals from the survey to register data cannot address non-sampling errors (i.e. the underrepresentation of the rich), which play a crucial role for top incomes. In order to address these shortcomings and to obtain a comprehensive data basis which allows for a valid analysis of changes over time, we apply a calibration procedure following Blanchet, Flores, and Morgan (2018) using generalised pareto imputation as suggested by Blanchet, Fournier, and Piketty (2017). The calibration especially upscales the top incomes before the structural break in 2008 and enables an unbiased analysis of income growth rates in the pre-crisis period, since the lower uncalibrated incomes before 2008 would lead to an overestimation of the income growth. Specifically, we apply generalised pareto imputations for wages and pensions as well as other income which mainly consists of self-employment and rental income. As information on capital income[7] is fairly limited and incomplete in tax data, we are not able to correct the distributional information on capital income. The distribution of capital income thus still relies on survey data information. Since capital income typically is concentrated at the top of the income distribution and the rich tend to be underrepresented in survey data, it is likely that we underestimate the concentration and thus inequality of capital income. However, by applying the DINA methodology we realign capital income such that the sum in the survey data matches the corresponding aggregate in the national accounts (see more details below in Section 2.3.3). Even though this procedure does not alter the distribution of capital income, it has an impact on the total income distribution. Ederer, Humer, Jestl, and List (2020) show that building DINA based on detailed sectoral national accounts results in scaling effects due to realining, among others, capital income[8] which is concentrated at the top of the income distribution. Figure A.5 in the Appendix illustrates the differences in the scaling effect between property income and labour income in 2016. We find that scaling effects, primarily related to property income, are concentrated at the top. Thus, the DINA methodology allows to distribute the sum of capital income registered in national accounts and to increase the role of capital income for total income at the top which in turn results in an inequality-increasing effect. We however acknowledge that this procedure is not able to fully account for a capital income correction using administrative data[9].

A detailed summary of the tax data calibration procedure can be found in the Appendix.

2.3.3 Micro-Macro-Matching

By constructing distributional national accounts, we use income concepts that add up to national income. Survey and tax data however are not fully consistent with national accounts data. On the one hand, survey and tax data do not cover all income components that are part of the national income, and on the other hand, there exist gaps in terms of the aggregated amounts reported in survey as well as tax data and the aggregates from national accounts for variables that are included in both sources.

[7]Capital income is defined as the sum of *property income*, including dividends, interest gains, reinvested earnings on foreign direct investment, investment income disbursements and land rents.

[8]The total impact of a variable on the income distribution is determined by three factors: its distribution in the enriched survey data; its coverage rate, that is the gap between its sum in the enriched survey data and national accounts; and its contribution to national income. As discussed, information on the capital income distribution comes from the original survey data. Capital income further shows to have a relatively stable coverage rate over time, however ranging at a very low level (see *"Interest w/o FISIM & distributed income of corporations"* in Table A.3 in the Appendix). This results in a relatively large scaling factor, whereby the impact is higher than for other variables (for differences in the scaling effects between property income and labour income see Figure A.5 in the Appendix). The contribution of capital income (*property income* – "PropInc") to national income can be found in Figure 3a and Figure 3b in Section 3 as well as in Table A.3 in the Appendix. For a more detailed discussion on data issues related to the DINA methodology see Ederer et al. (2020).

[9]This is also the reason why we do not analyse income groups above the top 1%. For example Piketty et al. (2018) utilise comprehensive tax data and analyse developments for income groups far above the top 1%.

Following the DINA guidelines, we apply imputation methods to balance the sums in micro – our enriched survey data – and macro data – the national accounts data. For variables that appear in both, the enriched survey data and national accounts, we compare the sums and scale up the enriched survey data to the national accounts counterpart[10]. Specifically, we use a proportional upscaling approach, where the scaling factor is the same for all individuals which eventually does not change the variable's distribution. Thus, information on the distribution of these variables still comes entirely from the enriched survey data.

In addition to the items for which we have direct distributional information in the survey, we have to rely on simulations and imputations of other variables needed for the calculation of income concepts. Thus, for variables that are only in national accounts, we need to find a valid allocation key to impute distributional information. On the one hand, we select comparable variables that are included in the survey data and adopt the corresponding distribution[11]. On the other hand, we use simple allocation keys – per-capita and equally proportional to income[12] – for variables for which not even indirect distributional information is available. An overview of the correspondence between individual variable and national accounts and of the allocation procedure is illustrated in Table A.3 in the Appendix. For a more detailed discussion on the procedure see Ederer et al. (2020).

As already discussed above, Blanchet et al. (2019) generate DINA for 34 European countries including Austria. Although they use similar data sources as we do, such as EU-SILC and tax data, they use a different approach to scale up micro data. While we seek to match micro income variables with national accounts and subsequently scale up the survey data, Blanchet et al. (2019) only scale up a limited number of income components[13]. Accordingly, they do not use detailed sectoral national accounts data and apply a more aggregated approach.

2.3.4 From Survey to DINA

By applying the DINA methodology, we add income to our enriched survey data to make them fully consistent with national accounts. Since we construct a full synthetic micro data set based on survey, tax and national accounts data, we can provide detailed insights into how the application of the DINA methodology impacts the income distribution that comes from the initial survey data.

[10]This predominately applies to variables that refer to the household sector (S14). For an overview of this variable group see the first section in Table A.3 in the Appendix.

[11]For instance, following Piketty et al. (2018) we distribute retained earnings in the same way as capital income (i.e. property income) for which we have distributional information in the survey data.

[12]For example, we distribute social transfers in-kind and collective consumption equally by means of a per-capita allocation across the population.

[13]Since we apply a proportional upscaling approach, the distribution of the respective variables remain unaffected. However, differences in the upscaling factor across variables result in changes in the distribution of the total income. For a detailed discussion on the impact of scaling and variable imputations on the income distribution using the DINA methodology see Ederer et al. (2020).

Overall, we distinguish between three important steps that determine the way from the original survey data to the final distributional national accounts[14]: First, we adjust the gross income in the survey data by using tabulated tax data and applying generalised pareto imputations (see Section 2.3.2). Second, we compare the variables in the enriched survey data with their national accounts counterparts and scale up these variables in order to balance the sums (see Section 2.3.3). This predominately applies to variables that refer to the household sector (S14)[15]. Third, we employ simulation and imputation methods to import income components for which we do not have direct distributional information in the enriched survey data. This applies to items from the household sector and from other sectors in the national accounts (e.g. the nonfinancial and the financial corporations) (see Table A.3 in the Appendix).

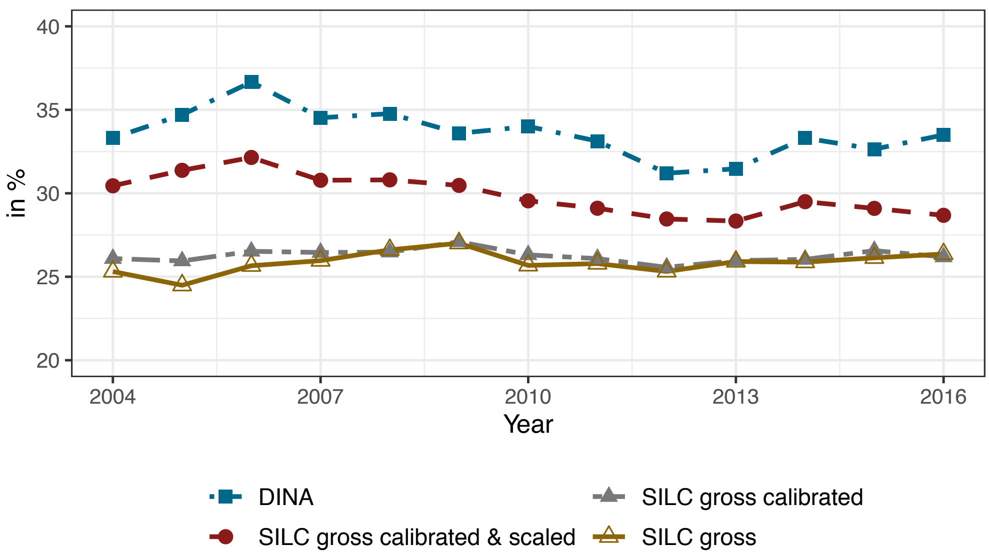
Figure 1 shows the pre-tax income share of the top 10% for four different income concepts: the original survey data ("SILC gross"), the enriched survey data ("SILC gross calibrated"), the scaled enriched survey data ("SILC gross calibrated & scaled") and the pre-tax national income in accordance with the DINA methodology ("DINA").

Within the household sector, we can see that the tax data calibration leads to an increase in the top 10% share, especially in the pre crisis period. This is not that surprising, as survey income has only been linked to register data from 2008 onwards (see Section 2.3.2). Next, the upscaling of the income components from the enriched survey data to the national accounts aggregates results in an substantial increase in the top 10% income share. This is primarily related to the poor survey coverage of income components, most notably property income (see *"Interest w/o FISIM & distributed income of corporations"* in Table A.3 and Figure A.5 in the Appendix), that are concentrated at the top of the income distribution. We observe a further large increase in the top 10% income share when we move from the scaled and calibrated SILC gross income to the DINA income concept. On the one hand, this effect refers to the import of income components from the household sector that are not available in the enriched survey data; and on the other hand, to the incorporation of income components from other sectors in the national accounts, such as the nonfinancial and the financial corporations.

Accordingly, Figure 1 indicates that we do not only substantially increase income inequality by applying the DINA methodology; we also implement larger dynamics in inequality over time. Interestingly, this is not only due to the import of income components for which we do not have direct information in the enriched survey data; it also applies to the scaling procedure that exclusively operates in the household sector.

[14]For an overview of the relationship between the different income concepts see Table A.3.
[15]See first section in Table A.3 in the Appendix.

Figure 1 **From survey to DINA – top 10% income share by income concept**



Source: Statistics Austria, EU-SILC.
Notes: Own illustration.

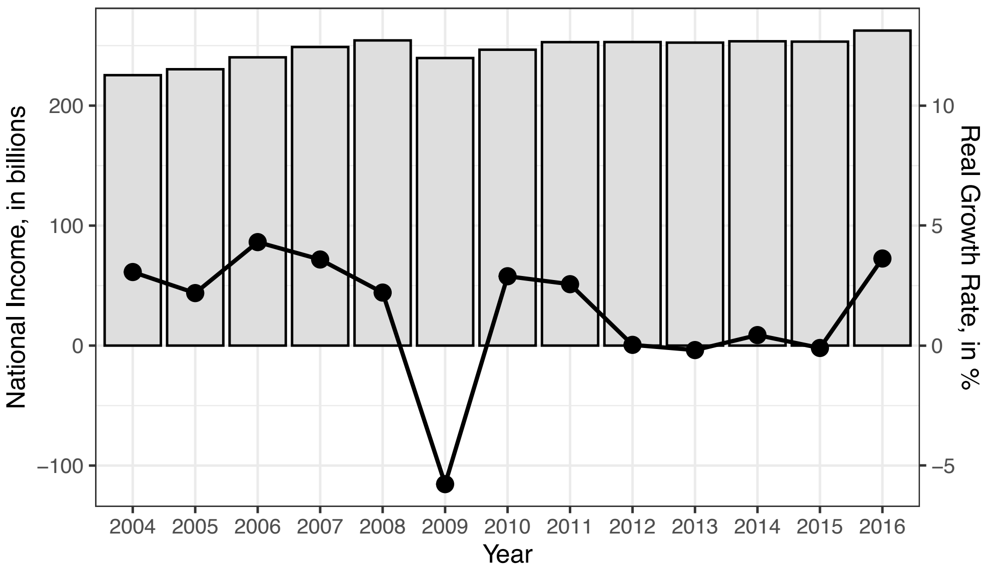
3 Results

We then move on to the results of our analysis. We start by looking at the general macroeconomic development in Austria. After that, we analyse and discuss the distribution of pre-tax national income, how economic growth has been distributed and what are the repercussions on income inequality. We further shed light on capital income in particular at the top of the distribution and explore redistribution mechanisms that operate in Austria.

3.1 Economic Development

Before we embark on a detailed analysis of the distribution of the national income, it is useful to look at the evolution of the aggregated national income in order to give an insight into the overall economic development. Figure 2 shows the development of the national income in Austria over the period 2004-2016. The y-axis on the left-hand side records the real national income (in billions), while the axis on the right-hand side illustrates the real annual growth rates. From 2004 to 2008, Austria shows constant annual growth rates above 2%. In 2008 the global economic and financial crisis however hit the Austrian economy. As we can see, national income declined by more than 5% from 2008 to 2009. Austria, however, experienced a fast recovery in 2010. Automatic stabilizers and the pronounced social security system helped to stabilize economic development in the period after 2009 (see Famira-Mühlberger & Leoni, 2014). After national income had been stagnating from 2013 to 2015, it started to grow again in 2016.

Figure 2 **National income in Austria, 2004-2016**



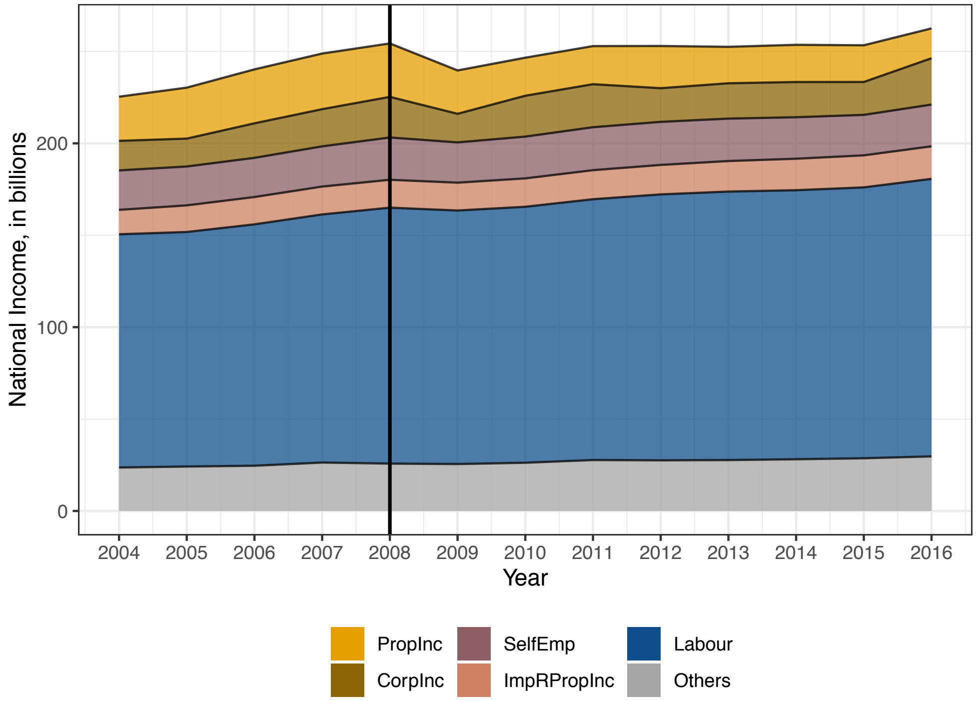
Source: Statistics Austria, 2019.
Notes: Own illustration.

To take an even closer look at the economic development, we further split the national income into its major components. To do so, we distinguish between *property income* ("PropInc"), *primary income of the corporate sector* ("CorpInc"), *mixed income* (self-employment income – "Self-Emp"), *operating surplus* ("ImpRPropInc" – imputed rents & rents), *compensation of employees* ("Labour") and "Others" that capture the residual. Figure 3a shows the composition of the absolute national income and Figure 3b illustrates the corresponding shares. Interestingly, labour income and imputed rents grew at a relatively constant rate from 2004 to 2016, with a short period of stagnation in 2009. So, as it is clearly visible in Figure 3a, the drop in the Austrian national income stems from a decline in property income "PropInc" and retained earnings "CorpInc". We observe a sharp drop in those two income components. Retained earnings reveal a small decline in 2012 as well. This pattern can also be found in Figure 3b, where the shares of both components are lower in the years after than before 2008. Thus, the crisis did not only affect the Austrian national income in general, but also restructured its composition.

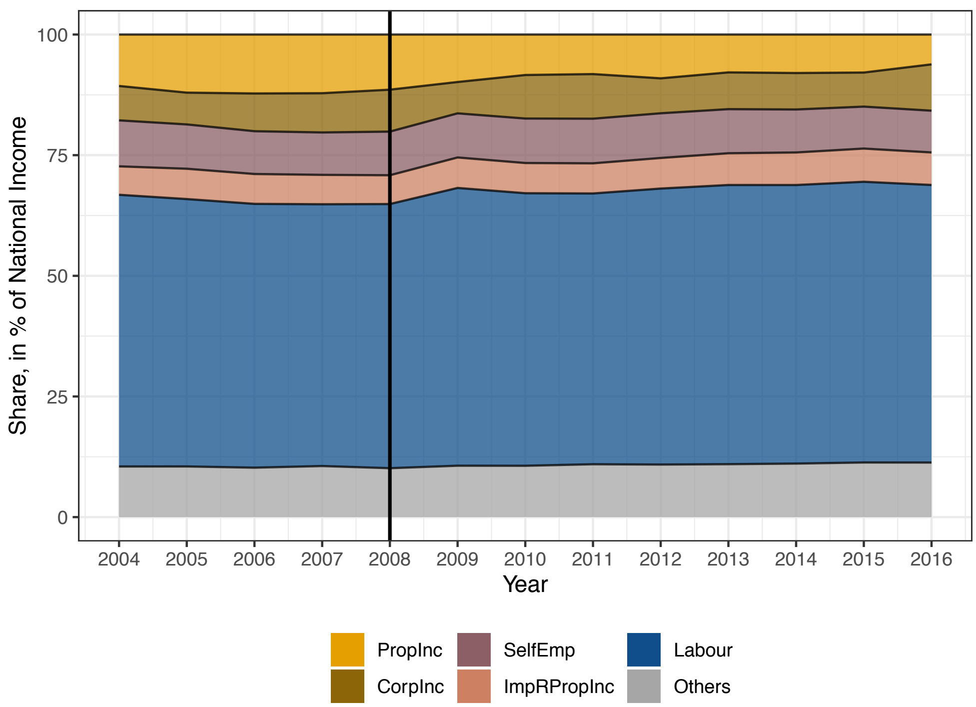
3.2 Distribution of Economic Growth

After having discussed the general evolution of the national income, we focus in the following on its distribution. To give a first insight into the general standard of living in Austria, we take a look at the pre-tax income levels across Austrian residents.

Figure 3 **Composition of national income in Austria, 2004-2016**



(a) **Absolute**



(b) **in %**

Source: Statistics Austria, 2019.
Notes: Own illustration.

Essentially, the per-capita (average) national income is the commonly used measure to capture a country's prosperity. This however totally ignores the distribution of income among a society. Importantly, our dataset allows us to compare income levels of different income groups where income adds up to national income. Table 1 reports the level of real pre-tax income for various income groups in 2016.

Table 1 **Pre-tax national income, 2016**

	Population	in EUR
Total population (P0-P100)	7,291,881	36,035
Median (P50)	73,038	26,999
Bottom 50% (P1-P50)	3,645,658	16,854
Bottom 30% (P1-P30)	2,185,480	12,483
Next 20% (P31-P50)	1,460,178	23,411
Middle 40% (P51-P90)	2,916,668	38,790
Top 10% (P91-P100)	729,556	120,417
Top 5% (P96-P100)	364,612	169,323
Top 1% (P100)	73,248	390,407

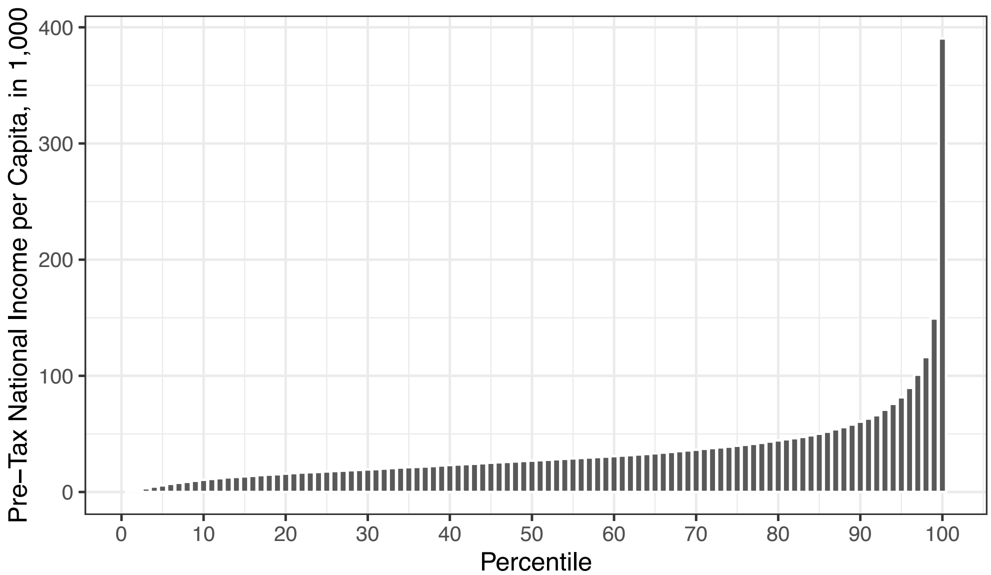
Source: Statistics Austria, 2019.

The average pre-tax income among Austrian residents amounts to 36,035 € in 2016, while the income for individuals located at the middle of the income distribution (P50) is 26,999 €. The difference between those two numbers indicates that the pre-tax national income distribution is somehow skewed to the right. As the average national income takes into account the total income distribution, high income values push the average upwards. This becomes even more visible, when we turn to the income levels for groups along the pre-tax national income distribution. While the bottom 50% of the income distribution (P1-P50 – from the 1^{st} percentile to the median) earn on average only 16,854 €, the upper middle class (P51-P90 – from the median to the 90^{th} percentile of the distribution) receives 38,790 € and the top 10% (P91-P100) 120,417 €. Interestingly, the upper middle class earns almost the same average income as the total population. In contrast, the top 10% receive a 3.3 times higher average income than the total population. Thus, when we move up the distribution, differences in income become larger. Especially within the group of the top 10%, we observe remarkable differences in income levels. The top 5% receive an average income that is 4.7 times higher than the population-wide average. The ratio even amounts to 10.8 for the top 1%.

This pattern in income levels across the pre-tax national income distribution is also clearly visible when we look at average incomes by percentile in Figure 4. We find a linear increase in income levels from the bottom to the 80^{th} percentile at around 50,000 €. Accordingly, approximately 80%

of the population in Austria earn less than 50,000 € before taxes and transfers in 2016. Moving further up the distribution, income levels start to increase exponentially. Remarkably, the average income of the top 1% (P100) is more than two times higher than that of the previous percentile (P99). Thus, there is a sharp increase in pre-tax income at the very top of the distribution.

Figure 4 **Pre-tax national income in Austria, 2016**

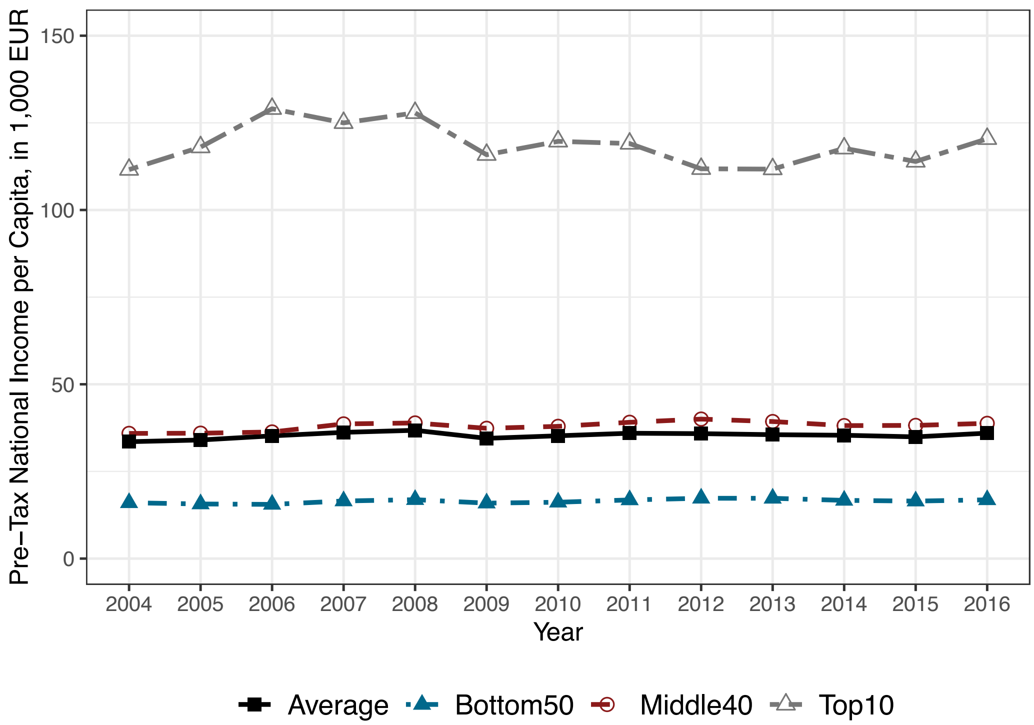


Source: Statistics Austria, EU-SILC.
Notes: Own illustration.

Our constructed dataset also allows to explore the evolution of pre-tax income levels across the distribution over time. Figure 5 plots the average pre-tax income for the total population, the bottom 50%, the upper middle class (P51-P90) and the top 10% from 2004 to 2016. The bottom 50% earn an average pre-tax income a year lower than 25,000 € over the entire period. The average income of the upper middle class follows closely the path of the population-wide average income. Although we see a small increase in average income until 2008, both average income levels show a rather constant path over time. Unsurprisingly, most changes are visible for the top 10%. Here, we observe a considerable increase in the pre-crisis period. From 2008 to 2009, the top 10% however experienced a drop in average pre-tax income of around 20,000 €; while from 2009 onwards, the average income has remained fairly constant.

In order to give a closer insight into the evolution of pre-tax income across the distribution, we now turn to the analysis of income growth. Importantly, pre-tax income growth across the distribution is fully consistent with the macroeconomic growth. This allows us to address the question of how economic growth has been distributed among Austrian residents. To do so, we calculate the average real annual growth rates by percentiles across the pre-tax income distribution for several

Figure 5 **Pre-tax national income in Austria, 2004-2016**



Source: Statistics Austria, EU-SILC.
Notes: Own illustration.

time periods.

We start with the growth incidence curve for the pre-crisis period (2004-2008) in Figure 6a. The black solid line at above 2% indicates the macroeconomic growth. When we compare this growth rate with the percentile-specific growth rates, we find a clear pattern. Although we observe positive annual growth rates across the total distribution, percentiles up to 85^{th} reveal growth rates that are below the macroeconomic growth rate. Accordingly, nearly 85% of the Austrian population have been left behind in the period 2004-2008. By contrast, the top 10% have increased their average income at rates above 3%, with the exception of the 99^{th} percentile. In particular the top 1% have experienced a relatively high increase in average income of above 4%, which is significantly larger than the macro growth rate. Overall, this picture clearly indicates that economic growth was very skewed across the Austrian population in the pre-crisis period.

Next, we take a look at the average annual real growth rates for the period 2008-2016 in Figure 6b. As it is clearly visible, this pattern is completely different as compared to the pre-crisis period. First, we find a negative macro growth rate of almost 0.3%. Second, roughly 80% of the Austrian population reveal a growth rate at around zero. Third, the top 20 percentiles predominantly show negative growth rates which eventually accumulates to the negative macro growth rate. In particular the average income of the top 3% (P97-P100) collapsed in the period 2008-2016. The growth rate for the top 1% was almost -2%[16]. Contrary to the pre-crisis period, the lower 80% of the Austrian population suffer from an income stagnation while the top 20% suffer from income losses.

In Figure 7a we combine the two time periods and plot the average annual real growth rates for the period 2004-2016. We find the same pattern for almost the entire Austrian population. For the majority of the Austrian population, income has grown closely at the macro growth rate of around 0.6%. Interestingly, the top two income percentiles reveal growth rates that are close to zero. Accordingly, income losses for the top 1% in the period 2008-2016 nearly entirely offset the income gains from the pre-crisis period. Since the crisis has had a major impact on income growth, we additionally look at the growth rates for the period 2008-2009. As it is illustrated in Figure 7b, pre-tax income across the total income distribution has collapsed. Income has predominantly declined from -4% to -6% for the lower 97% of the Austrian population, while it has decreased even more at the top of the distribution ranging from -6.5% to approximately -17%.

[16]Please note this negative growth rate at the top is not only due to a hard hit immediately after the outbreak of the global financial and economic crisis (see Figure 7b). We also identify negative growth rates at the top of the income distribution for the period 2010-2016.

Overall, we find considerable changes in income growth patterns over time at the top of the distribution, while relatively constant patterns for the lower and upper middle income class. Table 2 summarises the growth rates for broader income groups for the selected time periods. We find again the same pattern: in the pre-crisis period the further one moves up the ladder, the higher are the average growth rates. From 2008 onwards, the lower and upper middle income class experienced an income stagnation, while the very top income losses. This pattern is in line with the findings of Blanchet et al. (2019), who show that income growth has been highly concentrated at the top of the distribution in European countries in the years until the crisis. In the period after 2008 however pre-tax income barely grew across the total distribution.

Table 2 **Average annual real growth rates – pre-tax national income**

	2004-2008	2008-2016	2004-2016	2008-2009
Average	2.35	-0.28	0.59	-6.27
Median (P50)	1.50	0.26	0.67	-4.56
Bottom 50% (P1-P50)	1.36	-0.03	0.43	-5.86
Bottom 30% (P1-P30)	0.94	-0.23	0.16	-6.83
Next 20% (P31-P50)	1.72	0.13	0.65	-5.07
Middle 40% (P51-P90)	2.02	-0.04	0.65	-3.94
Top 10% (P91-P100)	3.46	-0.75	0.64	-9.39
Top 5% (P96-P100)	3.60	-0.97	0.53	-11.01
Top 1% (P100)	4.17	-1.57	0.30	-16.72

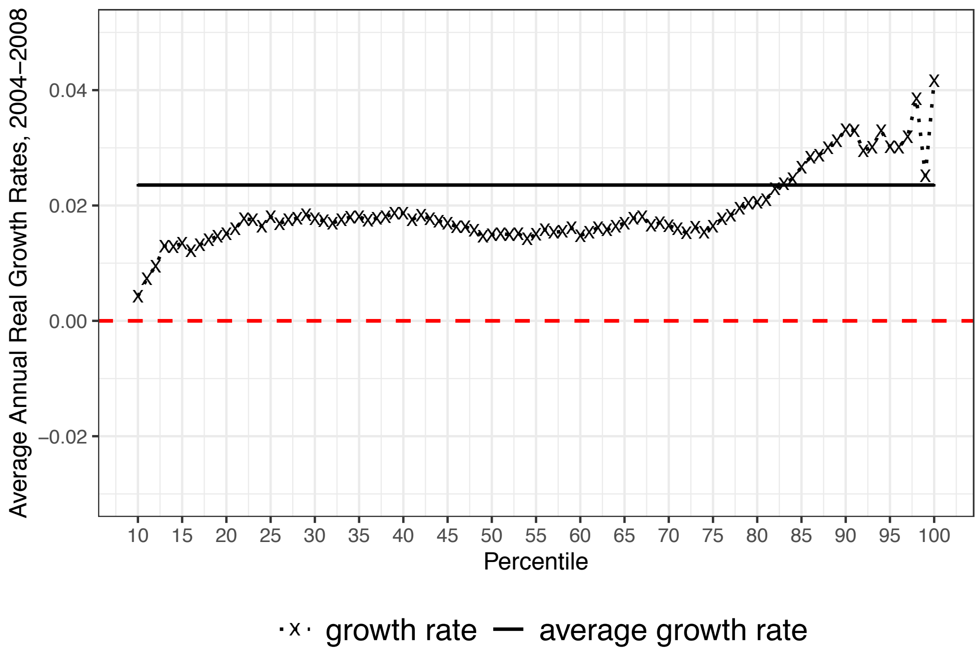
Source: Statistics Austria, 2019.

3.3 Inequality

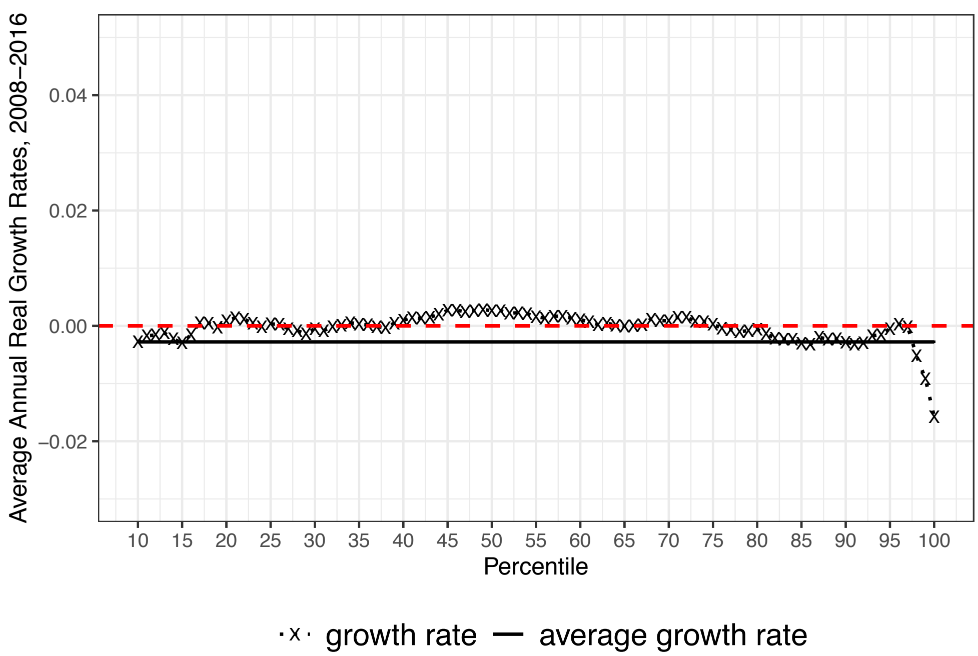
An uneven distribution of economic growth has repercussions on income inequality. The global financial and economic crisis has affected the distribution of economic growth substantially. As growth patterns before and after the crisis are significantly different, we expect to find dynamics in income inequality over time.

Figure 8a shows the share of the pre-tax national income by income group. We distinguish again between the bottom 50%, the middle 40% and the top 10%. The bottom 50% have the lowest pre-tax national income share which amounts to around 25%. Even though the share is relatively stable over time, we find a slight increase between 2006-2012. After 2012, the bottom 50% share however levels off and even started to decline marginally. Turning then to the share of the middle 40%, we observe a similar pattern: an upward trend between 2006-2012 and a declining trend after 2012. For the upper middle class the share however ranges between 40% and 45%. The remaining 30%-35% of the pre-tax national income are earned by the top 10%. Accordingly, around one

Figure 6 **Growth incidence curves – pre-tax national income**



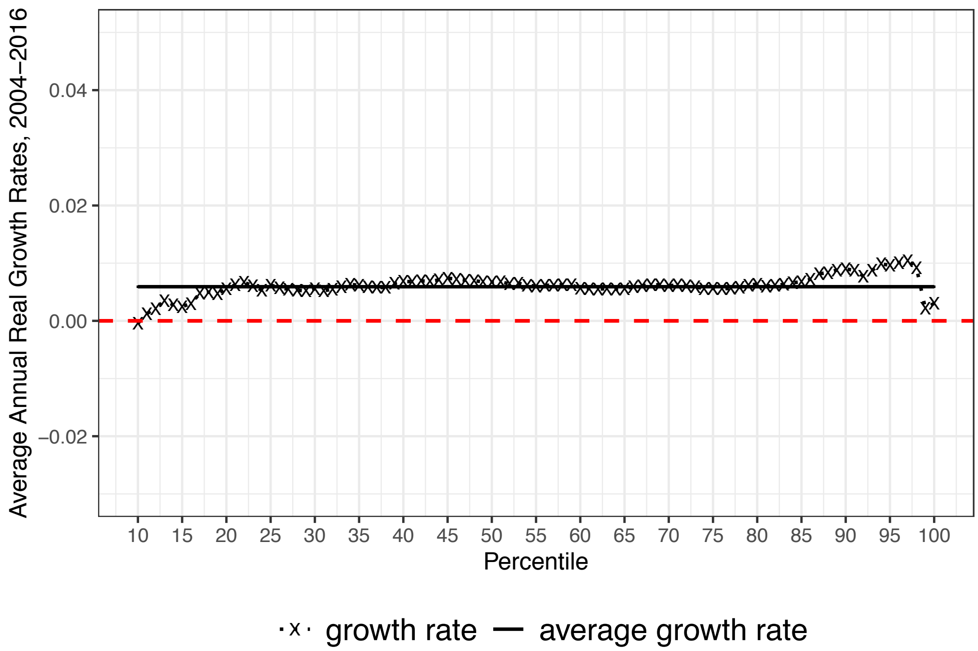
(a) **2004-2008**



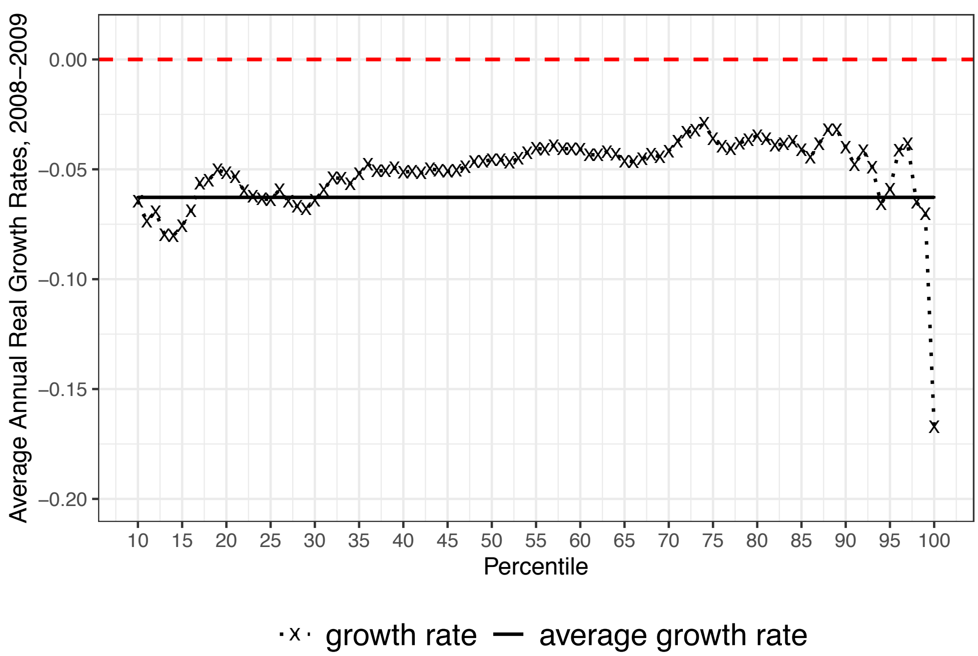
(b) **2008-2016**

Source: Statistics Austria, EU-SILC.
Notes: Own illustration.

Figure 7 **Growth incidence curves – pre-tax national income**



(a) **2004-2016**



(b) **2008-2009**

Source: Statistics Austria, EU-SILC.
Notes: Own illustration.

third of the total pre-tax national income accrues to the highest income group. Unsurprisingly, the pattern of the top 10% share is rather the opposite of the middle 40%. The top 10% reached its peak in 2006. Within the period 2006-2012, we then observe a continuous decline in the top share. However after the turning point in 2012, we see again an upward trend in the top income share. Interestingly, these findings point out that inequality has already started to decline at the very beginning of the global economic and financial crisis in 2007.

The findings in Figure 8a suggest that income inequality in pre-tax national income started to decline after 2006 and to increase again after 2012. In line with this pattern, the Gini coefficient for the pre-tax national income in Figure 8b shows a pretty similar evolution. The Gini coefficient reveals its highest point in 2006 at around 45%, while it reaches its lowest at approximately 40%.

3.4 Capital Income

In their seminal paper Piketty et al. (2018) demonstrate the overwhelming role of capital income[17] for the top income group in the US. While capital income is more than 50% of pre-tax income within the group of the top 10%, it only amounts to 10% for the bottom 90% of the US population.

In particular, when capital income is concentrated at the very top of the total income distribution, dynamics in this income component are influential for inter-personal income inequality (see Milanovic, 2016). It is therefore reasonable to explore the evolution of capital income over time and examine its concentration among top income groups. Our dataset allows to apply a comprehensive definition of capital income[18]. Specifically, we define capital income as the sum of *property income*, including dividends, interest gains, reinvested earnings on foreign direct investment, investment income disbursements and land rents; and *primary income of the corporate sector*[19] which covers principally retained earnings.

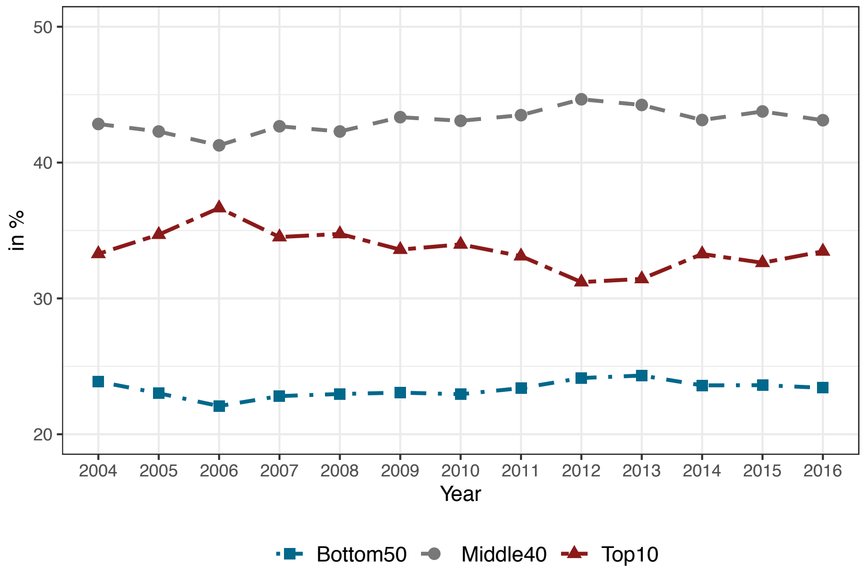
In Figure 9 we see the evolution of capital income in the group of the (a) top 10%, (b) top 5%, (c) top 1% and (d) bottom 90%. The yellow area indicates the property income ("PropInc"), the brown area the retained earnings ("CorpInc") and the grey area captures all other income components ("OtherInc"). In general, we find a clear pattern when we compare the four income groups. The more we move up the income ladder, the more important capital income is relative

[17]They define capital income as the sum of imputed rents of homeowners, property taxes, returns of pension funds, corporate retained earnings, capital income earned by trusts and estates, and corporate taxes.

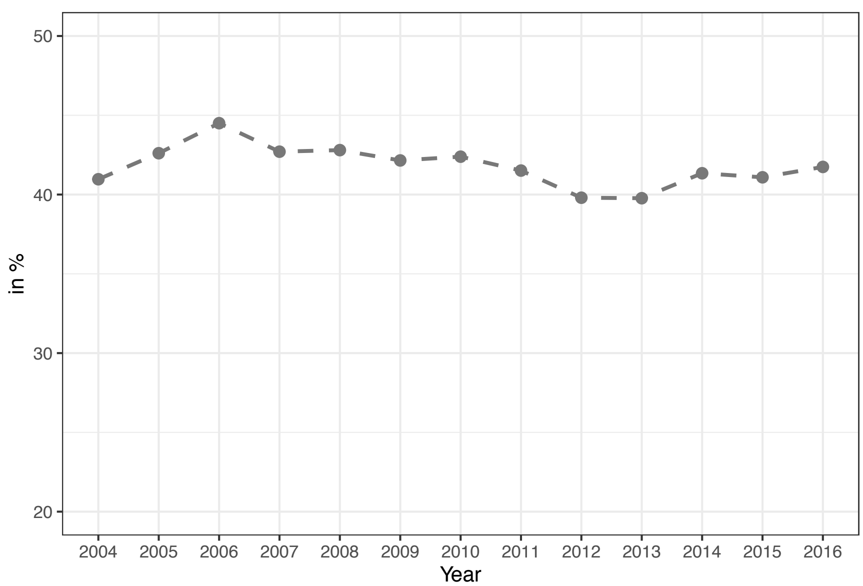
[18]We stress again that distributional information on capital income entirely comes from survey data. Although the DINA methodology allows to put more weight on capital income at the upper tail of the income distribution (see Section 2.3.2), it is likely that we underestimate the concentration of capital income at the very top.

[19]Following Piketty et al. (2018) we distribute the primary income of the corporate sector in the same way as capital income (i.e. property income) for which we have distributional information in the survey data. For a critical note on the assumption that retained earnings are distributed like dividends and realised capital gains see Alstadsæter, Jacob, Kopczuk, and Telle (2017). They use comprehensive register information for Norway to show that the approach of Piketty et al. (2018) results in an underestimation of inequality when retained earnings are large.

Figure 8 **Inequality in pre-tax national income in Austria, 2004-2016**



(a) **Pre-tax national income shares, 2004-2016**

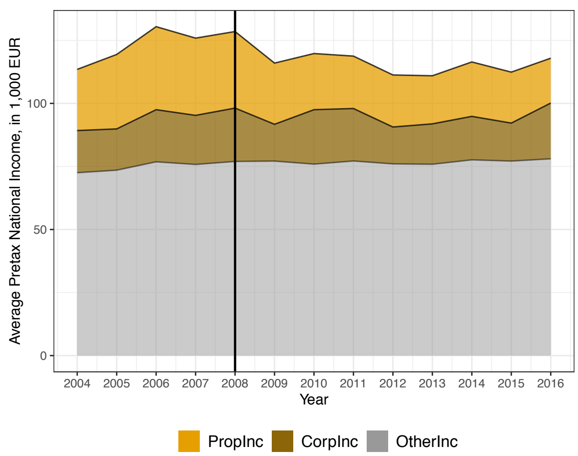


(b) **Gini coefficient – pre-tax national income, 2004-2016**

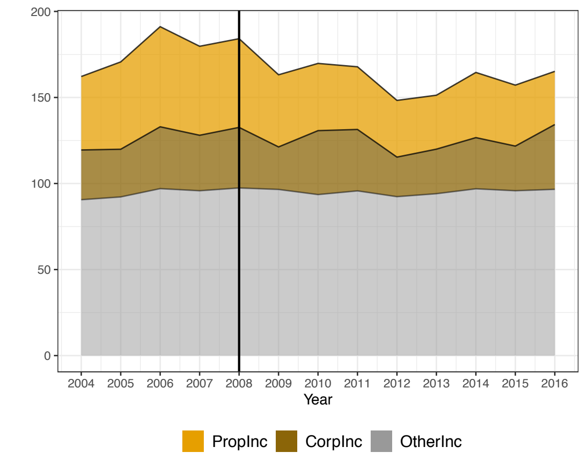
to pre-tax income. This pattern becomes even more striking, when we take a look at the shares of capital income in Figure 10. Capital income amounts only to around 10% of pre-tax income for the bottom 90%, while the top income groups reveal a share that ranges from 30% to even 60%. Accordingly, capital income is rather unevenly distributed among the Austrian population. Even more surprisingly, these shares of capital income across the distribution are not far below the shares for the US. Turning back to the capital income levels in Figure 9, we also identify an interesting pattern in its evolution over time. As it was already highlighted in Figure 3a and Figure 3b, both capital income components aggregated experienced a significant decline in the years after 2008. Retained earnings additionally dropped from 2011 to 2012. This pattern is also reflected in the evolution of capital income among the top income groups. Starting in 2006, but in particular after 2008, capital income shows a decline until 2012. After 2012, capital income however seems to recover again. These results are consistent with the findings of Roine, Vlachos, and Waldenström (2009), who show that the financial development is pro-rich and primarily impacts the income of groups at the very top of the distribution.

Another striking finding is that the evolution of capital income at the top resembles the dynamics in income inequality that we found in Figure 8b. Capital income therefore appears to have had an important impact on income inequality. This is again in line with previous findings for Austria (see, for example, Rocha-Akis et al., 2019). Moreover, Roine et al. (2009) also find that banking crises have a strong negative effect on the income share of groups at the very top of the income distribution. Our findings in combination with the decline in the income share of the top 10% in Figure 8a correspond to such an effect.

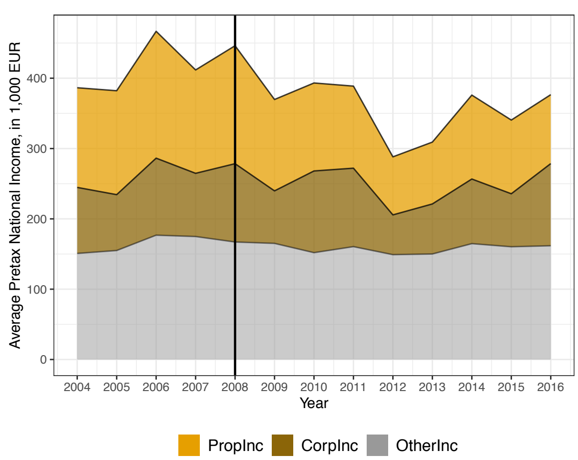
Figure 9 **Capital income by income group – levels, 2004-2016**



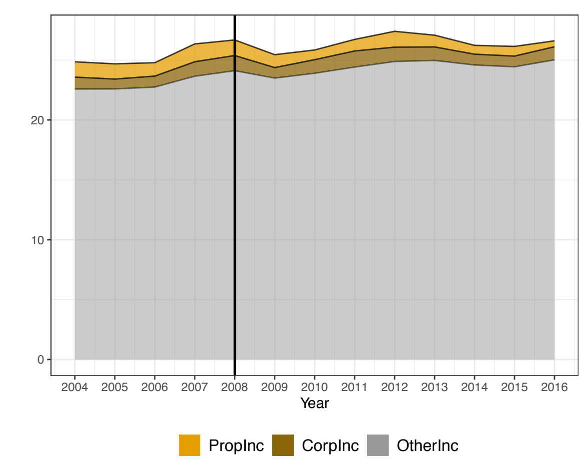
(a) **Top 10%**



(b) **Top 5%**



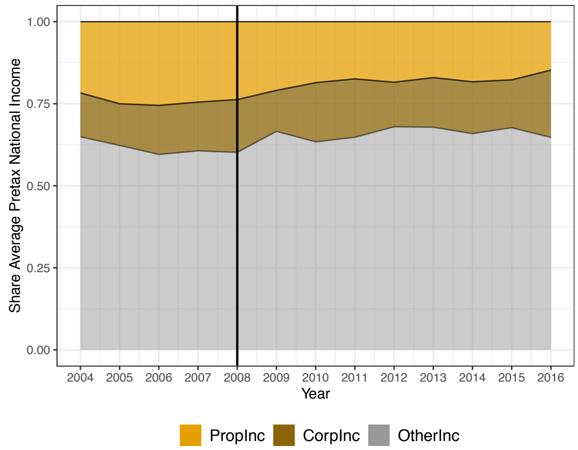
(c) **Top 1%**



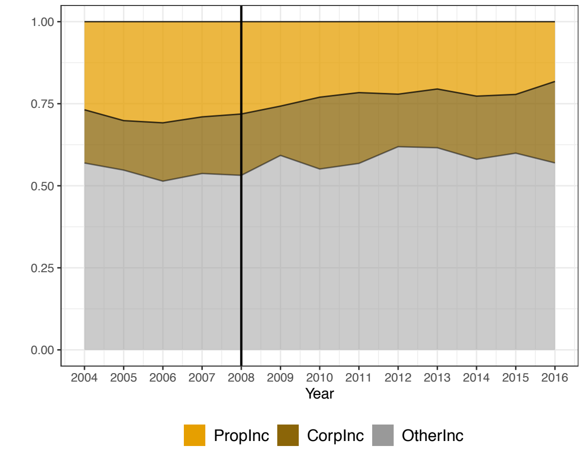
(d) **Bottom 90%**

Source: Statistics Austria, EU-SILC.
Notes: Own illustration.

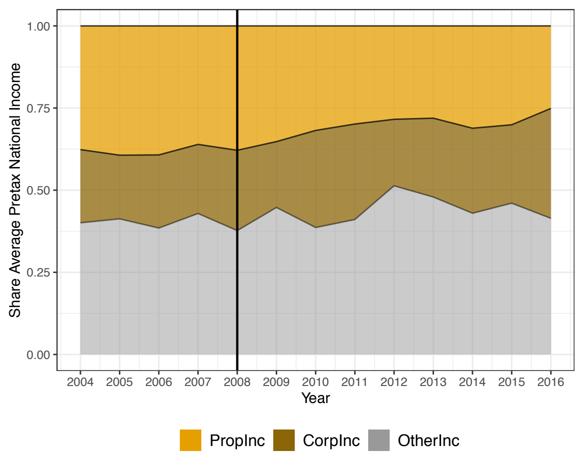
Figure 10 **Capital income by income group – shares, 2004-2016**



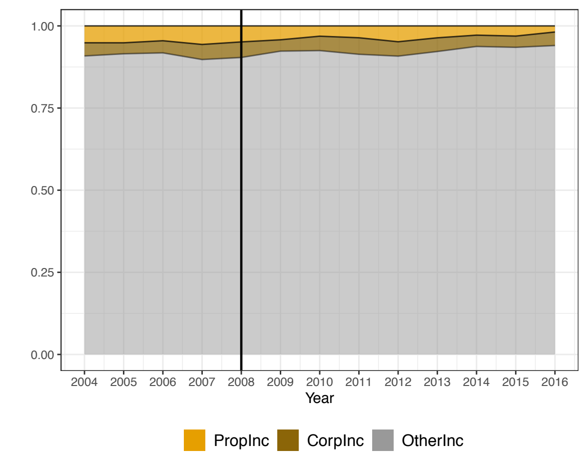
(a) **Top 10%**



(b) **Top 5%**



(c) **Top 1%**



(d) **Bottom 90%**

Source: Statistics Austria, EU-SILC.
Notes: Own illustration.

3.5 Redistribution

So far, we have primarily addressed the pre-tax income and have looked at its evolution in the period 2004-2016 from different perspectives. As discussed in Section 2, pre-tax income is defined as the sum of all factor income, before taking into account the operation of the tax and transfer system, but after taking into account the operation of the pension and unemployment insurance system[20]. In the next step, we evaluate the redistribution mechanisms that operate in Austria. To do so, we now introduce the post-tax income which includes income from all sources, after additionally taking into account the operation of the tax and the other transfer system[21]. Most importantly, it also considers all transfers and public spending. In addition to the pension and unemployment insurance system, the social insurance system in Austria additionally covers the sickness and the accident insurance. Further monetary transfers are in particular family-related benefits. The major part of in-kind transfers can be ascribed to benefits in the field of education and health (see Rocha-Akis et al., 2019). Recommended by Alvaredo et al. (2020), government expenditures – transfers in-kind and collective consumption – are allocated in a distribution-neutral way. Only transfers in-kind related to health are equally allocated per capita.[22] We however deviate from this procedure in our baseline scenario and allocate all of government expenditures equally per-capita. Rocha-Akis et al. (2019) show for Austria that absolute transfers in-kind expenditures tend to be equally distributed across the distribution. A per-capita allocation therefore seems to be a more accurate approach. We also calculate post-tax national income following the assumptions about government expenditures in Alvaredo et al. (2020). The results are shown in Figure A.6 in the Appendix. The per-capita distribution of social transfers in-kind and collective consumption results in redistributive effects by definition. We therefore find higher redistributive effects in our baseline scenario as compared to the results following Alvaredo et al. (2020).

To get a sense of the overall redistribution mechanisms in Austria, we first take a look at income inequality before and after redistribution. Figure 11a contrasts the Gini coefficient for pre-tax and post-tax national income over time. By looking at this figure, we observe two key findings: First, income inequality after redistribution shows a parallel movement to income inequality before redistribution. Accordingly, redistribution mechanisms operate rather constant over time. Second, the large gap between the two measures points to substantial redistributive effects. Redistribution lowers income inequality by around 14 percentage points on average. Likewise, we also find important redistributive effects when we contrast the income shares of pre-tax income (see Fig-

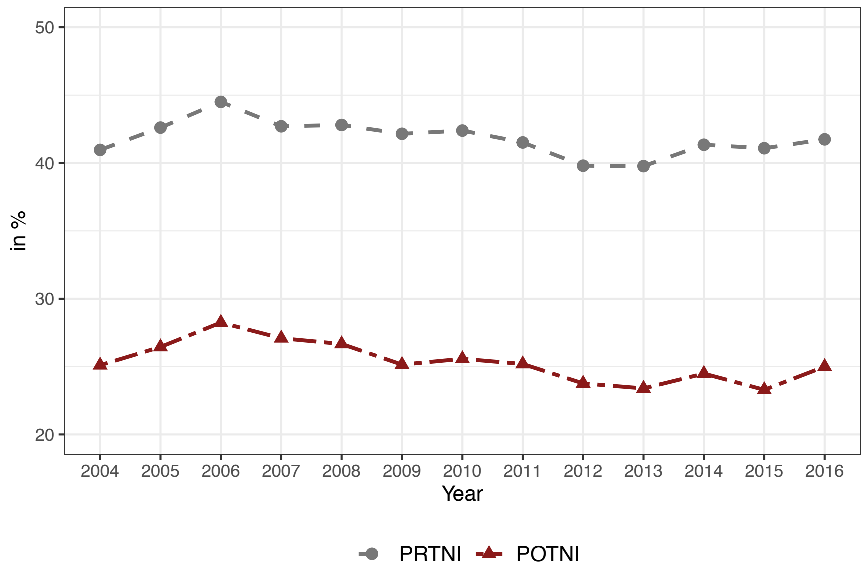
[20]As already discussed, in pre-tax national income we include pensions and unemployment benefits, however deduct the total sum of social contributions.

[21]We follow Piketty et al. (2018) and assume that indirect taxes are paid proportionally to pre-tax factor income (see Table A.3). Thus, the redistributive effects of indirect taxes are limited. Rocha-Akis et al. (2019) show that indirect taxes reveal small redistributive effects in Austria. In fact, relative indirect tax burden slightly diminishes across the income distribution.

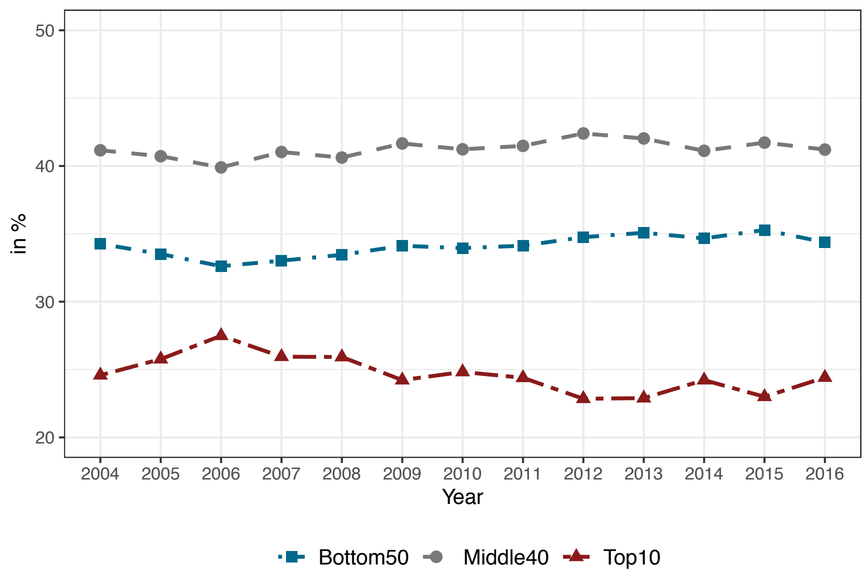
[22]For a detailed discussion on the allocation of government spending see Alvaredo et al. (2020). A critical note on the allocation of government spending can be found in Auten and Splinter (2018).

ure 8a) with those of post-tax income in Figure 11b. Interestingly, the income share of the middle 40% is more or less the same; irrespective of looking at pre-tax or post-tax income. However, we identify substantial changes when we compare the income shares of the bottom 50% and the top 10%. Remarkably, the income share of the bottom 50% increases from below 25% to above 30% as a result of the operation of the redistribution system. As expected, redistribution benefits especially population groups at the lower part of the distribution. Importantly, contrary to the income shares of pre-tax income, the top 10% hold the lowest proportion of post-tax income with below 30% throughout the total period.

Figure 11 **Inequality in pre-tax and post-tax national income, 2004-2016**



(a) **Gini coefficient – pre-tax income & post-tax income, 2004-2016**



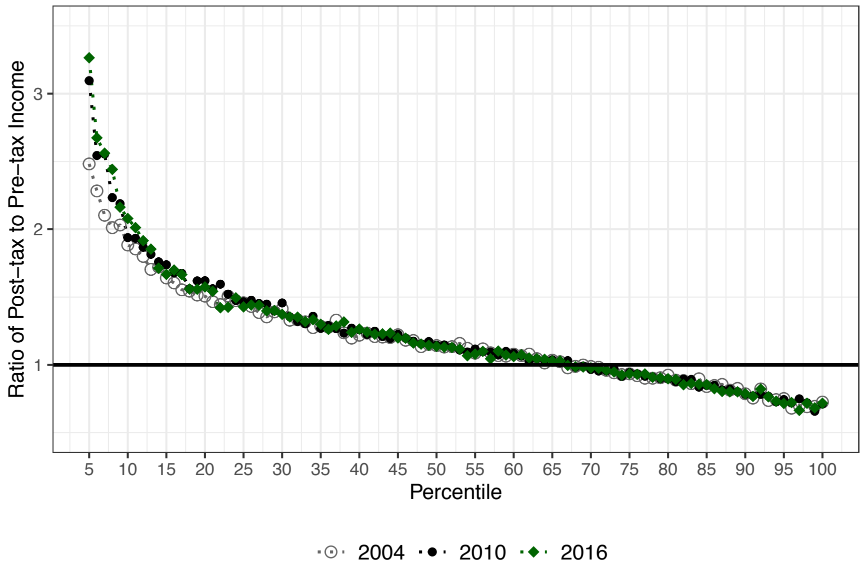
(b) **Post-tax national income shares, 2004-2016**

Source: Statistics Austria, EU-SILC.
Notes: Own illustration.

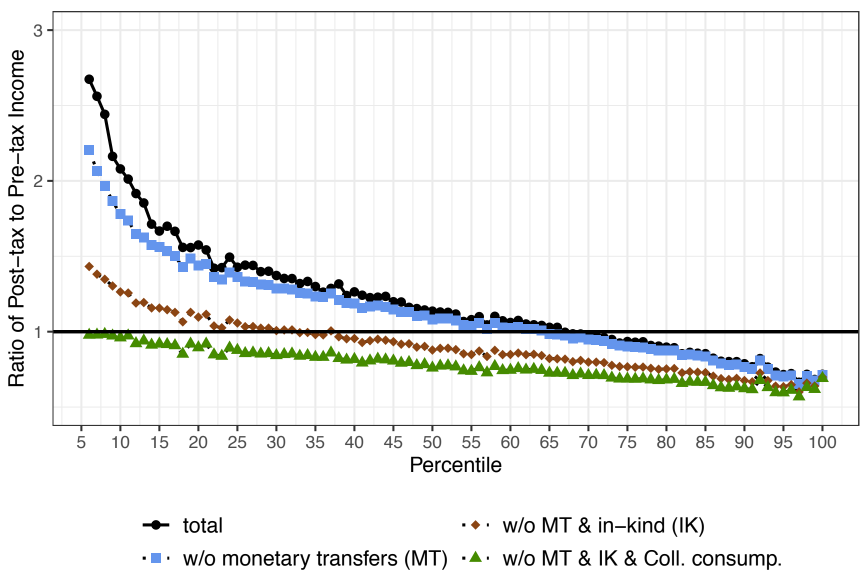
To provide a deeper insight into the overall redistribution mechanisms in Austria, we compare in a next step pre-tax and post-tax income by percentile in Figure 12a. We do this separately for the years 2004, 2010 and 2016. The black solid line indicates a ratio of one, which means that average pre-tax income equals average post-tax income. A ratio above (below) this line indicates that post-tax income is higher (lower) than pre-tax income. We find again two key findings: Similar to Figure 11a, redistribution mechanisms work rather equally over time. The ratios across the percentiles for the three years are largely overlapping. Moreover, we observe an approximately linear decline in the ratios when we move up the percentiles. For roughly 70% of the Austrian population, the post-tax income is higher than the pre-tax income. In contrast, around 30% of the Austrian population pay more than they receive through the redistribution process. This pattern demonstrates again that redistribution mechanisms operate on a large scale in Austria.

Redistribution mechanisms principally reflect operations of the tax and the transfer system. Even though, the tax burden, in particular on labour, is relatively high in Austria (OECD, 2019), redistribution mechanisms largely emanate from the operation of the transfer system (see Rocha-Akis et al., 2019). Especially, transfers in kind account for a vast part of income that is allocated to the Austrian population via redistribution. Our dataset allows to specifically evaluate the role of transfers for the redistribution process. In Figure 12b we compare pre-tax and post-tax income in 2016. This time however we also make a comparison between pre-tax and post-tax income by excluding social monetary transfers, transfers in-kind and additionally collective consumption. The blue line indicates redistribution when we exclude monetary social transfers (others than pensions and unemployment benefits) from post-tax income. By doing so, the redistribution line shifts downwards. The red line further illustrates the redistribution when we exclude monetary social transfers and additionally transfers in-kind from post-tax income. As it is clearly visible, this shifts the redistribution line significantly downwards and furthermore it becomes flatter. Accordingly, the Austrian population at the bottom of the income distribution benefits substantially from transfers in-kind. Likewise, when we additionally exclude the collective consumption from post-tax income, the redistribution line shifts further downwards and flattens even more. The effects are however smaller as compared to the effects of transfer benefits. The remaining redistributive effects in the green line come solely from the tax system. As it is visible, the line is fairly constant across the distribution. Accordingly, the Austrian tax system hardly affects the income distribution.

Figure 12 **Redistribution in Austria – pre-tax vs. post-tax national income**



(a) **Redistribution in Austria in selected years**



(b) **Redistribution in Austria – transfers & collective consumption, 2016**

Source: Statistics Austria, EU-SILC.
Notes: Own illustration.

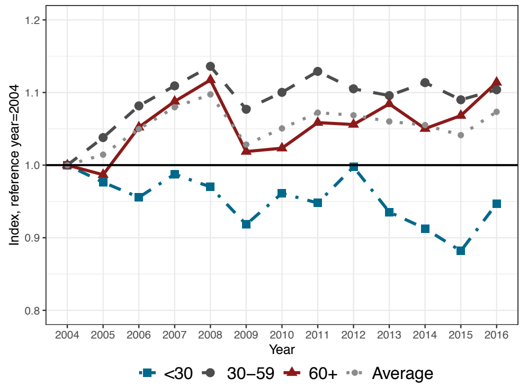
3.6 Population Subgroup Analysis

Since we build synthetic microdata files based on survey, tax and national accounts data, the dataset also contains a rich set of individual characteristics. We therefore do not only enrich the distributional information in the survey data, but also maintain the advantage of detailed information about socio-economic variables. Exploiting this information allows us to expand our analysis and to shed light on heterogeneous income developments and effects across population subgroups. This subgroup analysis again demonstrates the richness of our microdata files and points to additional research possibilities to use the data. Future research can address heterogeneous effects and developments across social groups in several additional ways. The dataset could also be used for policy evaluations and simulations.

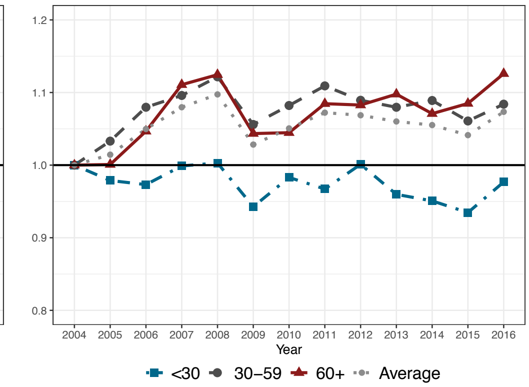
In Figure 13, we plot the income paths by age cohort, gender and educational attainment group, separately for the pre-tax and post-tax national income. The income of each group is indexed by using 2004 as the reference year. Overall, we find interesting heterogeneous patterns of income paths across the social groups. One common finding that applies to all social groups is a drop in income growth caused by the global financial and economic crisis after 2008. For age cohorts, we observe a different pattern over time with a large deviation between the groups. People aged under 30 experienced a negative income growth, while the trajectory of older individuals shows an overall positive trend. After accounting for redistribution in the post-tax national income in Figure 13b, the negative income growth of the youngest individuals is alleviated and the gap in income growth between the two older age cohorts becomes smaller. We further find that the income growth did not differ between men and women, irrespective of looking at pre-tax (see Figure 13c) or post-tax national income (see Figure 13d). This indicates that there has been no convergence in income levels between men and women as men tend to have higher incomes on average. After a sharp drop in 2008, the income grew again in the following three years and has remained on a stable level until 2016. Finally, income growth across educational attainment groups shows to differ considerably. Individuals with the highest education are the only group with a positive growth in pre-tax income over the entire period. By contrast, low educated individuals suffered from a negative pre-tax income growth and income stagnation. Interestingly, all groups face an income growth below the average after 2012, which is due to the fact that the proportion of individuals with higher education has significantly risen over the recent years. The redistribution among the educational attainment groups seems to be comparatively strong, since it brings all income paths to a similar trajectory. Remarkably, redistribution shifts the income growth path of individuals with the lowest education from below to above the positive growth line at one.

To give a more detailed insight into the redistribution in Austria, we also explore heterogeneous redistributive effects by the population subgroup. Analogous to our previous procedure (see Section 3.5), we compare average pre-tax and average post-tax income by age cohort, gender and educational attainment group over the period 2004-2016 in Figure 14. Overall, the results suggest considerable differences in redistributive effects within the groups. In line with our previous findings, with the exception of younger and lower educated individuals, redistribution shows to have rather stable effects over time. Among age cohorts, younger and older individuals benefit from redistribution, while middle-aged individuals receive a lower post-tax income compared to pre-tax income. For gender, we find that men pay on average more than they receive through the redistribution process; while females benefit from redistribution on average. In this respect, we have to bear in mind that females earn less than men on average. Women therefore tend to be located lower than men across the income distribution. As illustrated in Figure 12, redistributive effects are positive particularly at the lower part of the income distribution. Moreover, the paths by gender are almost identical, even though in different directions, over time. As the proportions for men and women are fairly balanced in Austria, the redistributive effects of one group offset the effects of the other group. In Figure 14c, we find the results for redistributive effects over time by educational attainment group. While average pre-tax and average post-tax income almost coincide for individuals with medium education, we observe large redistributive effects for individuals with low and high education. As expected, the lowest educated benefit to a large extent from redistribution and highly educated pay more than they receive on average. This is again related to the different positions of these groups across the income distribution: lower (higher) educated tend to be lower (higher) located across the distribution, which results in heterogeneous redistributive effects. The strong positive redistributive effects for the lowest educated individuals are consistent with the findings in Figure 13f.

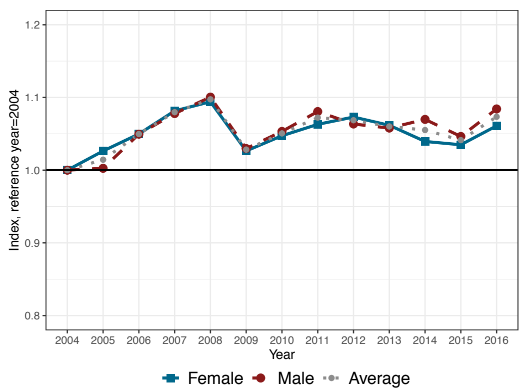
Figure 13 **Pre-tax and post-tax national income by population subgroup, 2004-2016**



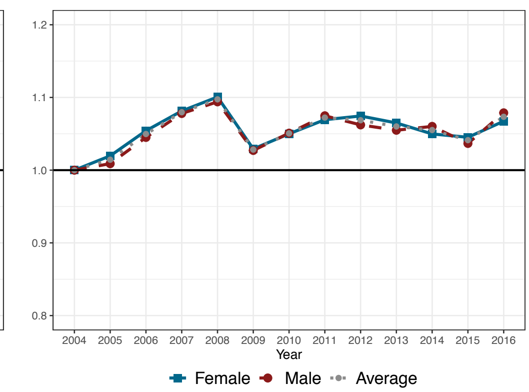
(a) **Pre-tax national income by Age Cohort**



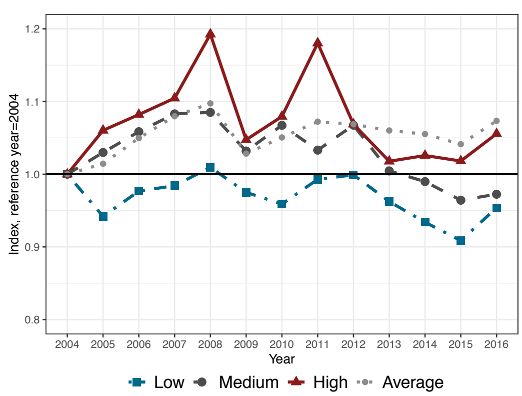
(b) **Post-tax national income by Age Cohort**



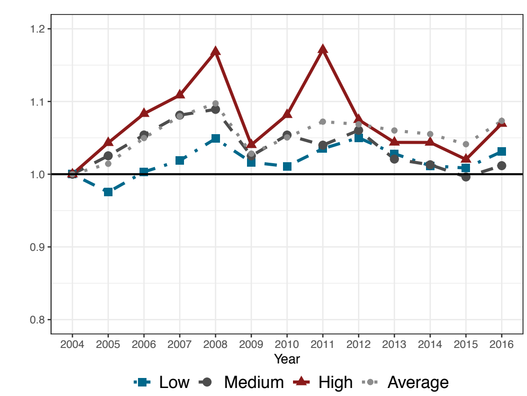
(c) **Pre-tax national income by Gender**



(d) **Post-tax national income by Gender**



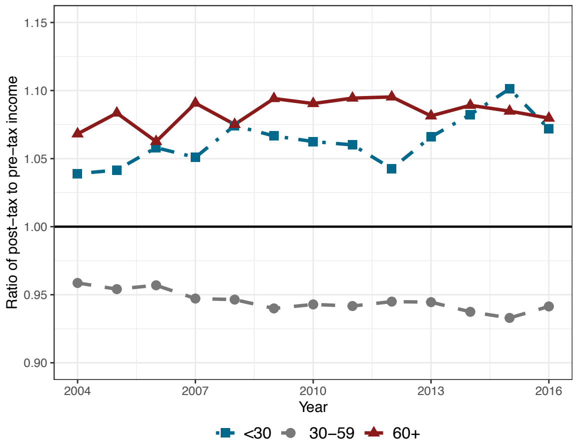
(e) **Pre-tax national income by Educational Attainment**



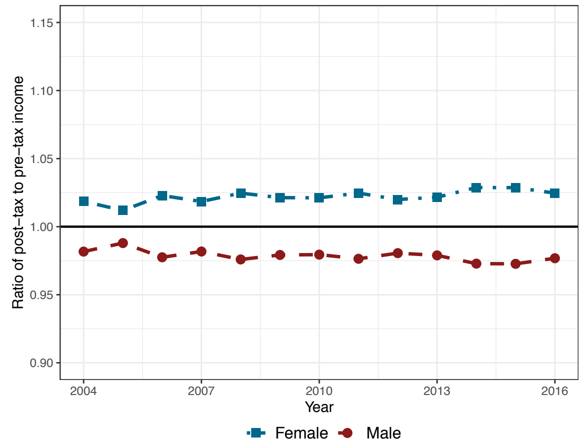
(f) **Post-tax national income by Educational Attainment**

Source: Statistics Austria, EU-SILC.
Notes: Own illustration.

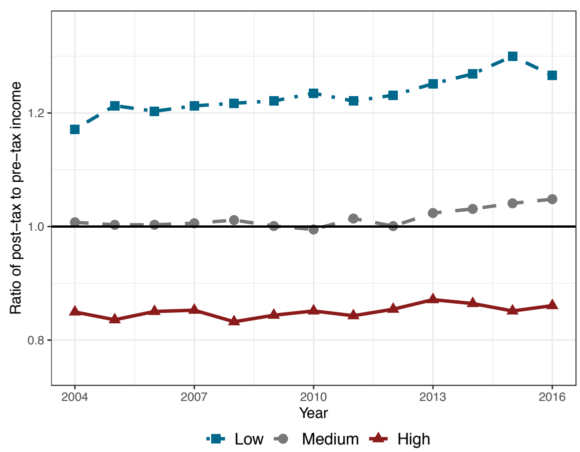
Figure 14 **Redistribution in Austria by population subgroup, 2004-2016**



(a) **Age Cohort**



(b) **Gender**



(c) **Educational Attainment**

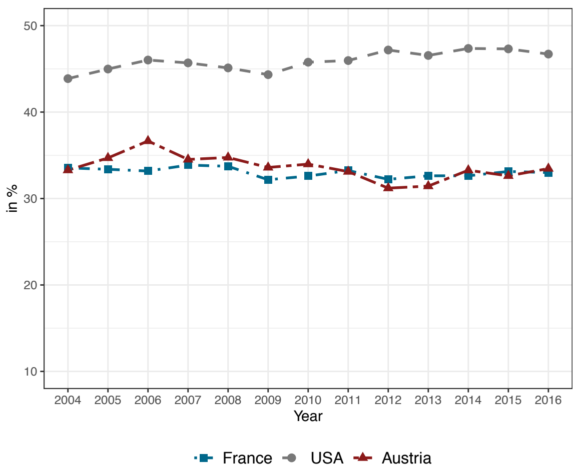
Source: Statistics Austria, EU-SILC.
Notes: Own illustration.

3.7 Cross-Country Comparison

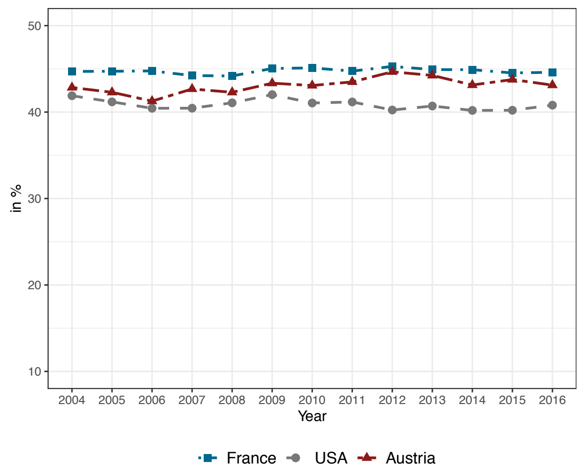
Throughout our analysis, we have explored income inequality in Austria from several perspectives. In order to assess whether income inequality is high or not, it is useful to make comparisons with the situation in other countries. Since we apply a disaggregated appraoch to construct our DINA series, we have to be cautious when we make cross-country comparisons due to differences in the methodology. In Figure 15, we compare the shares of the pre-tax national income by income group between Austria, France and the United States. Garbinti et al. (2018) for France and Piketty et al. (2018) for the United States apply a similar disaggregated approach to build DINA series as we do. Thus, a direct comparison seems to be appropriate.

When we compare the results for the three income groups, we only find differences across the countries in the shares of the top 10% and bottom 50%. In all three countries, the middle 40% reveal similar shares over time that range between 40% and around 45%. Unsurprisingly, the results suggest than income inequality is the highest in the United States. The top 10% in the United States earn approximately 10 percentage points more from pre-tax national income than in Austria and France. While the share for the top 10% evolves in a similar way in Austria and France, the gap to the American top 10% income share widens a bit over time. The highest income group in the United States experienced a continuous increase in its share of pre-tax national income from 2009 onwards. We observe a similar pattern for the income share of the bottom 50% in Figure 15c. Austria and France show similar shares above 20% that are rather constant over time. The United States again differs from the other countries: The bottom 50% hold less than 15% of the pre-tax national income over time. This clearly indicates that the pre-tax national income is highly unequally distributed in the United States.

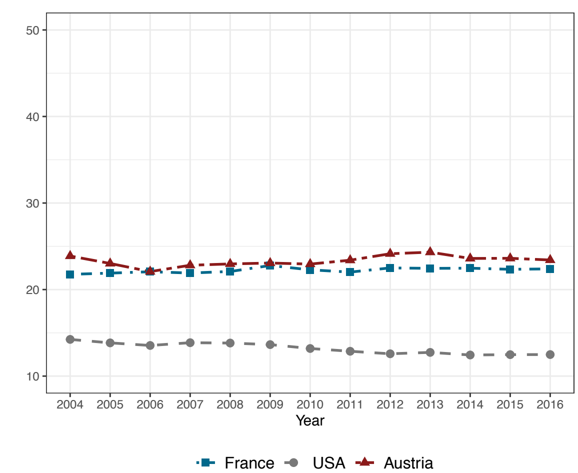
Figure 15 **Pre-tax national income shares by country, 2004-2016**



(a) **Top 10% – Share**



(b) **Middle 40% – Share**



(c) **Bottom 50% – Share**

Source: Statistics Austria, EU-SILC, World Inequality Database.
Notes: Own illustration.

4 Conclusion

This paper combines survey data, tax data and national accounts data to produce distributional national accounts for Austria for the time span 2004-2016. We adjust survey data with tabulated tax data to correct for underreporting at the top of the income distribution for income components included in tax data. To make the enriched survey data consistent with macroeconomic aggregates, we apply further methodical steps to fill existing gaps. The income concepts we use in the analysis add up to the total Austrian national income.

Our constructed data set allows to analyse the distribution of macroeconomic growth across the income distribution. We identify changes in the patterns of the growth distribution over time. While the pre-tax income for the major part of the Austrian population barely grew over the time period, income growth has been concentrated at the top in the pre-crisis period. Likewise, income growth has also been skewed in the period after 2008. However, for that time, we find a decline in pre-tax income, in particular at the very top of the distribution.

We find significant changes in pre-tax income inequality over time. Income inequality has already started to decline at the very beginning of the global economic and financial crisis from 2007 onwards. After having reached its lowest level in 2012, it has started to increase again afterwards.

Furthermore, our results point to a strong concentration of capital income at the top of the income distribution. Due to the absence of tax data for capital income, it is likely that we underestimate the concentration of capital income at the top of the distribution. While the bottom 90% of the Austrian population shows a capital income share (relative to pre-tax income) of around 10%, the top income groups reveal corresponding shares ranging from 30% to 60%. In addition, we find that the evolution of capital income is very important for dynamics in income inequality over time.

We explore redistribution mechanisms in Austria. Our dataset allows to draw a comprehensive picture of redistribution, including also transfers in-kind and collective consumption. We find that redistribution mechanisms operate on a large scale in Austria. Specifically, the Austrian population at the bottom of the income distribution benefits from both, monetary and in-kind transfers.

Finally, we investigate heterogeneous income paths and redistributive effects across different social groups. We identify substantial differences in income development between age cohorts and educational attainment groups. In particular, lower educated and younger individuals faced negative growth in pre-tax income over the years, but also considerably benefited from redistribution in Austria.

To sum up, using distributional national accounts allows to shed light on the income distribution from many perspectives. Our results emphasise the importance to use data sources and approaches to get a comprehensive picture of the total income distribution and to improve the understanding of its dynamics. However, further research is needed to improve the quality of data used in this analysis. More variables could be merged with tax or register data to improve their distributional information. The lack of suitable tax data for capital income constitutes a major issue for the analysis of inequality in Austria. Although the DINA approach increases the impact of capital income for top income groups, our constructed data are likely to underestimate the concentration of capital income at the top and eventually the total income inequality. Improving data quality on capital income would allow to better capture the very top of the income distribution and to provide more exact inequality indicators. Moreover, detailed micro information (e.g. from survey data) could be used to directly link the distribution of social transfers in-kind to an empirical basis.

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Appendices

A.1 Income Concepts and Micro-Macro Matching

Table A.3 **Income concepts**

		National Accounts	in %	SILC	Coverage
Gross wages and salaries		D11	46.58	PY010G + PY020G + HY110G	95.43
Employer social contributions	+	D12	9.88	EUROMOD	97.09
Gross operating surplus & rents received	+	B2G + D45	6.35	HY040G + HY030G	86.84
Consumption of fixed capital	−	P51C [part]	1.78	IMP [B2G]	
Gross mixed income	+	B3G	9.05	PY050G + HY170G	84.26
Consumption of fixed capital	−	P51C [part]	2.53	IMP [B3G]	
Interest w/o FISIM & distributed income of corporations	+	D41G + D42	9.60	HY090G	7.95
FISIM for interest received	+	D41G – D41	0.75	IMP [D41G + D42]	
Other property income received	+	D43 + D44	1.83	IMP [D41G + D42]	
Interest paid	−	D41G	1.90	neutral	
FISIM for interest paid	+	D41 – D41G	0.79	IMP [D41G]	
Other property income paid	−	D4 (exc. D41G)	0.00	neutral	
Primary income (net)	=	PRINC (B5N)	78.62		
Primary income S14S15		B5N (S14S15)			
Primary income S11	+	B5N (S11)	6.06	IMP [D41G + D42]	
Primary income S12	+	B5N (S12)	1.80	IMP [D41G + D42]	
Net operating surplus & mixed income S13	+	B2A3N (S13)	0.06	IMP [D41G + D42]	
Net property income S13	+	D4 (S13)	-1.91	IMP [D41G + D42]	
Net indirect taxes	+	D2 – D3 (S13)	15.37	neutral	
Pre-tax factor income	=	PRTFI	100.00		
Social contributions	−	D61 (S14S15)	9.44	EUROMOD	97.73
Employer social contributions	−	D12	9.88	EUROMOD	97.09
Pensions	+	D62 (S14S15)	16.84	PY100G + PY110G	93.26
Unemployment benefits	+	D62 (S14S15)	1.44	PY090G	88.13
Difference D61 & D62	+	D61 – D62 (S14S15)	1.05	neutral	
Pre-tax national income	=	PRTNI	100.00		
Other monetary transfers	+	D62 (S14S15)	4.94	PY120G + PY130G + PY140G + HY050G + HY060G + HY070G	86.82
Net indirect taxes	−	D2 – D3 (S13)	15.37	neutral	
Current taxes on income and wealth S14S15	−	D51 + D59 (S14S15)	13.25	EUROMOD + IMP	
Current taxes on income and wealth (other sectors)	−	D51 + D59 (other)	2.68	IMP [D51 + D59 (S14S15)]	
Post-tax disposable income	=	POTDI	73.65		
Social transfers in kind	+	D63 (S14S15)	14.56	equal	
Collective consumption	+	P32 (S13)	9.18	equal	
Primary surplus S13	+	D2 – D3 + D51 + D59 – D63 – P32 (S13)	2.61	neutral	
Post-tax national income	=	POTNI	100.00		

Notes: Own illustration; IMP – imputed values; * average values 2004-2016; Column four indicates the share of each component in national income; Column six reports the coverage rates of variables, that is the difference between variables' sum in micro data and in national accounts.

A.2 Tax Data Calibration

Survey data, which serve as the primary data source for the construction of the DINA series in this paper, have the advantage of assembling various socio-economic variables and is therefore of great importance for distributional analysis. However, the economic literature has increasingly emphasised its limitations in the last years, especially on the poor coverage of incomes at the very top of the distribution.

Tax data, on the other hand, have the potential to cover top incomes, but come along with its own limitations. In Austria, tax data are not available on the individual level, but only in tax brackets and only cover incomes above a certain threshold. Moreover, the amount of available covariates is limited. Unfortunately, there are no tax data available which are suited to enrich the distributional information on capital income.

To cope with the limitations of both data types, we incorporate information from tax data to the survey data, as the population coverage of the tax data is limited to individuals with a certain amount of income. In 2012 Statistics Austria started to adjusted the SILC data with register data for certain income concepts such as wages, pensions and unemployment benefits and revised data back until 2008 (Jäntti et al., 2013; Statistics Austria, 2014). However, self-employment income and rental income are not adjusted and furthermore the linking of individuals from the survey to register data cannot address non-sampling errors, which play a crucial role for top incomes. In order to address these shortcomings and to obtain a comprehensive data basis which allows for a valid analysis of changes over time before 2008, we apply a calibration procedure to the survey data.

There are various approaches to combine survey and tax data which can be categorised in reweighting methods, scaling methods and combinations of both of them. Blanchet et al. (2018) criticise that existing methods rely on arbitrary decisions for merging points and that reweighting or rescaling can disturb the original population size or distribution of covariates.

We therefore determine the merging point, which is the value of the calibrated income variable y at which we start to use the tax data, similar to the data-driven approach suggested by Blanchet et al. (2018). From the Austrian "Integrierte Statistik der Lohn-und Einkommensteuer", we can obtain tabulated tax bracket data for Wages & Pensions and Other Income, which mostly comprises of income from self-employment and rental income and both income groups are net of social contributions[23]. Since we simulated the social contributions before, we can construct a suitable income variable to perform the calibration.

We use the generalised pareto interpolation method of Blanchet et al. (2017) to transform the

[23] For a detailed documentation see Statistics Austria (2016).

tax data into a continuous functional form[24]. This allows us to discretise the distribution to a desired number of individual observations. We choose 1 million observations and add additional observations with zero income to obtain the same proportion of non positive observations as in the survey data. As we believe that the survey represents lower incomes better and tax data is more adequate for incomes at the top of the distribution due to the absence of non-sampling errors, the density of the tax data should be higher at the top. This would indicate that high incomes are underrepresented in the survey and therefore there must be individuals with low incomes who are overrepresented at the lower part of the distribution. Accordingly the densities must cross at some point by definition in theory. Accordingly, also the empirical quantile mean estimates based on the survey and tax data must cross eventually at the top. We choose this point as the merging point.

In Figure A.1 (1a & 1b) we see that this holds true for the observed empirical densities[25] and the quantile estimates of the two income forms. The trustable span of the tax data is not directly detectable, but the reliability of the tax data is believed to increase with income to a certain extent. Furthermore, we only want to start replacing the survey data at a point, where there is clear evidence of bias. For the first year of our time-series (2004) the merging point for Wages & Pensions is at the 887. 1000-quantile and for Other Income at 988. (2a & 2b).

In each year we start drawing 5000 observations[26] from the functional form of the tax data for Wages & Pensions and map the covariates from the survey observations to the new observations by duplicating them proportional to their survey weight. In a next step, the weights of the new top are calibrated linearly such that they again represent the survey observations above the merging point. By doing so, we obtain a data set which precisely represents the original survey[27]. This procedure is then repeated for Other Income. In 3a & 3b the calibrated data is shown, whereby the tax brackets from which the new income observations drawn are graphically indicated. For Wages & Pensions the degree of calibration is small at the beginning and also overall distinctly smaller compared to the calibration for Other Income. This was already indicated by the stronger discrepancy of the densities for Other Income in 1b.

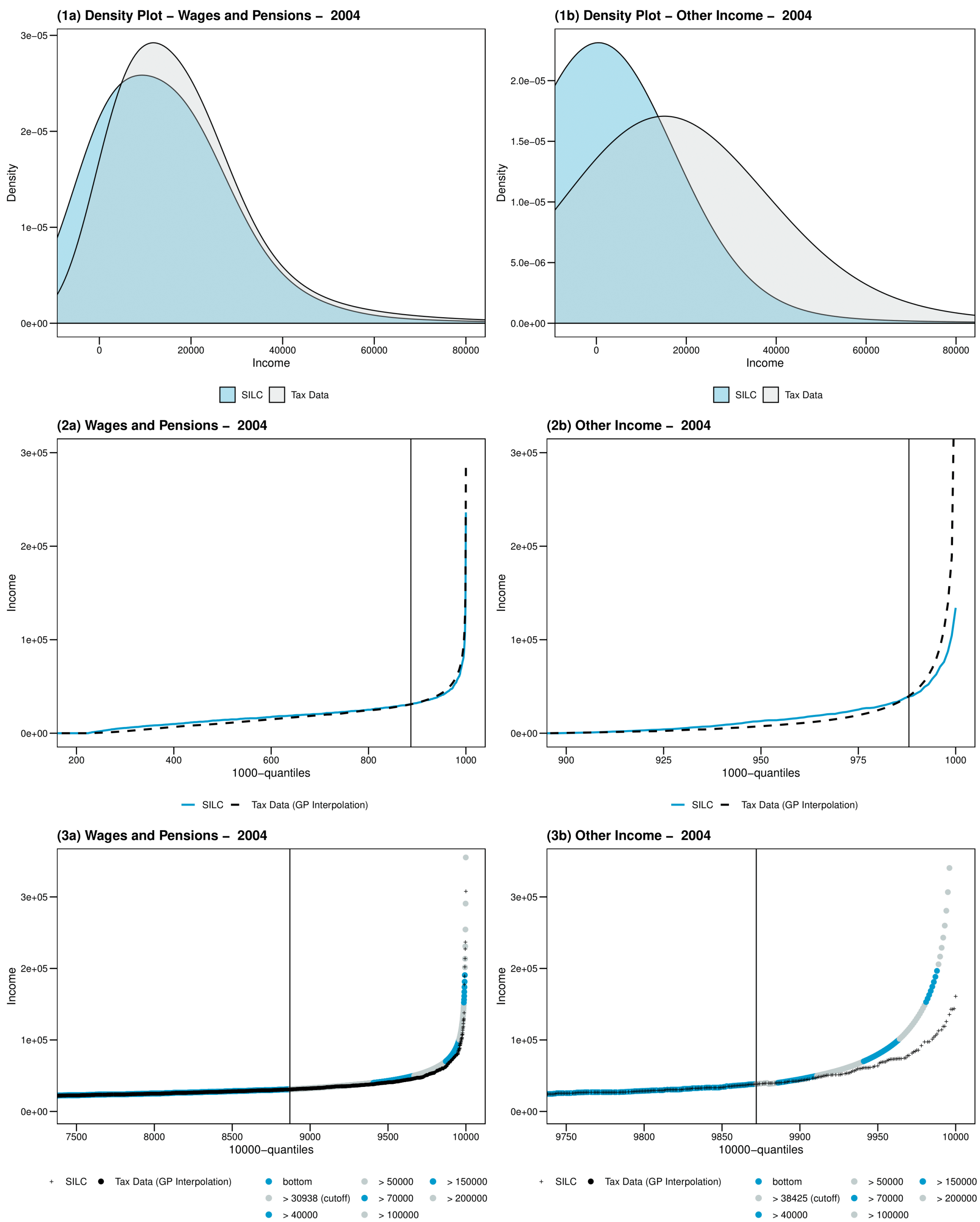
[24]See wid.world/gpinter for a R package and a detailed documentation.

[25]Since the densities are only estimated by gaussian kernel densities the exact merging point cannot be detected by the crossing point of the densities. However, the picture illustrates the intuition of the method.

[26]The number of drawn observation is chosen according to the cutoff point. However, the selection only affects the trade-off between computational parsimony and a lower degree of rounding errors, as the newly added observations are reweighted proportional to the substituted survey population.

[27]Small deviations can occur due to rounding errors, as the covariates are mapped per row.

Figure A.1 **Trustable span and cutoff point**

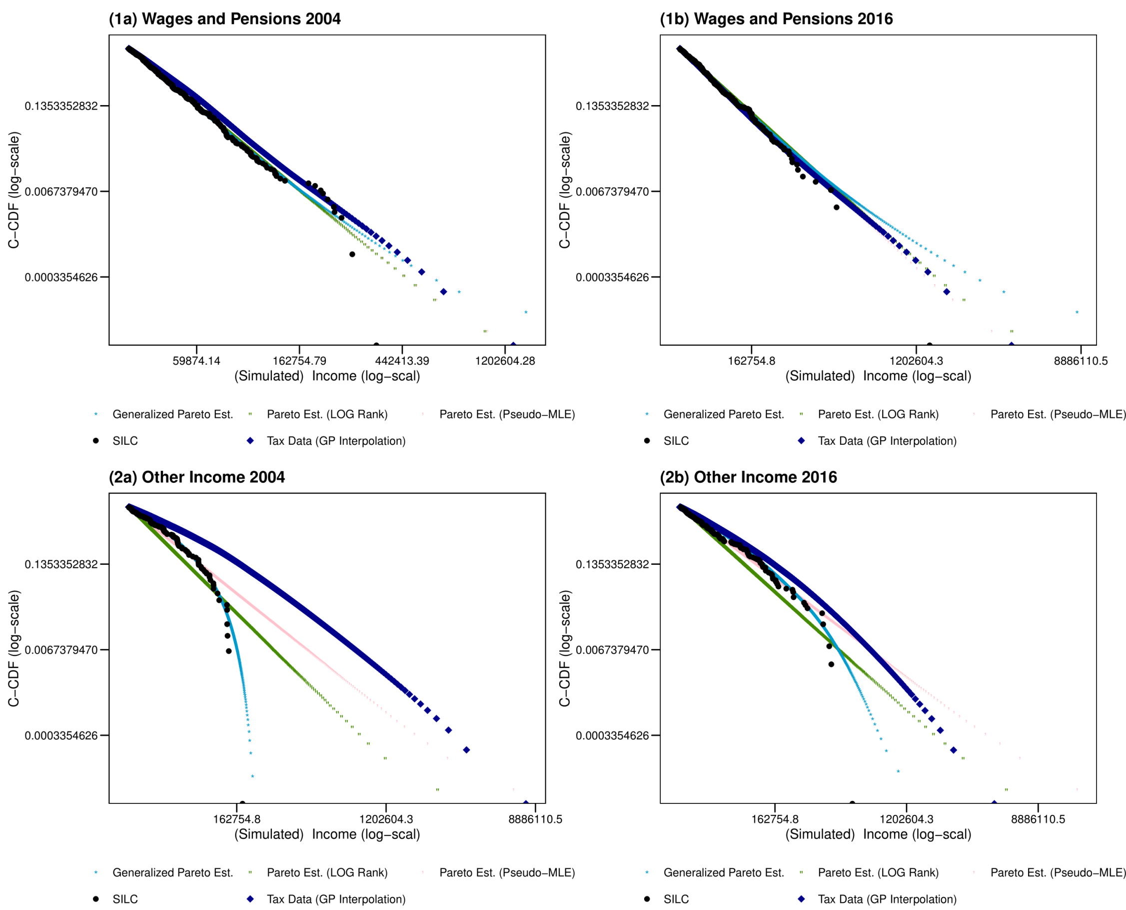


Source: Statistics Austria, EU-SILC.

Notes: Own illustration.

In Figure A.2, we show the original SILC data and the tax data from the generalised pareto interpolation as well as pareto estimations, which are based on the survey data only. For the pareto curves, we apply the linear LOG-Rank and the Pseudo-Maximum Likelihood Estimators suggested by (Vermeulen, 2018) and for the generalised pareto approximation, we estimate the parameters at 20 to 60 quantiles, after the merging point in order to obtain a functional form which approximates the survey data very closely. However, since we can use the tax data for the calibration, we do not rely on the pareto estimations.

Figure A.2 **Tax data interpolation and pareto estimation**

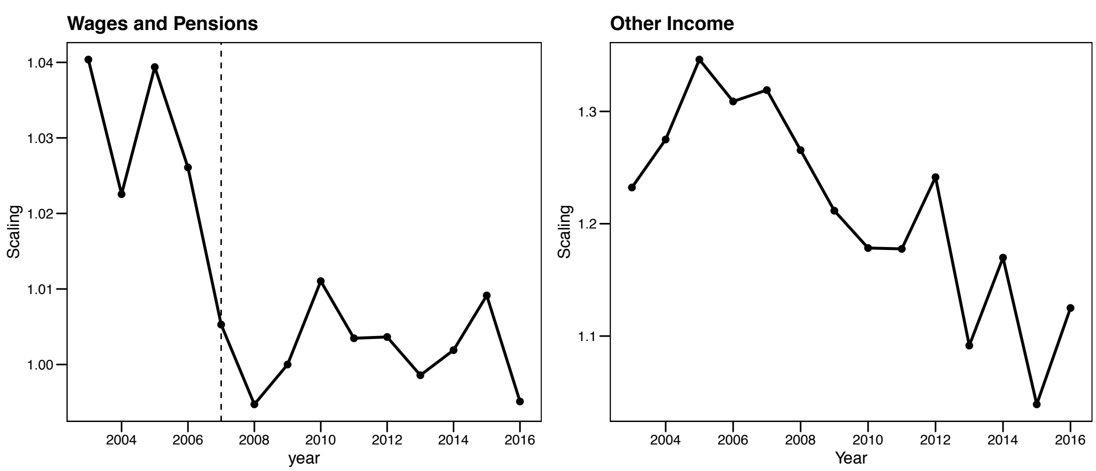


Source: Statistics Austria, EU-SILC.
Notes: Own illustration.

When comparing the difference of the SILC data and the interpolated tax data (1a & 1b), it can be seen, that in 2004, which is before the SILC was linked to register data, the divergence is evidently larger than in 2016, where the divergence should only stem from non-sampling errors. For Other Income (2a & 2b) the pattern in 2004 and 2016 looks more similar. However, also here the divergence decreases, although this income type is not affected by the change of the survey methodology. Figure A.3 shows the scaling of the income aggregates over the years. The structural change, that is indicated by the dotted line, becomes evident, as the scaling drops from approximately +2 % to +4% to 0 % to +1%. The scaling for Other Income is substantially higher with rates between 34 % and 3% and also decreases over time. This could be linked to various aspects like enhanced survey quality or different structural changes throughout the economic cycle.

Table A.4 contains summary statistics on the distributional effects of the calibration process. On average, the merging point for Wages & Pensions is approximately at the 93. percentile, where the income amounts to 59,300 €. The calibration leads to a scaling of +0.9%, the Gini and the Top5 share increase slightly. For Other Income the merging point is at the 99. percentile with an income of 35,800 €. The calibration scales the aggregate by 21.2 % on average. The Gini decreases minimally[28], whereas the Top5 share increases. The highest income observed increases for both types, however the level is affected by the number of observation drawn from the tax data distribution.

Figure A.3 **Scaling of income aggregates**



Source: Eurostat, Statistics Austria, EU-SILC.
Notes: Own illustration.

[28]Due to negative observations it is above 100.

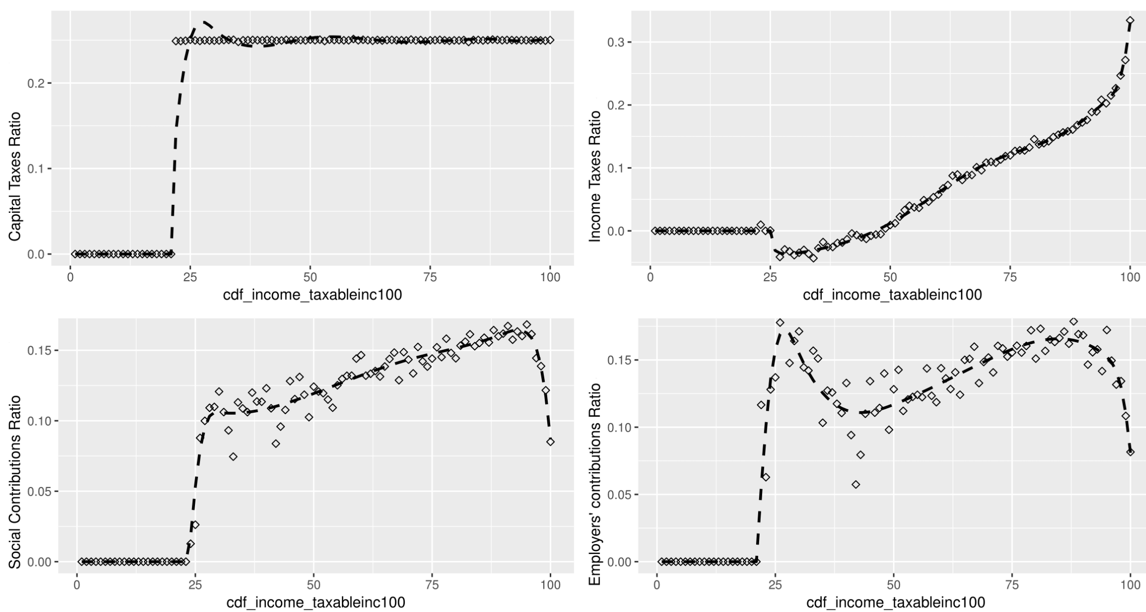
Table A.4 **Generalised pareto tax data calibration – 2004-2016**
Summary Statistics of calibrated and original (o.) measures

	Cutoff	in €	Scaling	Gini (o.)	Gini (GP)	Top5 (o.)	Top5 (GP)	Max Inc. (o., Mio. €)	Max. Inc. (GP, Mio. €)
Wages & Pensions	0.931	59, 299.8	1.009	54.782	55.138	0.216	0.221	0.631	2.894
Other Income	0.985	35, 712.3	1.211	111.335	109.542	0.937	0.948	0.440	8.282

Source: Eurostat, Statistics Austria, EU-SILC.

A.3 Tax Rates Simulations

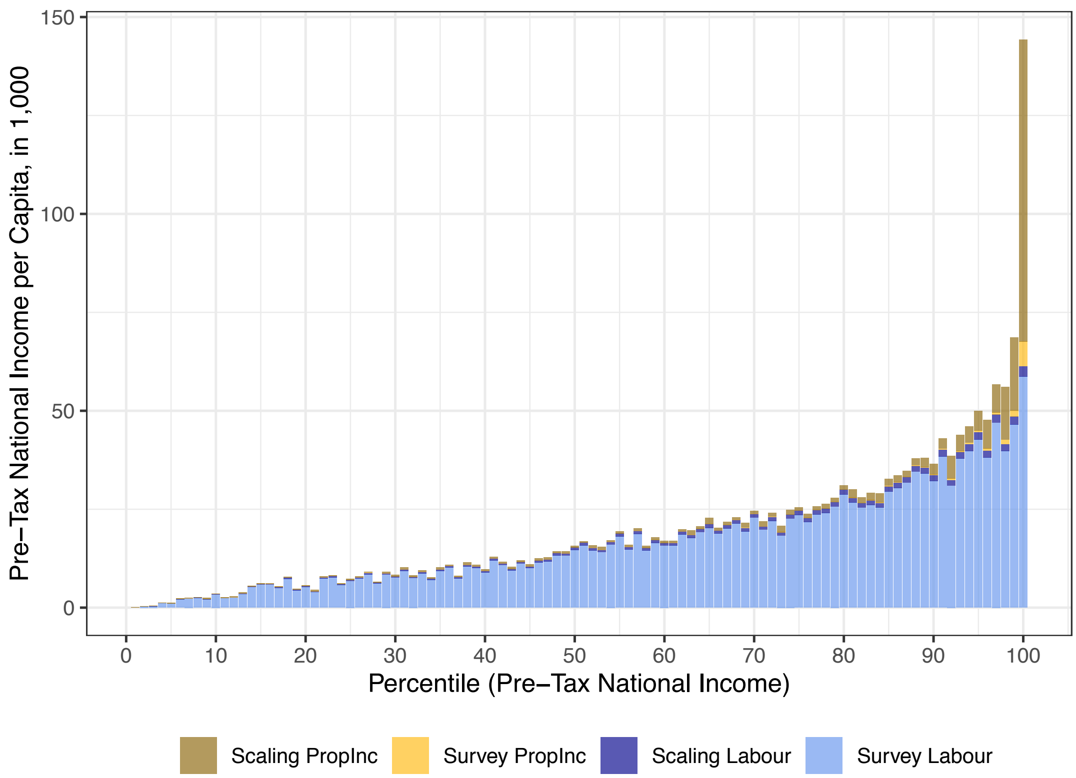
Figure A.4 **Contribution rates from Euromod simulations, 2016**



Source: EU-SILC.
Notes: Own illustration; dots indicate the average tax and contribution ratios by percentile using Euromod simulations; dashed lines show the applied smoothing splines.

A.4 Scaling Effects – Property and Labour Income

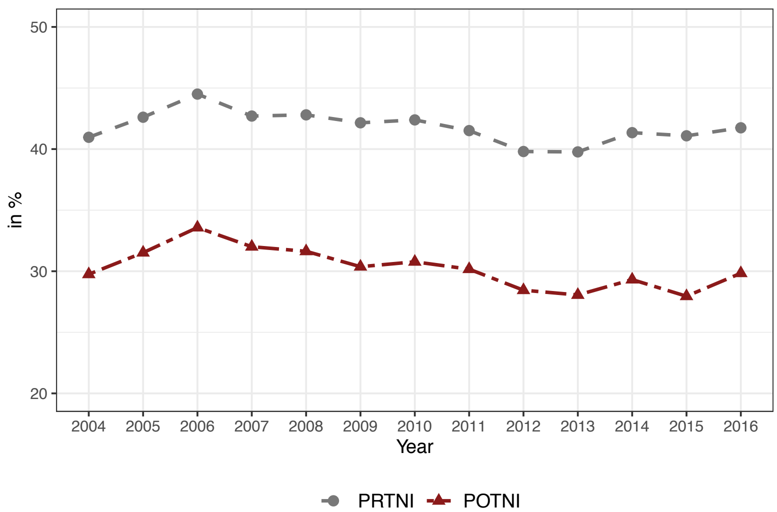
Figure A.5 **Property und labour income – scaling effects and original data, 2016**



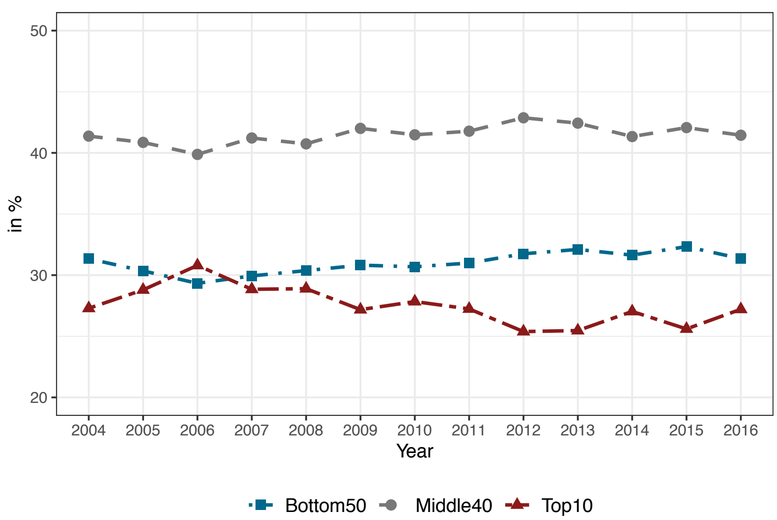
Source: Statistics Austria, EU-SILC.
Notes: Own illustration. *Property income* here only refers to the variable *"Interest w/o FISIM & distributed income of corporations"* (see Table A.3 in the Appendix).

A.5 Post-Tax National Income – WID Benchmark

Figure A.6 **Inequality in pre-tax and post-tax national income (WID-Benchmark), 2004-2016**



(a) **Gini coefficient – pre-tax income & post-tax income, 2004-2016**



(b) **Post-tax national income shares, 2004-2016**

Source: Statistics Austria, EU-SILC.
Notes: Government spending allocated in accordance with Alvaredo et al. (2020) – health transfers in-kind equally distributed, while other transfers in-kind as well as collective consumption proportionally distributed; own illustration.