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TOP INCOME INEQUALITY IN ISRAEL

OREN DANIELI, SHAI GILAT, AND DOR LEVENTER*

Abstract

This paper is the first to estimate top income inequality in Israel using administrative microdata. Using tax records from 2008–18, we find that the top 1% earned 14.7% of the total income during this period, a relatively high estimate compared to other OECD countries. For the top 1-0.1%, we find that the main income sources were labor and business income, and for the top 0.1% the main income source was capital income, primarily dividends. During the period studied, and especially after 2015, top income shares decreased, mostly due to a decline in labor income inequality. Classifying economic industries of top earners, we find that the most common industries in the top 1-0.05% are medical practices, high tech, and legal services. For the top 0.05% these are management consultancy, wholesale trade, high tech and real estate. Lastly, we estimate intragenerational mobility rates between 2008 and 2018 using total income. We find that the probability of being in the top 1% in 2018 for those who started in the bottom nine deciles in 2008 was 0.2%, compared to 6.1% for those who started in the top 10-1%, 38.5% for those that started in the top 1-0.1%, and 54.7% for those who started in the top 0.1%.

1 . INTRODUCTION

Income inequality in Israel is high compared to other advanced economies, based on measurements using survey data (Cornfeld & Danieli, 2015; Dahan, 2021). However, survey-based measures of income at the very top of the distribution are inaccurate for several reasons. First, since the top earners are a small group, they are not sampled precisely in the survey. Second, sampled top earners may not participate in the survey since the fine for not participating is small relative to their incomes. Third, surveys suffer from measurement errors, for example due to lies, confusion, or biases individuals have toward their income.

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Such measurement errors are probably larger for capital income, which is concentrated among top earning individuals, since such incomes go through lower scrutiny compared to labor income in such surveys (Rothbaum, 2015). Finally, many surveys censor top incomes due to privacy concerns. For these reasons, in many countries the measurement of top income inequality is done using administrative data (Blanchet et al., 2021; Piketty, 2001; Piketty & Saez, 2003). And yet, estimation of top income inequality using administrative data in Israel has not been previously conducted.

In this study, we use administrative datasets from the Israel Tax Authority (ITA) to estimate the differences in Israel between top income earners and the rest of the population, in the years 2008–18. We do this using income shares: the share of income of a group of individuals out of the entire income of the full population. In this research, we focus mainly on income shares of individuals at the top of the income distribution, namely the top 10%, 1%, 0.1% and 0.01%, which we term collectively as top income shares. Our rich data allows us to observe the demographic and economic characteristics of these groups. We also make use of our data to estimate intragenerational mobility based on total income, for the first time in Israel.

We find that top income shares in Israel are high compared to other advanced economies. Over time, income shares have moderately declined, mainly during 2015–18. Demographically, top income earners are mainly older males who reside in the Tel Aviv area. Classifying economic industries of top earners, we find that the most common industries in the top 1-0.05% are medical practices, high tech, and legal services, while for the top 0.05% these are management consultancy, wholesale trade, high tech, and real estate industries. When measuring intragenerational mobility, we find that high income earners tend to stay in the top of the income distribution over time. Specifically, individuals belonging to the bottom nine deciles in the income distribution in 2008 have a 5.2% probability of climbing to the top decile after a decade. This is compared to a probability of 61% of staying in the top decile for individuals who started in that decile.

We begin by discussing the datasets and methodologies we use to estimate top income shares. The data is compiled using individual micro tax datasets for the years 2008, 2010, and 2012–18. In our main specification, we limit our focus to individuals aged 20 years old and above. Our data include all taxpayers in Israel, which are 80% of the population. For the 20% of the population that do not file taxes to the ITA, we impute an income of zero and add them to the data. We rank all individuals by their declared total income before taxes within each year.[1] In our main specification, we exclude income from capital gains in our ranking procedure, since capital gains are usually more volatile and might reflect gains that have been made over several years (Piketty & Saez, 2003). This specification is in line with studies conducted on other countries, and hence facilitates cross-country comparison.

[1] Dividend income that is filed by an individual has already been taxed at the firm level. Hence, in practice this income is reported after income tax for the firm and prior to income tax for the individual.

We assign each income to the year it is reported, except for one specific type of income: dividends that were filed with the ITA as part of a tax reform in 2017. The reform temporarily reduced the tax rates for dividends of main shareholders of "wallet companies" as part of a larger reform dealing with tax evasion. The goal of this reduction was to incentivize individuals to take dividends from firm profits that have accumulated over several years. Indeed, we find a spike in the annual income from dividends in 2017. Since this income represents profits from previous years, we evenly smoothed dividend incomes due to the 2017 reform, which are observable due to their unique tax, over a ten-year period (2008–17). We also discuss alternative approaches to including these tax-cut dividends and show that our results are robust to these alternative specifications.

Our main finding is that in 2008–18 the average income shares of the top 1% was 14.2%, which is relatively high compared to other advanced economies. Likewise, the average income shares of the top 0.1% was 5.4%, and for the top 0.01% the average income share was 2.4%. That is, the share of income that went to 0.01% of the population in Israel (around 500 individuals) was 240 times larger than their share in the population. In comparison with other OECD countries, we find that Israel has one of the highest levels of top income shares for all top income groups, below only the US, Chile, and Turkey.

We find that the income sources of the very high earners are different from the rest of the population. We show that most of the income for P0-99.9 consists of labor and business income.[2] In contrast, the top 0.1% rely mainly on capital income and capital gains income. When solely considering labor income, we find that labor income is more evenly distributed. For example, income shares for the top 1% using solely labor income were 10.6% on average, 3.6 percentage points below the estimated income shares based on all income sources (14.2%). We also find heterogeneity in capital income sources between top income groups: for P90-95, the majority of capital income (around 60%) is generated from rents. As we look at higher income earners, the composition changes such that dividends become the highest income source, topping at above 70% of capital income within the top 0.1%.

Over the period 2008–18 we document a moderate decline in top income shares. The income shares of the top 1% declined from 14.8% in 2008 to 12.9% in 2018, with a slight increase in 2012-2014. We also observe a decline for the top 0.1%, from 5.5% in 2008 to 4.8% in 2018, with a peak of 5.69% in 2013. Similarly, for the top 0.01%, income shares declined from 2.29% in 2008 to 2.18% in 2018, with a peak of 2.59% in 2016.

Most of the decline in top income share stems from a decline in inequality in the distribution of labor income, particularly between the top 10% and the bottom 90%. To show this, we develop a new decomposition method, of the change in top income shares over time by income type. The decomposition also shows that an increase in the overall share of capital in the Israeli economy moderated the decline in income shares for the top 1%, as capital

[2] We use of the notation PX-Y to denote income group from percent X to percent Y. For example, P90-100 represents the top decile, P90-99 represents the top decile without the top 1%, and so on.

income is concentrated in higher income groups. Our decomposition method may help future research on changes in the income distribution due to different income sources.

We find that our main results do not change substantially if we change our specification. In our main specification, we used an age threshold of 20 years and above, in line with other studies of income shares. When we increase the age threshold to 23, the income shares of the top 1% decline by 0.2 percentage points, and when we decrease the age threshold to 15 (official working age) top 1% income shares increase by 0.7 percentage points. We also test different assumptions on the smoothing of dividends from the 2017 tax reform. Using this income as it is observed decreases the average income share of the top 1% in 2008–18 by 1 percentage point, and causes an increase of 9.1 percentage points in 2017, from 13.6% to 22.7%.

While our data allows us to conduct the most comprehensive analysis of top incomes in Israel to date, there are still missing income sources in our data, and we estimate their possible effects on our results. We discuss three income types that are missing from the ITA data: capital income of employees, tax-exempt housing rents, and undistributed profits of firms. For each missing income we identified, we made use of an auxiliary data source and calculated the sum of the missing income before tax for the whole population. We find that the ITA data that we use comprises 76% of total annual household income on average. After calculating the sum of the missing income, we impute its distribution using a distribution of a similar, yet observed, income type. For example, we distribute the sum of undistributed firm profits to different income groups using the observed distribution of dividend income. After distributing each missing income by income group, we recalculate income shares to test how inequality changes after accounting for the missing income. We also check the robustness of our results to an imputation of a positive income to individuals who are not in ITA data, for whom in our main specification we imputed an income of zero.

We show that adding all missing incomes generates an absolute (relative) increase in the income shares of the top 1% by 5.9 percentage points (41%). We also find a greater relative increase for higher top income groups. This increase is mainly due to the addition of undistributed profits of firms, which by our measurements are mainly focused in top income groups. Hence, when considering all income sources, top income shares in practice are higher than our estimates, and probably much higher for the topmost earners, e.g., the top 0.01%. Finally, when we take undistributed profits of firms into account, the decline we documented in our main specification between 2008 and 2018 for the top 1%, 0.1%, and 0.01% is reversed and instead we observe a positive trend.

Our detailed data allows us to characterize the top earners by their age, geography, and industry. We find that individuals in the higher top income groups tend to be older, with higher shares of men and married individuals, and they are geographically concentrated around Tel Aviv. Looking at industries, we find that individuals at different income levels tend to work at different industries. Individuals in P99-99.95 worked mainly in medical practices, high tech, and legal and accounting services, and the top 0.05% mainly worked in management consultancy, wholesale trade, high tech, and real estate industries. Focusing specifically on the high tech industry, we find that this industry employs a large share of individuals from the top 10%-0.5% (19% in 2018), however, it hires a lower share (6.6%) of the individuals from the top 0.5-0.05%. For the top 0.05% income group, 7.7% were employed in the high tech industry, making it one of the three most common industries for this income group.

In addition to estimating top income shares, another major contribution of the paper is the estimation of intragenerational income mobility in Israel based on all income sources. We estimate the probability of individuals climbing, staying, or descending from their income group over a maximal span of ten years. We find that most of the mobility of top income earners happens within the top decile. The probability for an individual from the top 1% to stay in the top 1% after ten years is 38.5%, and her probability to stay in the top decile is 76%. In comparison, the probability of an individual from the bottom nine deciles climbing to the top decile after ten years is only 5%, and the probability of the same individual to climb to the top 1% is only 0.2%. Comparing the results for Israel to four countries with existing comparable results shows that the top 1% and 0.1% in Israel are relatively mobile, while the top 10% are relatively lesser mobile.

This paper contributes to the literature on income inequality in Israel by providing more accurate estimates of the inequality between the top income earners and the rest of the population. In general, contemporary academic research on income inequality in Israel is scarce compared to other countries. The most comprehensive studies done on income inequality trends in Israel cover two periods: from 1985 to 1998 (Dahan, 2002) and from 1995 to 2017 (Dahan, 2021). The latter finds a rising trend in income inequality from the 1990s until 2002, primarily due to technological changes, higher demand for high-skilled workers, and massive immigration waves from the former Soviet Union countries. However, Dahan (2021) finds a unique phenomenon in the post-2002 period: a decrease in market-income (gross income) inequality with an increase in disposable income (net income) inequality, which originates in relatively low income-tax rates and low social transfers levels to low-income recipients. Cornfeld and Danieli (2015) document similar results.

The only study on income inequality dedicated to top earners in Israel is Sinko (2015). His estimates were created using aggregated income tabulations and interpolation and not by using micro-level tax records as is standard today in the literature for estimating top income shares in developed countries. Hence, it is not surprising that his estimates are different from ours: Sinko estimates that in 2009, top income shares of the top 10% (1%) were 40.3% (12.8%) using one series and 31.6% (9.1%) using another estimation process. These results are below our estimates for 2008 of the top 10% (1%) of 47.4% (14.8%).[3] Since our estimates are based on administrative micro data, they are more likely closer to the targeted values. Moreover, our data allows us to further characterize the individuals in top income groups, e.g., demographic characteristics or mobility rates.

[3] We compare between 2008 and 2009, since we do not have data on 2009, and Sinko (2015) does not report results for 2008.

Our paper is also related to the literature on short-term mobility in Israel. Prior work in Israel has estimated short term mobility for top earners, but only using labor earnings of employees (Ben-Naim & Blinski, 2012; Endeweld, 2012). Hence our estimates are also the first short term mobility estimates in Israel using gross income measures. Comparing their results with ours suggests that using gross income instead of solely labor of employees decreases top earners mobility estimates.

Finally, our paper is related to the literature on income inequality that focuses on the top of the distribution (e.g., Atkinson & Piketty, 2007; Piketty, 2001; Piketty & Atkinson, 2010; Piketty & Saez, 2003). Over the past decade, top income inequality measures have been estimated for many countries, allowing researchers to consider global trends (Alvaredo et al., 2018) and compile country level statistics in one dataset (World Inequality Database, 2021). Our paper contributes to this literature by adding reliable estimates for top income shares in Israel, as well as conducting a thorough exploration of top income groups, including economic industries. Also, this literature emphasizes the importance of examining trends in capital income, besides trends in labor income, to better understand income inequality (Hoffman et al., 2020; Piketty et al., 2018). We contribute to this literature by providing a methodology to decompose income share time trends into changes between and within income types.

2. DATA

a. Data Sources

Our primary data sources are individual tax records collected by the ITA for the years 2008, 2010, and 2012–18, with gaps due to missing datasets in 2009 and 2011. The income tax legislation in Israel requires all Israeli citizens and foreign citizens working in Israel who live and earn income in Israel to annually declare their income to the ITA. However, the Israeli regulation allows extensive bypassing declaration mechanisms. For example, an employer reports her employees' earnings and deducts taxes from their wages. Another mechanism designated to ease income declaration allows couples to file their tax returns together through the same form to the ITA. These conditions correspond to three separate datasets for individuals in the ITA, which we merge into a single dataset: individuals who report their income directly to the ITA, individuals who are added as partners in the direct report, and employees whose employers report for them.

The dataset of employees contains income from two sources: wages and pensions.[4] The datasets for the direct reporters and their partners are more comprehensive, and include capital and business, as well as income from labor. We observe capital income variables as

[4] Also reported are "income related to work" and capital gains related in the workplace, such as employee stock options. But, these other income sources amount to a very small share in income of employees.

aggregated sums by the tax rate applied on them, meaning all capital income categories that are taxed at the same rate will appear under one non-separable variable.[5] In addition, all datasets include demographic information about the filers, such as age, gender, marital status, economic industry, and place of residence. Appendix A.1 presents further details on the data.

In addition to the ITA datasets, we also make use of several datasets compiled by the Israeli Central Bureau of Statistics (CBS). Specifically, we use Household Income and Expenditure Surveys (Central Bureau of Statistics, 2021a) and National Accounts data (Central Bureau of Statistics, 2021b) for validation of our population and income, and for imputation of missing income. Finally, we use data from the World Inequality Database (World Inequality Database, 2021) for international comparisons.

b. Sample Definition

We merge all the yearly ITA datasets for direct-filers, partners of direct-filers, and employees into a single unbalanced panel dataset. When an individual appears in more than one dataset, we take the income as reported in the direct filer data. Further details on the construction of the panel are presented in Appendix A.1. We now turn to discussing our main specification regarding population and income.

Population. Our data includes all individuals who reported, or for whom their employer reported for them, an income to the ITA. But the target population of our research is the total adult population living in Israel. This definition includes Israeli citizens who live in Israel but have an income source abroad, and foreign workers who are not Israeli citizens but live in Israel and earn income in Israel. For the results to be valid for the target population, we need to take into account individuals who are missing in the ITA data. We do so by comparing the population in our data to aggregated statistics, which is often termed as Control Totals in the literature. We define our Control Total for Population to be the total population in Israel aged 20 and above, including foreign citizens.

We omit individuals under the age of 20 for two reasons. First, this is the age threshold used in the World Inequality Database, and aligning our age restriction with the World Inequality Database facilitates international comparisons. Second, our research focuses on income, and while the official labor force is defined using age 15 and above, the inclusion of individuals aged 15–19 in the workforce is limited due to participation in secondary education systems until age 18 and the mandatory military service until ages 20–21. Therefore, due to the institutional context, when discussing the labor force it is best to focus on individuals aged 20 and above.

When we compared the population in Israel aged 20+ from the Central Bureau of Statistics (CBS) to the number of individuals aged 20+ in the ITA data, we find that the

[5] For example, in 2018 in the ITA form for direct filers (Form 1301) section E variable 211 the filer should report the sum of several incomes with a tax rate of 15 percent: interest on stocks, interest and revenue from Gemel funds, and dividends from a subsidized plant.

average coverage is 80% over the years 2008–18. For more discussion on the definition and calculation of Control Totals see Appendix A.2, and for the coverage see Appendix A.3. To align the number of individuals in the ITA data with the number of individuals in our target population, we artificially add individuals with zero income to the data until the population in our specification matches the total population in Israel aged 20+, taken from CBS records.[6] We note that adding individuals with zero income increases top income share mechanically.

Income. The ITA data incorporates information on various income sources of individuals. We categorize the different incomes into five types: labor and pension, termed labor income; self-employment income and income received directly from a self-owned business, termed business income; dividends, rents, interests and royalties, termed capital income; income from realized capital gains, e.g., income from selling equities, termed capital gains;[7] and other small income components, termed other. The incomes in the ITA data are reported annual cash flows, before individual-level taxes and transfers, and after corporation-level taxes.

Our working definition for income is gross individual income. In the main specification, we exclude capital gains from the definition of income, since they are not an annual cash flow and could significantly vary from year to year (Piketty & Saez, 2003). For several results we also make use of an alternative definition of income that includes capital gains as well.

We define the Control Total for Income as the economy aggregate of gross income of individuals, similar to Atkinson (2007). In contrast to Atkinson (2007), we exclude imputed rents[8] and employers' social security contributions due to data limitations. Also, for our results to be valid for the Israeli economy, we need to consider incomes that are missing in our data but present in the Control Total. For example, tax-exempt income or income sources that do not need to be reported are missing from the ITA data. In Appendix A.3 we compare the sum of income in the ITA data with the Control Total for income, and find that the average coverage is 76%. To test the sensitivity of our results to the missing incomes, we estimate the effect of adding different types of missing incomes on top income shares, discussed in Subsection 5.3.

[6] The population aged 20+ that is not seen in ITA data is mainly composed of young (15-17) and old (75+) individuals, as discussed in Appendix A.3. It is plausible to assume these individuals have a low income, which we verify using the CBS's household income and expenditure surveys. In Subsection 5.3 we test how different assumptions on the income of these individuals, which are unobserved, may affect our estimates of top income shares.

[7] Capital income and capital gains income are similar, in that both incomes are related to assets owned by the individual. The difference is that capital gains income is from selling an asset, e.g., selling a stock, while capital gains is from ownership of the asset, e.g., renting a house.

[8] Counterfactual sums of housing rents, which are imputed and assigned to individuals that reside in a dwelling which they own, and therefore are not paying housing rent to another individual.

Our main results focus on household income and exclude government and corporate income, as is common in the literature on top income inequality (Atkinson, 2007). However, the more recent framework of Distributional National Accounts (Blanchet et al., 2021) treats corporate income as undistributed individual income, attributes its components to individuals and includes it in their income share computation. We perform a similar exercise as a robustness test to our results in Subsection 5.3, where we impute and distribute undistributed firm profits to individuals and test its effect on top income shares.

c. The 2017 Dividend Regulation

During the past two decades, thousands of individuals registered new firms under their full control (referred to as ''wallet companies'' in Hebrew) which functioned as a tax evasion mechanism.[9] In practice, the firm's owner registered payments for her work and services as the firm's profits, hence gaining control over volume, timing, and type of her compensation (dividends or wages), or used it directly through the firm for consumption or investments. The latter action bypasses the two-stage taxation procedure applied on dividends, as the owner pays only corporation tax, while evading paying individual income taxes on dividends drawn out of the firm. This taxation loophole was first recognized in 2004 but was legally addressed only in the national budget legislation of 2017, when legislators allowed the tax authorities to tax the undistributed profits of those firms, in a way that removes the incentives to use them for tax evasion purposes.

Before changing the taxation of wallet companies, the ITA temporarily lowered the tax rate on dividends for main shareholders of wallet companies for several months in 2017. This led to an abrupt increase in capital income in 2017, as can be seen in Appendix Figure 1.[10] For this reason, we see the tax reform dividends as representing accumulated profits over several years and not profits earned in 2017.

In the ITA data, the income from the dividend tax reform of 2017 is reported separately from other capital incomes.[11] Since we focus on annual cash flows, in our main specification we evenly allocate, or smooth, the dividends received at lower tax rates in 2017 backwards for their receivers for a ten-year period, from 2008 to 2017. Subsection 5.2 discusses robustness of the results to different approaches on including the tax-cut dividends in the data.

[9] Information regarding wallet companies and the tax legislation of 2017 is based on a special report written on the reform conducted by the State Comptroller of Israel (State Comptroller, 2020).

[10] We cannot produce this graph for dividends, since capital incomes are bundled by tax rates in our data. While we do observe the specific income of dividends due to the tax reform, we do not observe dividends from other sources directly.

[11] In 2017 there are three main dividend variables in the ITA data: dividend income (25% tax rate), dividend income for main shareholders (30% tax rate) and dividend income for main shareholder in the reform period (25% tax rate).

d. Calculating Income Shares

In each year, we rank individuals by their total income excluding capital gains. We estimate the income share for an income group by the ratio of the total income of that group in some year, divided by the total income reported in the main specification in the same year.

3. TOP INCOME SHARE ESTIMATION

a. Top Income Levels in 2018

Table 1 reports the number of individuals, bottom income threshold, and average income for selected income groups in 2018. The reported incomes are in new Israeli shekel (NIS) and nominal prices. For example, in 2018, an individual had to earn an income higher than NIS 8 million annually to enter the top 0.01% (P99.99-100), which was made up of 568 individuals. The income thresholds provide a preliminary glimpse into the heterogeneity within the top decile, and indicate that the various income groups differ from each other by their income level in a non-linear manner as we get closer to the top: the income threshold of the top 0.1% is almost three times higher than the threshold of the top 1%, while the threshold of the top 0.01% is 4 times higher than the top 0.1% threshold.

b. Top Income Shares 2008–2018

Table 2 presents the main results of the paper: top income shares between the years 2008–18. In each year (row) we report the number of individuals (column (2)) and average annual income in the population (column (3)). Columns (4)–(11) present the income shares of selected top income groups. On average over the observed period, the income share of P90-100 was 45.9%, of P99-100 was 14.2%, of P99.9-100 was 5.4%, and of P99.99-100 was 2.4%.

When capital gains are included, top income shares increase and are more volatile.[12] Column (12) reports the income share for the top 1% when we include capital gains in the income share calculation, while income ranking is done without capital gains, as in the main specification. Column (13) reports income shares where we include capital gains in both the ranking and income share calculations. As expected, adding capital gains makes top 1% income shares more volatile, and increases their income shares by 1.8 percentage points on average if we keep rankings constant, and by 2.8 percentage points on average if capital gains affect the rankings as well.

[12] Subsection 2.2 discusses why we do not include income from capital gains in the main specification. However, these are observed incomes we can allocate to specific individuals, and which affect the income share distribution when included. Hence we also provide results when these incomes are included.

Figure 1 presents selected time series of top income shares. Figure 1a focuses on the top decile, where we observe a decline from 47.4% in 2008 to 43.3% in 2018. This negative slope is not linear and is composed of a mild decrease in income-shares per year in the period 2008–11, a flat trend in 2012–14, and a sharp decrease in 2015–18. Decomposing the top decile, as shown in Figure 1b, we see that the fluctuations originate mainly from the top 1%. While the bottom nine percentiles (P90-95, P95-99) demonstrate a monotonic and mild negative trend over the whole period, the top 1% (P99-100) income shares decrease in 2008–11, increase in 2012–14, and decrease in 2015–18, similar to the trend of the (aggregated) top 10%. Similarly, decomposing the top 1% and 0.1% income shares, presented in Figures 1c and 1d respectively, shows that almost all top income groups have a stable trend until approximately 2015, and then a decline. In contrast, the top 0.01% (P99.99-100) experiences a substantial increase until 2016, and then sharp decline in the following two years.

c. Top Income Shares International Comparisons

In Figure 2 we compare the average top income share of the top 1% over 2008–17 between the countries of the OECD, using top income shares series in the World Inequality Database.[13] We find that Israel's top income share levels are one of the highest among advanced economies, below only the US, Turkey and Chile. This relative place among OECD countries is similar to other international comparisons concerning income inequality in Israel (Dahan, 2021). Nevertheless, the large gap between the top three countries and the rest of the distribution puts the top 1% income share levels of Israel (14.4%) closer to European countries, e.g. Germany (12.3%), the UK (12.6%), and Poland (13.5%), than to the high levels of the US (19.9%). Appendix Table 1 reports similar results for the top 0.1% and the top 0.01% respectively. That is, the income shares of the top 0.1% and top 0.01% in Israel are high in an international comparison.

We also compare income share levels and trends internationally, reported in Appendix Figure 2. The Y-axis presents the average income share of the top 1%, while the X-axis presents the relative change of the top 1% income shares from their 2008 levels to 2017 levels. We find that most European countries, including Israel, with relatively high top 1% income shares levels also demonstrate some sort of negative trend in 2008–17. In contrast, the three countries with the highest income shares for the top 1% (US, Turkey and Chile) had a positive trend. Appendix Figures 3 and 4 provide similar results for the top 0.1% and top 0.01%. The results in Appendix Figures 2, 3, and 4 are concentrated in Appendix Table 1.

d. Assessing Top Income Inequality Using the Gini Coefficient

In the last part of this section, we turn to estimating the income inequality in our main specification using the Gini coefficient. As discussed above, the literature on top income

[13] Most of the countries in the WID do not yet have income shares estimates for 2018. For some countries, e.g., Chile, Turkey and Australia, data is not available after 2016. Latest year of data availability by country is documented in the right most column in Appendix Table 1.

inequality commonly measures inequality using income shares, for which we have presented results above. However, the Gini coefficient is a commonly used income inequality measure in Israel, and in the inequality literature in general. Hence, it is of interest to measure the Gini coefficient in our main specification, using total income and including top earners. We show that not including top income groups while measuring income inequality using the Gini coefficient biases the income inequality estimates downward. We also estimated the Gini coefficient within top income groups and found that there is in fact some level of inequality within the top 10% and within the top 1%, but the inequality is lower than the inequality in the whole population.

The estimated value of the Gini coefficient in our main specification, reported in Table 3 column (1), is different than the common value reported using survey data. The main difference is that we discuss individuals, while common measurement focuses on households. While our main specification includes many individuals with low income, households often include a mixture of low income and high-income individuals. Hence, we expect the value of the Gini coefficient to be higher in our main specification compared to other studies that use household surveys. It is then of no surprise, due to the above argument, that we estimate a high value for the Gini coefficient, between 0.6 and 0.65 in 2008–18. For comparison, Dahan (2020, table 1) reports a Gini coefficient that varies between 0.47 and 0.52 for 2008–15 using the CBS household income surveys.

Column (2) reports the Gini coefficient within the top 10%, and column (3) reports the Gini coefficient within the top 1%. As discussed in the introduction, there are reasons to believe survey data do not accurately cover the incomes of the top earners, and hence do not allow estimation of inequality between top earners. We find that the value of the Gini coefficient is between 0.307 and 0.327 when estimated within the top 10%, in 2008–18. This finding suggests that income inequality does exist within the top income decile, but it is lower than the income inequality in the whole population. Within the top 1%, the estimated Gini coefficient is between 0.37 and 0.397. That is, the income inequality within the top 1% is higher than within the top 10% but is still lower than the whole population.

Finally, we discuss how measuring income inequality is affected by the exclusion of top income earners. Our data allow us to measure the Gini coefficient with and without certain income groups and to estimate how this affects the measure of inequality. Column (4) reports the Gini coefficient without the top 1%, and column (5) reports the Gini coefficient without the top 0.1%. Comparing these results to column (1), we observe a significant decrease in measured income inequality when it is measured without top income groups. For example, in 2018, without the top 1%, the value of the Gini coefficient decreases from 0.605 to 0.558, a relative decrease of 7.7 percent. Without the top 0.1%, the Gini coefficient decreases to 0.582, a relative decrease of 3.8 percent. These results support the hypothesis proposed in the introduction, that inequality measurements using survey data that do not reliably cover top earners are downward biased, even if capital income is included in the measurement. When using solely labor income, as reported in column (6), the value of the Gini coefficient decreases. For example, in 2018 the Gini coefficient decreased to 0.446, a relative decrease of 26 percent, when using solely labor income based on the specification discussed in Subsection 4.3.

4. INCOME COMPOSITION OF TOP EARNERS

In this section, we will discuss which income types make up the top income shares, and show using a decomposition exercise by income type that most of the decrease in the time trend of income shares is due to an increase in the equality of labor income. We will finish with discussing top labor income inequality.

a. Income Composition

We find that in Israel, similar to other countries, as you climb the income ladder the main source of income changes from labor to capital. In Figure 3, we show the income composition of different income groups in 2018. We find that the main income type shifts from work related income (labor or business) to capital related income as you move up the income distribution. Similar results have been shown in other advanced economies (Atkinson, 2007; Piketty & Saez, 2003). As discussed in Section 2, we omit capital gains from our analysis. However, including capital gains does not change the results, where for higher income groups the main income types are capital income and capital gains, as shown in Appendix Figure 5. Appendix Table 2 reports the composition of the different income types for selected top income groups for the time period 2008–18.

The top income groups are not solely characterized by higher shares of capital income, but also by capital income that is based on dividends. We classify income into subtypes: dividends, rents, interests and securities, and show their ratio out of capital income by income group in Figure 4.[14] We find that in the bottom nine percentiles of the top decile, P90-99, most of capital income comes from rents. In comparison, for the top percentile, most of the capital income comes from dividends, a relation that increases with income. When considering securities and interest, we find that each comprises around 10% of capital income for all top income groups.

As capital income is earned through ownership of different types of assets, the distribution of capital income is suggestive on the distribution of wealth in Israel (Milgrom & Bar-Levav, 2019). Individuals in the bottom part of the top decile make most of their capital income due to ownership of real estate. Individuals in the top 1%, and to a larger extent individuals in the top 0.1%, generate income by owning firms, as suggested by their large shares of dividends, or by trading financial assets, as suggested by their large shares of capital gains.

[14] For further discussion on the classification of capital income into subtypes see Appendix A.1.

b. Decomposing by Income Types

We now turn to analyzing the change in top income shares over time using a decomposition exercise by income types. This decomposition is the first of its kind in the literature and might be of interest for studies that try to connect changes in income with changes in income composition, as we will now demonstrate. We will quantify whether the decline is due to "changes **between** income types" or "changes **within** income types", which we further discuss below. We will show that most of the decline is due to closing disparities "within" labor income, meaning a more equal distribution of labor income over time. At the same time, we will also show that the decline could have been even larger, if not for changes "between" income types—namely, the relative increase of capital income in the population mitigated the decline of top income shares, especially for the very top.

Definitions. A change within an income type is a change in the distribution of an income type holding its share relative to other incomes constant. For example, assume between two time periods that labor income became more equally distributed, while the sum of labor income did not change between these periods. If this is the only change, such a scenario is expected to cause a decrease in top income shares due to the change in the labor income distribution, which will shift more income to lower income groups.

A change between income types is a change in the relative size of income types in the population holding the distributions of each income type constant. An example of a change between income types is a scenario where the total amount of capital in the whole economy increases, while the total amount of all other income types stays constant. If the distributions within each income type stay constant as well, we would expect such a change to increase income shares of income groups with higher shares of capital income. Since we saw above that capital income is concentrated in top income groups, such a scenario will cause an increase in top income shares. These two examples show that differentiation of "within" and "between" income type changes may help us understand the reasons behind the decline in top income shares. We now turn to discussing the decomposition exercise that enables to tease these two changes apart.

Denote by $\boldsymbol{Y_{j,f,t}}$ the total income from type $\boldsymbol{j}$ (e.g., labor income) of income group $\boldsymbol{f}$ (e.g., top 1%) in year $\boldsymbol{t}$. Denote the total income of group $\boldsymbol{f}$ at year $\boldsymbol{t}$ from all income types by $\boldsymbol{Y_{f,t} = \sum_j Y_{j,f,t}}$. Similarly, $\boldsymbol{Y_t = \sum_f Y_{f,t}}$ denotes the sum of total income for the whole population at time $\boldsymbol{t}$, and $\boldsymbol{Y_{j,t} = \sum_f Y_{j,f,t}}$ the sum of total income of type $\boldsymbol{j}$ in year $\boldsymbol{t}$. Using these notations we define the income share of group $\boldsymbol{f}$ at year $\boldsymbol{t}$ by $\boldsymbol{S_{f,t} = Y_{f,t}/Y_t}$ and the income share of the same group and time for income type $\boldsymbol{j}$ by $\boldsymbol{S_{j,f,t} = Y_{j,f,t}/Y_t}$. The income share of a group is equal to the sum of shares by types $\boldsymbol{S_{f,t} = \sum_j S_{j,f,t}}$.

We will now define more variables that will represent the two income changes, within and between income types. The within change variable is $\boldsymbol{W_{j,f,t} = Y_{j,f,t}/Y_{j,t}}$. This variable represents the income share of group $\boldsymbol{f}$ from type $\boldsymbol{j}$, out of the sum of income type $\boldsymbol{j}$ in the whole economy. For example, $\boldsymbol{W_{labor,P90-100,2018}}$ represents the income share of labor of the top decile, out of the whole population, in 2018. A change in this variable over time represents changes **within** income types.

The “between” variable is $\boldsymbol{B_{j,t} = Y_{j,t}/Y_t}$. This is the share of income type $\boldsymbol{j}$ out of the total income in the whole population in year $\boldsymbol{t}$. For example, $\boldsymbol{B_{labor,2018}}$ represents the share of labor income out of total income in 2018. Changes in this variable over time represent changes **between** income types. Note that the income share of income group $\boldsymbol{f}$ from income type $\boldsymbol{j}$ in year $\boldsymbol{t}$ is equal to the product of these two variables:

$$\boldsymbol{S_{i,f,t} = \frac{Y_{j,f,t}}{Y_t} = \frac{Y_{j,f,t}}{Y_{j,t}} \times \frac{Y_{j,t}}{Y_t} = W_{j,f,t} \times B_{j,t}}$$

We will now use these variables to decompose the changes in income shares over time of some income group $\boldsymbol{f}$ between two time periods $\boldsymbol{t_0}$ and $\boldsymbol{t_1}$, written as $\boldsymbol{\Delta S_{f,t_0,t_1} = S_{f,t_1} - S_{f,t_0}}$. From the above definitions, we get that

$$\Delta S_{f,t_0,t_1} = \sum_j \Delta S_{j,f,t_0,t_1} = \sum_j S_{j,f,t_1} - S_{j,f,t_0}$$

$$+ \sum_j \frac{W_{j,f,t_0} + W_{j,f,t_1}}{2} * (B_{j,t_1} - B_{j,t_0}) = \sum_j \left(B_{j,t_1} * W_{j,f,t_1} - B_{j,t_0} * W_{j,f,t_0}\right)$$

$$= \sum_j \frac{B_{j,t_0} + B_{j,t_1}}{2} * \left(W_{j,f,t_1} - W_{j,f,t_0}\right)$$

$$= \underbrace{\sum_j \overline{B_j} * \Delta W_{f,t_0,t_1}}_{\text{Within Type Changes}} + \underbrace{\sum_j \overline{W_j} * \Delta B_{f,t_0,t_1}}_{\text{Between Type Changes}}$$

Where $\overline{B_j}$ and $\overline{W_j}$ denote averages over years t_0 and t_1. The bottom line in the equation decomposes the change in income share into changes within income type (left) and changes between income types (right). Using this equation, it is possible to calculate for an income group the extent to which a change in income shares is explained by these two changes. Furthermore, since each of the components in the equation (“between” and “within”) is a sum over income types, it is possible to further decompose how each income type contributes to each change.

Results. We find that the decline in top income shares is mainly due to changes within income types. Figure 5 presents the results for the decomposition exercise between 2008 and 2018 for four income groups: P90-99, P99-99.9, P99.9-P99.99, and P99.99-100. The right-most bars in each plot, titled “Total”, represent the change in total income shares for the respective group (black right bar), the contribution of all within type changes (dark gray middle bar) and the contribution of all between type changes (light gray left bar). The sum of the two types, within and between, is equal to the overall change between the two periods. For example, the right black bar in the top left plot shows that the income shares of P90-99 declined by 2.1 percentage points between 2008 and 2018. This change is due to a decline of 2 percentage points in changes within income types, as shown by the middle dark gray bar, and only 0.1 percentage points of the decline are due to between income types changes, as shown by the left light gray bar.

In each income group presented in Figure 5, we find that changes within income types explain most of the decline in income shares between 2008 and 2018. For the P99-99.9, P99.9-99.99 and P99.99-100 income groups, the right-most black bars show a greater decline than the dark gray bars, meaning that within income type changes explain a larger decline than was observed in practice. This is because between income changes increased top income shares. For example, between 2008 and 2018, the income shares of the P99.99-100 went down by 0.1 percentage points. Within income type changes would have caused a decrease of 0.16 percentage points. But, between income type changes caused an increase of 0.06 percentage points, mitigating the observed decline.

Among the components that contributed to the change within income types, the decline in top income shares primarily stems from shifts in the distribution of labor income. The left bars in the four plots in Figure 5 represent the contribution of each income type (labor, business, capital, and other) to the overall change, as well as the change within income types and between income types. For each income group, the change within labor income (the leftmost dark gray bar) constitutes one of the most significant factors driving the decrease in income shares. For three out of four income groups, it is also the primary factor for the decline in income shares within that group.

The change within labor income represents a narrowing of disparities in labor income, echoing the finding in Dahan (2021), who observed a decline in pretax income inequality through analysis of household surveys. Dahan presents suggestive evidence that this decline stems from three mechanisms: a decrease in unemployment, a gradual increase in human capital for immigrants from the former Soviet Union, and a reduction in the proportion of migrant workers. These factors may also play a role in the decline in labor income inequality that we documented here.

Between income types changes have pushed for an increase in the income shares of the top decile, primarily due to a relative rise in total capital income compared to total labor income. This can be observed in the light gray bars under the label Capital, which are positive, compared to the light gray bars under the label Labor, which are negative. The high concentration of capital income in the top decile leads to a proportional growth in capital income shares, which causes a higher relative increase of the between types change due to Capital for higher income groups.

In summary, we find that the main reason for the decrease in income shares among high income groups between 2008 and 2018 stems from a more equitable distribution of labor income. For the top 1%, and especially the top 0.01%, we find that an economy wide increase in capital income partially offsets the decline in income shares. These findings align with the unequal distribution of capital income, which is concentrated in high income groups, as documented above. And, this explains the more moderate decrease in income shares observed from for the top 0.01% documented in Subsection 3.2. Since the primary change in income shares arises from shifts within labor income, we turn to explore labor income inequality in the next subsection.

c. Labor Income

In this subsection, we rank and calculate top income shares based solely on labor income, which is composed of wages and pensions. We analyze labor income separately for several reasons. (1) In the previous subsection we found that a significant portion of the decrease in top income shares stems from changes in the distribution of labor income. (2) The distribution of labor income can be estimated more accurately. Compared to other sources of income, the error in reporting labor income is lower because it is reported by employers. Additionally, almost all labor income is covered by the ITA data, so no additional assumptions need to be made on missing incomes. Finally, assumptions on observed capital income, such as the dividends from the 2017 tax reform, are not needed when we focus on labor income. (3) There is significance in measuring inequality in the labor market, as much of the research on inequality has primarily focused on the labor market (Katz 1999; Acemoglu & Autor, 2011; Danieli, 2022). The exercise itself is straightforward: similar to total income, we rank the individuals, allocate income groups and calculate income shares, based solely on labor income.

We begin by calculating the average income and income thresholds for top income groups based on labor income. The results are reported for the year 2018 in Appendix Table 3. Compared to the results in Table 1, which were created using total income for ranking and income shares, high income groups created using labor income alone tend to be closer to each other in average income levels and income thresholds (columns (3)-(4)). This finding suggests that labor income has a more equal distribution than total income. Additionally, we find that wages are the primary source of labor income, comprising over 90%, while the remainder comes from pensions.

Our comprehensive data allows us to observe that individuals with high labor income also enjoy high capital income. When examining the composition of total income (including nonlabor income sources) of individuals ranked with high labor income (Appendix Table 3 columns (6)-(9)), we observe that the share of capital income is significantly larger at higher labor income levels. This finding is consistent with our main results based on ranking individuals by their total income. A positive correlation between labor income shares and capital income shares is not unique to Israel, and has been reported for the US as well, with a positive time trend (Berman & Milanovic, 2020).

When looking at labor income alone, the top income shares are significantly smaller than the top incomes shares based on total income. Figure 6 compares the income shares time trend by top income groups using total income (circles with solid line) and using labor income (triangles with dashed line). The comparison shows that in each year, top labor income shares are lower, with larger relative differences for higher income groups. On average over the time period, the labor income share of the top decile is relatively 3% lower compared to the same share using total income. For P99-100 the ratio is lower by 28%, for P99.9-100 by 55%, and for P99.99-100 by 70%. These differences indicate that inequality in top labor income shares is lower than overall inequality in the top income shares in our main findings, with a greater reduction in inequality for higher income groups. This is due to the exclusion of capital incomes, which are mainly concentrated in the upper part of the income distribution, as we showed above.

Another finding that can be observed in Figure 6 is that the time trends of top labor income shares tend to be more negative and more monotonic compared to top income shares using total income. For example, when looking at total income, between the years 2012–14 the income shares of the top 10% and 0.01% remain stable over time, and for the top 1% and 0.1% even rise. In contrast, when considering labor income shares over 2012–14, the income shares of the top 10% and 1% decrease, and the top 0.1% and 0.01% remain stable. This finding indicates a convergence of wages in the top decile of labor income toward the general population, a trend that is more pronounced at the bottom of the top decile, i.e., P90-99, than at the top income groups within the top decile, i.e., P99.9-100. These results are not surprising considering the discussion above, which showed that the decrease in income shares of groups ranked by total income is mainly explained by a decrease in labor income shares.

The results in this subsection demonstrate the importance of including all sources of income when analyzing top incomes in Israel. Although the results based solely on labor income tend to be more accurate and require less assumptions, they only present a partial picture of income inequality, especially at the top. Since our focus is on inequality in gross income in Israel between the general population to the very top of the income distribution, our preferred estimates remain the main results presented in Section 3.

5. ROBUSTNESS TESTS

In this chapter, we examine the robustness of our top income share estimates. We test how the results vary for different choices in the main specification, particularly the age threshold and the allocation of the 2017 tax cut dividends. We finish with assessing how unobserved incomes affect top income shares.

a. Age Cutoff

We turn to examining the sensitivity of our estimates of top income shares to the choice of the age threshold. As discussed in Subsection 2.2, the age cutoff in the main specification was individuals aged 20 and above (20+), in accordance with the institutional context in Israel and to enable international comparison. However, as demonstrated in Atkinson (2007), the definition of the age cutoff may influence estimates of top income shares, as it omits individuals, thereby altering the composition of top income groups and the total observable income.

We compare our main specification to two alternative specifications: one with an age cutoff of individuals aged 15 and above (15+) and one with an age cutoff of individuals aged 23 and above (23+). We choose the lower age cutoff of 15+ to align with the definition of the labor force in Israel by the Central Bureau of Statistics (CBS) and other official institutions, and the upper age cutoff of 23+ to ensure at least two years after completing compulsory military service in the Israel Defense Forces for both men and women. The second definition is similar to setting the age cutoff to 20+ in countries without mandatory military service, which is two years after the end of compulsory education, set at age 18 in most OECD countries. We report population and income coverage in our data by age cutoff in Appendix Table 4.[15]

The contribution of the age cutoff to top income shares over time is presented in Figure 7. For the top 1%, we find that lowering the age cutoff to 15+ causes an average increase of 0.7 percentage points in income shares, while raising the age cutoff to 23+ results in an average decrease of 0.2 percentage points in income shares. The negative correlation between age cutoff and top income share is explained by the fact that when we include young individuals with low-income levels, the majority are added to the bottom of the income distribution. Conversely, raising the age threshold operates in the opposite direction, reducing top income shares. Finally, the long-term trends of top income shares remain unchanged when altering the age cutoff.

With regard to the international comparison, changing the age cutoff to 15+ or 23+ does not alter Israel's position compared to other OECD countries based on 20+. Since opting for a higher age cutoff (23+) reduces the top percentiles' income shares by only 0.2%, Israel will maintain its relative position. This indicates that the relatively low income earned by individuals during their military service is not the primary driver of relatively high inequality in Israel as measured by top income shares.[16]

b. 2017 Tax-Cut Dividends

We test the robustness of our results to various approaches for dealing with the tax-cut dividends of 2017. We will consider three different approaches to include them in

[15] The coverage rates of the population decrease as we lower the age cutoff to 15+, and increase slightly as we raise the age cutoff to 23+. A similar pattern is observed in the income coverage rates. This is consistent with the fact that individuals aged 15-19 are mostly outside the labor force.

[16] Also, in countries without mandatory military service, the income levels of individuals aged 20–23 are mostly low. And, a nonnegligible part of the Israeli society does not serve in the army. These reasons contribute to our decision not to omit this age group from our analysis.

individuals' incomes, and we will estimate top income shares using each of these approaches. For further details on the temporary reduction in dividend taxation in 2017, see Subsection 2.3.

The total amount of these dividends is NIS 80 billion, distributed among 26,000 individuals. A sudden increase in income from dividends affecting only 0.5% of the population may lead to extreme biases in our estimates. Therefore, we propose three possible approaches to handling this sudden income growth: as-is, omission, and smoothing. Table 4 reports the distribution of these dividends across different income groups under each of the approaches, and Figure 8 presents the income shares of high-income groups over time according to the different approaches. We will now discuss each of these approaches in detail.

The first approach to integrating these dividends is to use the raw data "as-is", and to treat the dividends with reduced taxation in 2017 as part of the total income received in that year. This approach assigns most of the recipients of the tax-reduced dividends to the top 1%, as seen in the first row of Table 4. The drawback of this approach is that the tax-cut dividend income essentially reflects a one-time response to a tax reform. This finding is reflected in the sharp increase in capital income in 2017 compared to other years, as shown in Appendix Figure 1. It is likely that the tax-cut dividends in 2017 included undistributed profits accumulated over several years, and hence their inclusion creates a misleading picture of economic activity in 2017.[17]

The second approach is to entirely omit the tax-cut dividends, presented in the second row of Table 4. While this approach resolves issues related to the temporary distortion of the income distribution, it creates other problems. First, by excluding these dividends from our analysis, we overlook a large and accurately measured amount of income that can be precisely attributed to individuals. The omission of these dividends means that our estimates will cover less income and will not capture the impact of this income on inequality. Additionally, individuals in 2017 likely adjusted their labor supply in response to the high income in dividends in that year. Consequently, the exclusion of these dividends may lead to a downward bias of income shares in the income group of the recipients of the tax-reduced dividends. This is evident in Table 4, as under this approach, 41% of individuals who received income from tax-cut dividends were assigned to P90-99, unlike the first approach, which assigns only 2% of these individuals to this group.

The third approach involves smoothing the tax-cut dividends equally over a 10-year period. This approach treats the tax-cut dividends as regular dividends distributed between 2008 and 2017, in an amount equal to 1/10 of the original income in 2017. Accordingly, this approach transforms the one-time jump in income into smaller annual increments. The aim

[17] Similar criticism was directed towards Piketty & Saez (2003), who observed a sudden increase in top income shares in 1986, which was later attributed to a tax reform in the same year. This reform changed the incentives for the highest income earners to realize their profits, rather than accumulating them in the corporations they owned, leading to the sudden increase in reported individual income (Blanchet et al., 2021).

of this approach is to account for the impact of this income on inequality, during the years when the dividends were plausibly earned. Due to the challenges discussed above, this is our preferred approach as it incorporates the reduced tax dividends into our estimates, while making more reasonable assumptions on the years they were accumulated, and without creating spikes in estimated incomes and income shares.

To illustrate the impact of the different approaches on the results, we calculate the top income shares using the three different approaches. The results are presented in Figure 8. For the years 2008–16 (prior to the tax rebate), not smoothing the tax-cut dividends (triangles and squares) leads to a decrease of 1% in the top percentile income share, and has a negligible effect on the top income shares time trend. In contrast, for the year 2017, when the tax-cut dividends are included in ranking and estimation of income shares but have not been smoothed over previous years (short dashed lines with triangles in Figure 8), all top income groups have a spike in 2017. For example, the income share of the top percentile experiences a sharp increase to 22.7 percentage points, a relative growth of 71.7% compared to the income share in 2016 (13.2%). This sharp increase followed by a sharp decrease in 2018, back to levels more similar to 2016, originated exclusively from the distribution of tax-cut dividends and suggests that the reform did not have a lasting effect on income. This outcome strengthens our view of this anomaly as a result of tax policy rather than a real economic phenomenon. In contrast, when 2017 tax cut dividends are omitted from ranking and estimates (squares), we observe similar income shares in 2017 as in previous years, for example at 12.7% without smoothing and 13.6% with smoothing when considering the top 1%.

To summarize, not smoothing the incomes that result from this one-time tax policy biases our income share estimates for top income groups, and so we smooth the tax-cut dividends in our main results. One can ask: over how many years should these incomes be smoothed? For this, it is useful to view the two first approaches as an upper and lower bound on the choice of smoothing period. The as-is approach can be viewed as smoothing over a single year, whereas the omission approach can be viewed as smoothing over an infinite number of years. It is worth noting that even the conservative approach that completely excludes the reduced tax dividends does not alter Israel's position in the OECD rankings by income share for the top percentile.

c. Missing Incomes

There are four main sources of income that are not included in our analysis. First, we do not include undistributed profits held by firms, as this constitutes corporate income, while we focus on individual income.[18] Additionally, there are three significant sources of private

[18] Recent studies, and among them Distributional National Accounts, have taken the approach of distributing undistributed profits to individuals (Blanchet et al., 2021).

income that are not observed in the ITA data: (1) employee's capital income deducted at source, (2) tax exempt rental income, and (3) unreported individual income.

Among the four types of missing income, undistributed profits are the largest. Figure 9(A) presents the total amount of each missing income. On average over the time frame of the analysis, undistributed profits constitute approximately 11% of total observed income in the data, which makes it the most significant missing income, followed by unreported income, employee's capital income, and finally tax-exempt rental income. Appendix A.4 specifies how these amounts are calculated.

We now turn to quantifying the impact of these missing incomes on top income shares. For each source of missing income, we conduct the following exercise. In a first stage, we estimate the total amount of missing income. In a second stage, we impute the distribution of the missing income, using the observed income in our main specification. These two stages are performed differently for each source of missing income, discussed further below and with additional details in Appendix A.4. In a third and final stage, we add this missing income using the imputed distribution, for the income groups calculated before the addition of the missing income, and recalculate income shares. That is, we do not re-rank incomes, but rather estimate how each missing income affects income groups that have already been calculated. We report the results in the following manner. Figure 9A shows the estimated sums of each missing income (step one). Figure 9B shows the imputed distribution of each missing income (step two). Figure 10 shows the top income shares time trend of the main specification, the main specification after adding each missing income separately, and the main specification after adding all missing incomes together (step three). Appendix Tables 5 and 6 report the absolute and relative changes in income shares and the levels of income shares, respectively, for each missing income.

Undistributed Profits. We incorporate undistributed profits into our analysis as annual flows of income. As discussed in Appendix A.4.1, we compute the annual amounts of undistributed profits based on the ITA's corporate datasets.[19] We impute the distribution of these profits in the population proportionally to the observed distribution of dividends in our data.[20] Since most dividends are received by individuals with high incomes, we expect larger shares of undistributed profits for individuals in higher-income groups. Figure 9B illustrates the resulting distribution of the missing income for each source. The panel under the title "Undistributed Profits" depicts the distribution of undistributed profits. As shown, we allocate the majority of this income to individuals with exceptionally high incomes, with the majority accruing to the top 0.1%.

[19] For this analysis we do not include the tax-cut dividends of 2017 that underwent smoothing, since we view these as distributed profits from 2008-2017 that were viewed collectively in 2017.

[20] Some of the firms are owned by the government, hence the private undistributed profits is probably lower in practice than the value which we use.

The inclusion of undistributed profits increases the shares of top incomes significantly. Figure 10 presents top incomes shares over time when various incomes are included. The triangles represent the top income shares after incorporating undistributed profits. When including undistributed profits, the income shares of the top 10% increased by an average of 10.6% (an average absolute increase of 4.9 percentage points) compared to the main specification (circles). The income shares of the top 1% increased by an average of 49.4% (an average absolute increase of 7 percentage points), and the income shares of the top 0.01% increased by an average of 150.1% (an average absolute increase of 3.6 percentage points). The positive relationship between higher-income groups and the increase of income shares caused by the addition of undistributed profits arises from the distribution of dividend income in our data, which is predominantly focused at the top of the income distribution.

Moreover, including undistributed profits caused the time trends to be positive between 2008 and 2018 for the top 1%, 0.1%, and 0.01%. This picture contrasts significantly with the documented decrease using the main specification, particularly for the top 1% and 0.1%. One possible explanation for this trend change is the increase in the total amount of undistributed profits over time, as seen in the temporal change in the bars in Figure 9A. The figure indicates that undistributed profits have grown over time, both in absolute and relative terms. Since undistributed profits are primarily imputed to the highest income groups (Figure 9B), their growth increases these income shares over time.

Employee's Capital Income. In contrast to individuals who report their capital income directly to the ITA, employees' capital income is deducted at the source and reported aggregately by financial institutions, and hence missing from our data. We estimate the sum of unobservable capital income based on the sum of taxes of these incomes as they appear in national accounts, and allocate them only to employees, based on the joint distribution of wage earners and observable capital income.[21] See Appendix A.4.2 for details on the imputation method.

The additional income from capital for employees causes almost no change in top income shares for all top income groups, as illustrated in Figure 10 by comparing the circles (baseline) with the squares.

Tax-Exempt Housing Rents. Legislation in Israel exempts housing rental income below a certain threshold from reporting and payment to the ITA, and hence such incomes do not appear in our data. To estimate the total amount of tax-exempt rental income, we utilize the household income and expenditure surveys conducted by the CBS. We find that tax-exempt

[21] It can be argued that capital income of employees, which is not directly reported to the ITA, is concentrated in the lower part of the income distribution, differently from the distribution of observed capital income of direct filers. To address this claim, we conducted exercises that fully imputed the missing capital income of employees solely to the bottom nine deciles, which we do not show. The results are insensitive even to this conservative imputation.

rental incomes amounted to an average of NIS 12 billion per year during our observed timeframe (on average 3% of observed income). We impute the distribution of tax-exempt rental incomes based on the distribution of taxed rental incomes observed in our data. The purple bars in Figure 9B illustrate that we allocate most of this income to the top decile, with 47% attributed on average to the P90-99, and an additional 27% attributed to the P99-99.9. We find that the addition of tax-exempt rent income slightly increases top income shares for all top income groups, with the most significant impact observed on the top percentile's income share, showing an average relative increase of 4.2% (an average absolute income of 0.6 percentage points).

Income of Nonfilers. Finally, we turn to estimate the impact of adding income for nonfilers. As mentioned in Subsection 2.2, when we inflate the size of the population to match the size of the Control Total for Population, we add to our analysis individuals with zero income, assuming that the reason for their absence from the ITA data stems from a lack of gross income. Alternatively, it may be assumed that some of these individuals have some form of gross income, which is not reported to the ITA either because it falls below the income declaration thresholds or because it is exempt from tax. Under this new assumption, we attribute to all the added observations a fixed income, 30% of the average income in our unadjusted data.[22] It is worth emphasizing that even under this new assumption, nonfilers are still situated in the bottom nine income deciles, and do not ascend to the top income groups.

We find that adding income to nonfilers as discussed above relatively decreases top income shares by 7% on average for all income groups, as depicted by the cross-filled squares in Figure 10. The uniform decrease across top income groups stems from the fact that all the additional income mechanically enters the bottom 90%, thus affecting only the overall income distribution while leaving the income of top income groups unchanged.

All Missing Incomes. Finally, we combine all missing incomes together and examine their combined impact on top income shares. We find that undistributed profits have the highest impact, slightly mitigated by the addition of income from nonfilers. Since undistributed profits are concentrated at the top of the income distribution, they have relatively greater influence on higher income groups. While the top decile's income share increases relatively (absolutely) by 5.2% (2.5 percentage points) on average, adding all missing incomes increases the top percentile's income share by 41.4% (5.9 percentage points, increases the top 0.1% income share by 93.6% (5.1 percentage points) and the income share of the top 0.01% by 131.7% (3.2 percentage points). Additionally, undistributed profits are the main component driving changes in the time trend of top income shares. Since all other added missing incomes had only a minor impact on income share trends, the collective trend after

[22] Unlike the analyses for previous income types, in this case, we are not attempting to estimate the total amount of missing income from this source. The same methodology was used by Piketty and Saez (2003).

adding all missing incomes is similar to the trend obtained by adding undistributed profits alone.

d. Conclusion

Among all the different robustness tests discussed in this chapter, we find that the most significant change to our estimates arises from the addition of the undistributed profits of firms, as can be seen comparing across rows in Appendix Table 5. We estimate that the inclusion of these profits substantially increases top income shares.

6. DEMOGRAPHIC AND ECONOMIC CHARACTERISTICS OF TOP INCOME EARNERS

Our rich data allows us not only to analyze the top income shares but also to characterize the individuals found in the upper tail of the income distribution. This section discusses the demographic and economic characteristics of high-income earners. Such characterization is not available in most advanced economies that lack access to extensive administrative data as we possess.

a. Demographic Characteristics

We begin by examining the distribution of gender, age, marital status, and place of residence within high income groups, reported in Appendix Table 7. In the upper tail of the income distribution, we tend to observe more males (e.g., males account for 87% of the P99.95-100), more married individuals, and also older individuals. When examining the joint distribution of income group and age, we find a high correlation with the primary source of income. The top income group P90-99 primarily consists of individuals under the age of 65 (89%), who predominantly earn their income from labor. In contrast, in the top percentile we observe a higher proportion of individuals in retirement, aged 65+ (18%), particularly in P99.9-100 (25%), who derive a higher share of their income from capital through holding assets and returns on investments accumulated throughout their lives. Appendix Table 7 also reports the geographic distribution of high income groups in Israel. Individuals belonging to higher income groups tend to reside around the central region, particularly the Tel Aviv district, with lower proportions residing in the northern and southern regions.

b. Economic Characteristics

We utilize industry classification to examine the sectors to which top income earners belong. Economic sectors in Israel have been classified since 2011 using the fourth edition of the International Standard Industrial Classification (ISIC4), which assigns a four-digit code to each business establishment specifying its primary economic activity.[23] A business establishment is defined as an economic unit engaged in a single economic activity, located at a single defined location, and having a separate accounting department. There are cases where multiple business establishments belonging to the same company are classified in different sectors. For example, a company with multiple factories and headquarters will have a separate economic sector code assigned to each factory and the headquarters independently, based on their primary economic activity.

Most individuals in our sample have an attributed industry, whether it is reported by their main employer (for employees) or by the individual (for direct filers). Note that industry classification does not specify the individual's occupation. For example, individuals attributed to the manufacturing industry could work as an assembly-line worker or an engineer.

The economic sectors characterizing the top percentile differ from those characterizing the rest of the population. Figure 11 presents the distribution of economic sectors in 2018 for the top percentile, using the broadest level of classification (letters). The figure presents the distribution for P99-99.9, P99.9-99 and P99.99-100. For comparison, the distribution of the entire population is marked by the black lines. For instance, 25% of individuals in P99-99.9 are classified as working in professional, scientific and technical services (M), compared to less than 10% of the entire population. Certain industrial sectors exhibit a high concentration for all three top income groups, meaning all three bars are above the black line for that industry: professional, scientific and technical services (M), real estate activities (L), and information and communication (J). Some sectors are more common in the lower parts of the top percentile, such as health and social work services (Q). In contrast, others show an inverse relationship, such as wholesale and retail trade (G), manufacturing (C) and financial and insurance activities (K).

To better understand the industry fields in the top percentile, we examine their representation according to a more detailed definition of economic sectors, two-digit codes. For economic sectors where there were not enough individuals from top income groups, we merged them into a broader industry category for privacy concerns. We identify nine groups of two-digit economic sectors that are common among the top percentile, presented in Figure 12.[24] For each sector, we report the proportion of individuals that work in that sector out of all individuals in the same income group with an observable economic sector in 2012 (dotted line with empty triangles) and in 2018 (solid line with filled squares). For comparison, we present the proportion of individuals working in the economic sector out of the entire

[23] The primary economic activity of a business is determined by the product with the highest value added. For further information on the ISIC classification in Israel see Central Bureau of Statistics (2015).

[24] The assignment to economic sector is further discussed in the notes of Figure 12.

population in 2018 using the dashed black line. The subfigures of each economic sector are arranged according to their frequency in the population.[25]

The most common economic sectors in 2018 for the top percentile, as presented in the different panels of Figure 12, are healthcare services (2), high-tech (3), legal and accounting services (7) and main office services and management consulting (9). While the first two sectors are more popular among the general population (8% and 6.4%, respectively), the latter two have lower overall proportions and are less common in the general population (around 1.7%).

We characterize three types of relationships between income level and economic sector: a ∪ shape relationship, a ∩ shape relationship, and a positive monotonic relationship. A relationship with a ∪ shape, meaning high representation in the lower parts of the top decile followed by a decline within the top 1% and an increase within the top 0.1%, can be found in economic sectors such as manufacturing (1), high tech (3) and finance (4).[26] This relationship suggests two separate groups working in these sectors: relatively high-wage employees entering the P90-99, and executives and company owners in the P99.9-100. This phenomenon is particularly pronounced in the high tech sector.

We also observe economic sectors with a ∩ shape relationship, meaning a high proportion of individuals in the P99-99.9 working in those sectors, compared to lower proportions in the P90-99 or the P99.9-100. These economic sectors mainly relate to free professions: physicians (2) and lawyers and accountants (7), who possess unique skills and high expertise, typically leading to high compensation levels enabling them to enter the top percentile.[27]

Finally, we observe economic sectors with a positive monotonic relationship: real estate (6), engineering (8), and main office and management consulting (9). While the economic sector of main office and management consulting is closely linked to ownership of companies,[28] and the real estate sector is associated with income from rent and property holdings, the engineering sectors present a surprising outcome, where we would expect it to resemble the patterns of physicians (2) or lawyers and accountants (7). It is possible that the salaries of individuals in the engineering professions are lower than those of lawyers or

[25] The bottom three sub-figures in Figure 12 belong to the same broad industry classification (M, which represents manufacturing), indicating the need for a more refined classification of economic sectors.

[26] The report for the industry sector (C) excludes economic sectors 21 and 26, which are included in the definition of the high tech sector.

[27] This pattern is not unique to Israel and is also found by Smith et al. (2019) for the distribution of small business (S-corporation industries) in the US.

[28] While management consulting covers various services related to firm management, such as financial and business strategy consulting, main offices refer to the entity within a company that controls and manages the entire organization, without specifying its primary sector. Therefore, this sector code can be seen as identifying managers and senior executives in companies.

physicians, and the observed trends reflect the income of managers and company owners with engineering backgrounds.

In certain economic sectors we observe changes over time in the proportion of high-income individuals as seen through the difference between the dotted (2012) and solid (2018) lines in Figure 12. In healthcare services (2), high tech (3), real estate (6) and main offices (9), we see an increase in the proportion of high income earners in these industries. In contrast, there is a decrease in high income earners in manufacturing (1), finance (4), wholesale trade (5) and engineering (8). These upward and downward trends are similar across different income levels within the top decile.

7. MOBILITY OF HIGH-INCOME EARNERS

There is a direct relationship between income inequality and income mobility. As income mobility increases among individuals, the average inequality over time diminishes, even when there is consistent high inequality year after year. From a normative standpoint, it can be argued that exceptionally high income levels do not necessarily reflect a long term inequality issue if they are accompanied by high intragenerational mobility rates (Auten, 2013; Kopczuk et al., 2010). Therefore, a complementary analysis to the above discussion is an examination of intragenerational mobility in Israel.

This section examines intragenerational mobility among the top income groups in Israel, compared to other advanced economies with available data. Intragenerational mobility in this context reflects the probability of individuals with lower incomes to reach high income levels, and the probability of high income individuals to reach low income levels. Studies from other countries have found that intragenerational mobility among these income groups is low, limiting the turnover of individuals with high income levels. Moreover, intragenerational mobility remains stable over time and is not aligned with the trend of inequality in the country (Jenderny, 2016; Kopczuk et al., 2010; Saez & Veall, 2005). In this section, we discuss intragenerational mobility among different top income groups over a time frame of one to ten years. In this section we exclude the tax-cut dividends of 2017. As discussed in Subsection 5.2, this approach introduces biases into the income distribution among income groups of 2017, and hence we simply do not conduct the mobility analysis for this year.[29]

[29] Smoothing the tax-cut dividend income will cause bias in mobility measures as it artificially keeps individuals that cash out those dividends in 2017 at the top of the income distribution, and hence decrease top-earners mobility. On the other hand, using the non-smoothed sample with 2017 data will increase top-earners mobility measurements, as many individuals enter the top income groups due to their temporally high dividend income, then exit them on the following year. We avoid these two problems by omitting 2017 data with its one-time tax-cut dividends income to receive mobility measures unaffected by this tax-related policy decision. However, these mobility measurements do not include any income that was eventually distributed in the 2017 dividend tax cut, which could affect the results.

Table 5 presents the transition probabilities by income levels from 2008 to 2018. Specifically, it illustrates the probability of an individual to belong to a certain income group in 2018 (in columns (3)-(6)) given their income group in 2008 (in rows). It should be noted that the income groups in Table 5 are not equal in size. Even under full mobility, when the starting point does not matter, the transition probabilities will not be equal between groups and will be equal to the population share in that group. We also present the probability of transitioning to any higher or lower income group relative to the initial group in 2008 (columns (7)-(9)).

We find that individuals tend to remain in similar income groups over a decade. Column (8) shows the likelihood of remaining in the same income group for a decade. For example, 95% of individuals in the bottom nine deciles stay in that group income. Among the P90-99, 53% remain in the same group (6 times the size of the group).[30] Among the P99-99.9, 34% remain in the same group (38 times the size of the group), and among P99.9-100, 25% remain in their group (252 times the size of the group). We also find that upward mobility at the top of the income ladder is challenging for all income groups. The probability of transitioning to a higher income group is approximately 5% for individuals starting in the P0-90, about 6% for individuals in the P90-99, and around 4% for those starting in the P99-99.9 (Table 5 column (9)).

The probability of remaining in the top 1% remains stable throughout the observed period. Appendix Table 8 displays the survival rate (the probability of staying in the same income group) for top income groups over varying time frames. As expected, the survival rate is lower for longer time frames. That is, within each income group, the probability decreases when moving from left to right columns. When examining a fixed time frame (column), we observe consistent values over time.

Figure 13 compares short term mobility levels in Israel with estimates for four other countries: the US, Germany, Switzerland and Canada, for which data were collected by Martinez (2018). The survival rates for each country, along with their data sources, are reported in Appendix Table 9. For the top 10%, 1% and 0.1%, Figure 13 presents the survival rate (vertical axis) by various time frames (horizontal axis). Estimates from other countries rely on data for an earlier period, spanning years between 1980 and 2010. Hence, differences in mobility rates may stem from temporal disparities. However, all studies estimating short term mobility in other countries with which we compare have shown remarkably stable survival rates at high-income groups. Therefore, we anticipate that more recent data would yield similar results.

[30] The P90-99 constitutes 9% of the population by definition. If mobility were absolute, meaning individuals were randomly assigned income groups, then only 9% of individuals starting in this group would remain in this group. We find that 53% of individuals starting in this group remain after a decade, corresponding to 6 times the expected percentage based on the group size.

We find that short-term mobility in Israel is higher for the top 1% and 0.1% compared to other countries. That is, while the income shares of the top 1% and 0.1% in Israel are high in international comparison, the turnover within these groups is higher in comparison to the four other studied countries. In contrast, we find that short term mobility for the top 10% is relatively similar to the four other countries. However, since the comparison is made only to four countries, it is not possible to infer Israel's position in a comprehensive international comparison.

8. CONCLUSION

In this study, we estimated the top income shares in Israel, i.e., the shares of the sum of income of groups situated at the upper tail of the income distribution out of the sum of gross income in the economy, using administrative data at the micro level collected from tax records for years 2008–18. Our estimates indicate that income inequality in Israel is high in international comparison, as Israel's top income shares are among the highest in the OECD. However, we find that the top income shares are declining over the short period we documented. This decline is primarily explained by a more equitable distribution of labor income between high- and low-income groups. In analyzing the potential impact of including unreported incomes in individual tax records, we find that our estimates for top income shares may be downward biased, mainly due to undistributed profits of firms. Additionally, we presented the demographic and economic characteristics of top income earners. Furthermore, we estimate for the first time intragenerational mobility between income groups, based on total income rather than just labor income.

Our findings align with other studies that find high levels of income inequality in international comparison (Cornfeld & Danieli, 2015; Dahan, 2002, 2021). It is worth noting that our analysis focused on gross income. Dahan (2021) finds that when focusing on net income, inequality has increased over time, unlike the decline found for gross income inequality. Similarly, we documented a decline in top income shares using gross income. Therefore, it would be interesting to replicate our analysis with a change in the income definition to examine whether top income shares of income post taxes and distributions exhibit a positive trend.

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TABLES

Table 1
Income Levels and Thresholds for Top Income Groups (2018)

Income Group	N	Lower Income Threshold	Average Income
General Population	5,676,000		108,989
P90-100	567,600	250,000	472,336
P90-95	283,800	250,000	291,230
P95-99	227,040	350,000	465,092
P99-100	56,760	700,000	1,406,838
P99-99.5	28,380	700,000	791,829
P99.5-99.9	22,704	950,000	1,222,831
P99.9-100	5,676	1,900,000	5,217,907
P99.9-99.95	2,838	1,900,000	2,267,015
P99.95-99.99	2,270	2,800,000	4,276,235
P99.99-100	568	8,100,000	23,725,345

Notes: The table presents the number of individuals, the lower threshold and average income for selected income groups in 2018. Incomes are reported on an annual basis. Income averages and thresholds are in new Israeli shekels (NIS), at nominal prices for the base year 2018. Lower income thresholds are rounded to NIS 50,000 up to the 0.1%, and to NIS 100,000 within the top 0.1%. The income groups are ranked using total income excluding capital gains.

Table 2
Top Income Shares (2008-2018)

Year	Population	Average Income	Income Shares Excl. Capital Gains								Incl. Capital Gains	
	(Thousands)	(Nominal Prices)	P90-100	P90-95	P95-99	P99-100	P99.5-100	P99.9-100	P99.95-100	P99.99-100	Shares Only P99-100	Ranks & Shares P99-100
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
2008	4,646	74,892	47.38%	14.12%	18.51%	14.76%	10.74%	5.53%	4.25%	2.29%	15.47%	16.38%
2010	4,892	78,042	47.06%	14.11%	18.42%	14.53%	10.54%	5.38%	4.09%	2.13%	15.39%	16.44%
2012	5,070	84,425	46.67%	14.13%	18.30%	14.24%	10.34%	5.40%	4.20%	2.40%	15.08%	15.68%
2013	5,162	88,766	46.76%	13.99%	18.18%	14.58%	10.66%	5.66%	4.43%	2.59%	15.59%	16.40%
2014	5,258	92,521	46.62%	13.88%	18.03%	14.72%	10.78%	5.69%	4.40%	2.45%	16.01%	16.88%
2015	5,359	96,859	45.65%	13.67%	17.64%	14.34%	10.53%	5.64%	4.40%	2.50%	15.84%	16.91%
2016	5,461	99,984	45.13%	13.51%	17.48%	14.14%	10.36%	5.59%	4.41%	2.59%	16.19%	17.13%
2017	5,566	103,695	44.44%	13.47%	17.38%	13.59%	9.85%	5.18%	4.08%	2.45%	16.41%	17.55%
2018	5,676	108,989	43.34%	13.36%	17.07%	12.91%	9.28%	4.79%	3.75%	2.18%	14.28%	15.41%
Average 2008-2018			45.89%	13.80%	17.89%	14.20%	10.34%	5.43%	4.22%	2.40%	15.58%	16.53%

Notes: Income and income shares calculated based on our main specification, with an inflated population and smoothing for the 2017 tax-cut dividends. Average income (3) is annual income at nominal prices for the whole population. Columns (4)-(11) represent the income shares of selected top income groups by total income excluding capital gains. Columns (12)-(13) represent the income shares of the top percentile by total income including capital gains. In column (12), individuals are ranked similarly to columns (4)-(11) (excluding capital gains), while in column (13), individuals are ranked by total income including capital gains. The last row averages the values for the years 2008-2018, excluding 2009 and 2011.

Table 3
Gini Coefficient by Population and Income

Year	(1)	(2)	(3)	(4)	(5)	(6)
2008	0.653	0.325	0.382	0.604	0.629	0.474
2010	0.651	0.321	0.377	0.603	0.628	0.465
2012	0.648	0.317	0.382	0.601	0.624	0.465
2013	0.646	0.324	0.392	0.597	0.621	0.46
2014	0.643	0.327	0.393	0.593	0.618	0.456
2015	0.63	0.325	0.397	0.58	0.605	0.453
2016	0.624	0.324	0.397	0.574	0.599	0.447
2017	0.617	0.317	0.382	0.568	0.593	0.485
2018	0.605	0.307	0.37	0.558	0.582	0.446
Population	Whole Population	P90-100	P99-100	P0-99	P0-99.9	Whole Population
Solely Labor Income						X

Notes: The table reports the Gini coefficient by year for different population and income definitions. Column (1) reports the Gini coefficient for the main specification. Columns (2)-(3) present the Gini coefficient calculated within the top decile and top percentile, respectively, measuring inequality within top income groups. Columns (4)-(5) report the Gini coefficient excluding the top 1% and 0.1%, respectively, illustrating the impact of disregarding high incomes on inequality measurement. Column (6) computes the Gini coefficient based on a specification that ranks income groups solely using labor income, as discussed in Subsection 4.3, demonstrating the importance of including capital income in inequality measurement.

Table 4
2017 Tax-Cut Dividends by Approach and Income Group

Approach			Share of 2017 Tax-Cut Dividends by Top Income Group					
	Smoothing	Incl. in Ranking	Period	P0-90	P90-99	P99-99.9	P99.9-99.99	P99.99-100
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
As Is	No	Yes	2017	0%	2%	25%	43%	31%
Omitted	No	No	2017	7%	41%	32%	13%	7%
Smoothed	Yes	Yes	Average 2008-2017	1%	13%	33%	35%	17%
	N		26,607					
	Sum of income (NIS Billion)		80.21					

Notes: The table presents details regarding tax-cut dividend income during the 2017 tax reform in 2017, and approaches to including this income in the analysis. Column (3) displays the period during which we include the tax-reduced dividends for each specification. Columns (4)-(8) report the distribution of income from the tax-cut dividends across income groups. The first row depicts the distribution of the tax-reduced dividends in 2017 using a specification where these dividends are including in the ranking process as they appear in the data. The second row illustrates the distribution of these dividends in 2017 if they were not including in the ranking process. The third row shows the distribution of the tax reduced dividends across income groups on average over the years 2008–17 in our main specification, which includes for each individual which earned a tax reduced dividend income an equal share of these dividends in each year 2008–17.

Table 5
Mobility over Ten Years

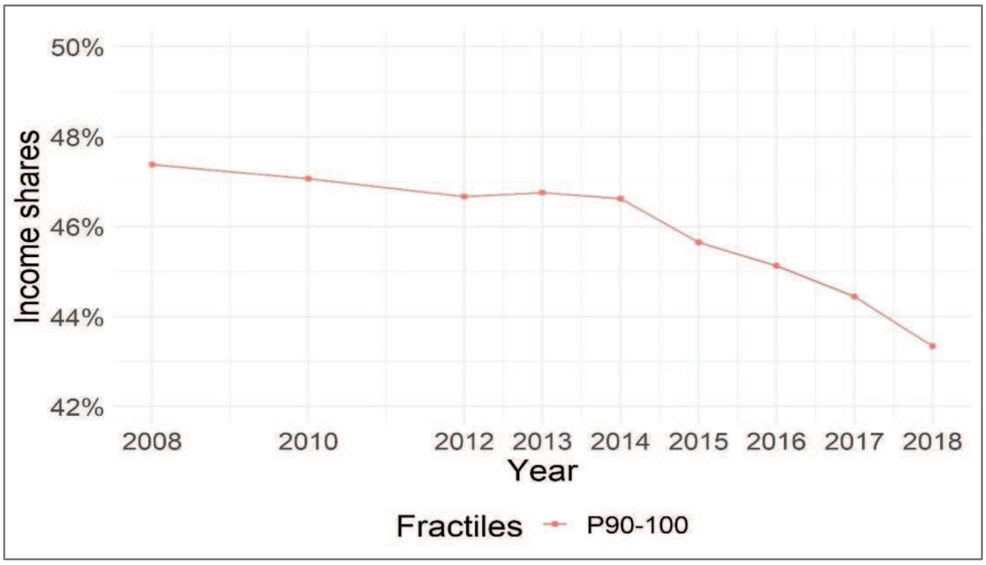
		Distribution over Income Groups 2018				Probability to Move		
Income Groups 2008	N	P0-90	P90-99	P99-99.9	P99.9-100	Down	Same	Up
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
P0-90	4,181,130	94.80%	5.00%	0.20%	0.00%		94.80%	5.20%
P90-99	418,113	40.80%	53.10%	5.70%	0.40%	40.80%	53.10%	6.10%
P99-99.9	41,811	24.00%	37.50%	34.30%	4.20%	61.50%	34.30%	4.20%
P99.9-100	4,646	21.30%	24.00%	29.50%	25.20%	74.80%	25.20%	

Notes: The table presents intragenerational mobility levels among four different income groups over a span of 10 years, conditional on the initial position in the distribution of income in 2008. Columns (3)-(6) display the probabilities (in percentages) of each individual being in each of the four income groups in 2018 (in columns), conditional on their income group in 2008 (in rows), so that each row sums up to 100%. Columns (7)-(9) represent the probability (in percentages) of moving downward, remaining in the same group, or moving upward in the income distribution of 2018 (columns), given the income group in 2008 (rows). Assignment to income groups for 2008 and 2018 is based on total income excluding capital gains and excluding the tax reduced dividends of 2017.

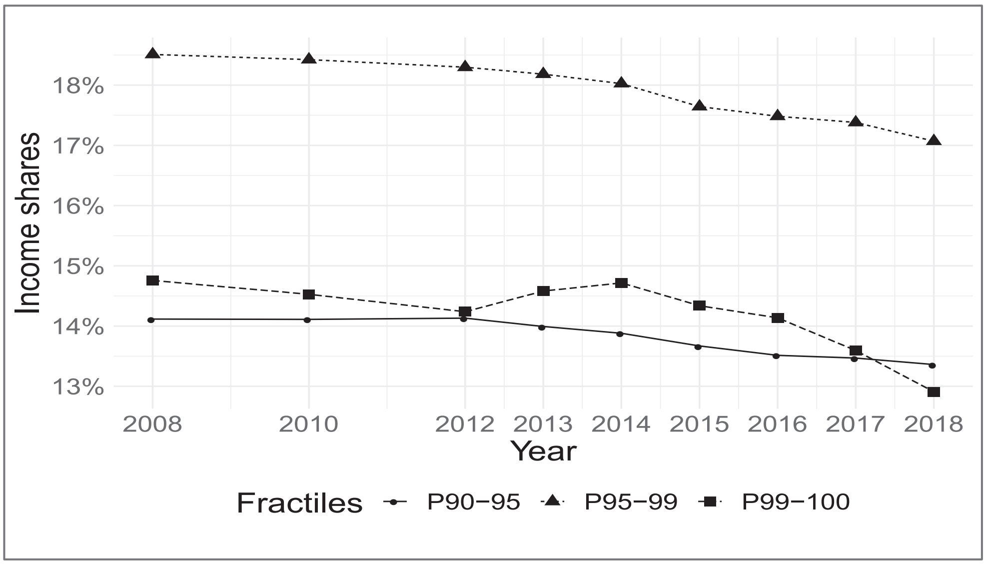
FIGURES

Figure 1
Top Income Shares over Time (2008-2018)

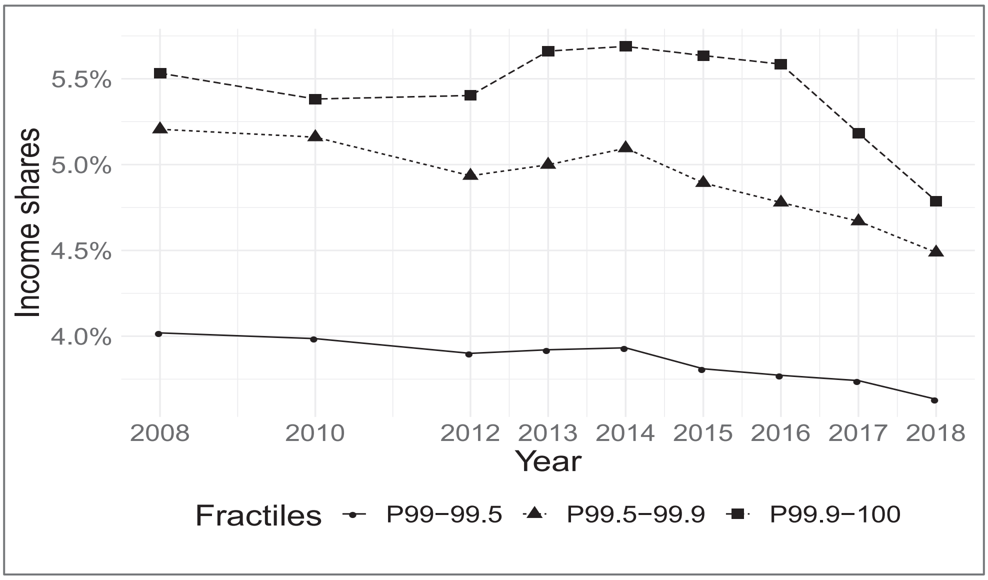
(A) Top 10%



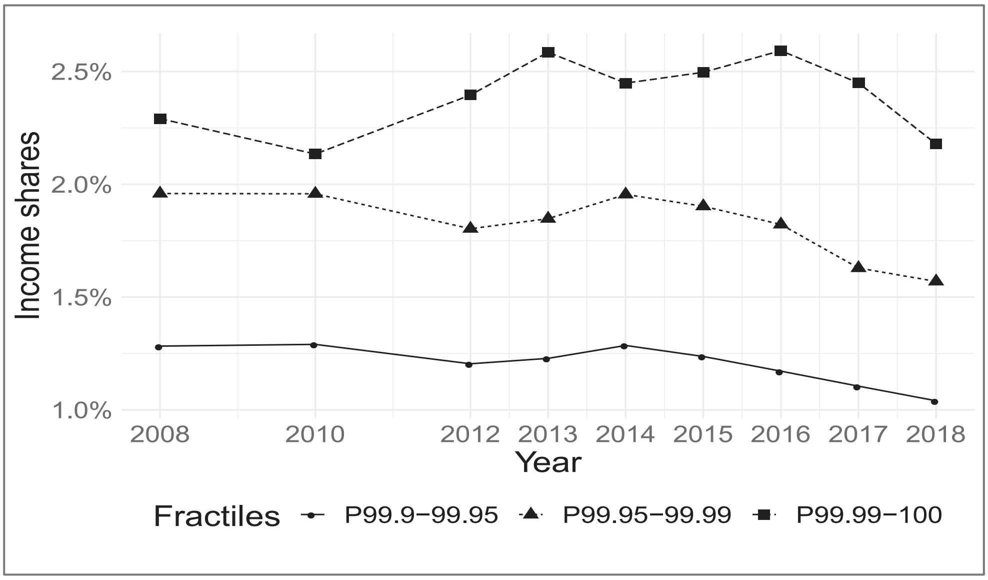
(B) Decomposed Top 10%



(C) Decomposed Top 1%

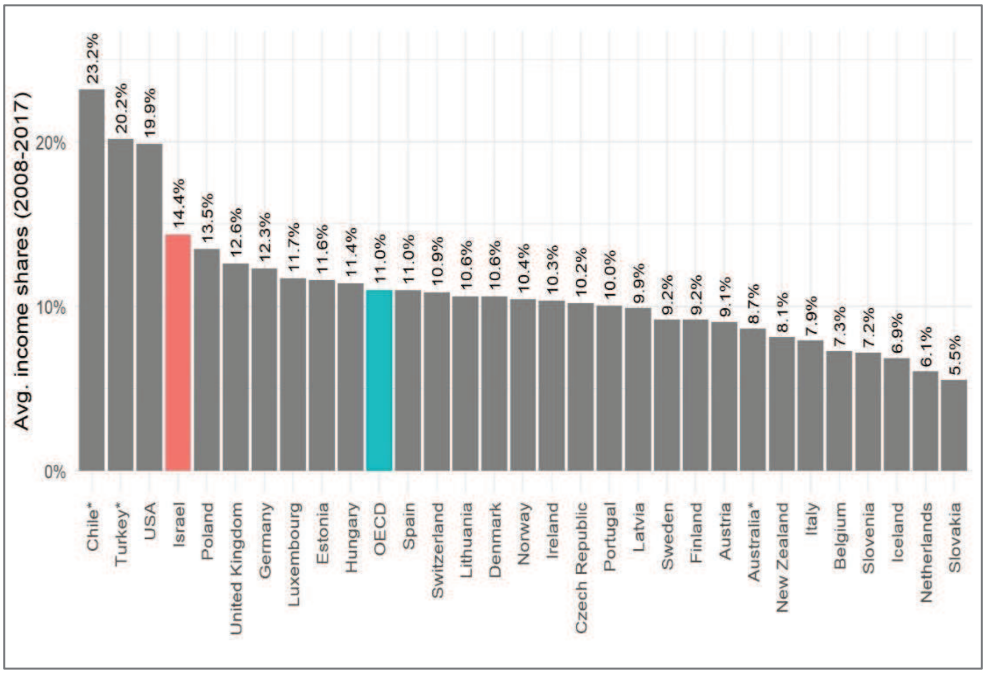


(D) Decomposed Top 0.1%



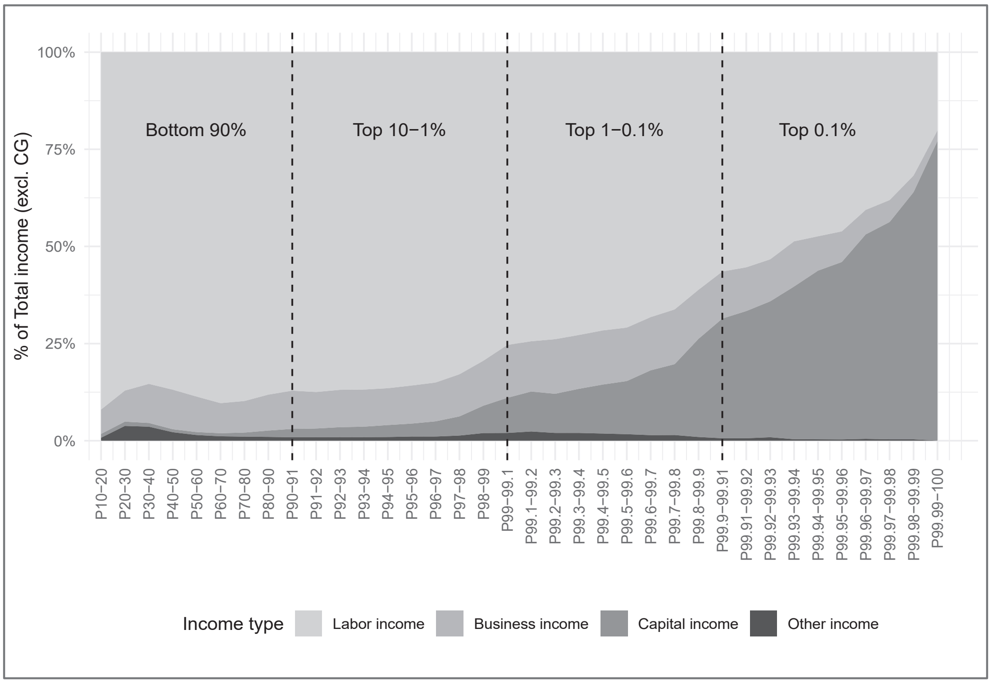
Notes: The figures present income shares for selected high income groups. Income shares are calculated according to our main specification (see Section 2), which uses total income excluding capital gains.

Figure 2
International Comparison of Top 1% Income Shares



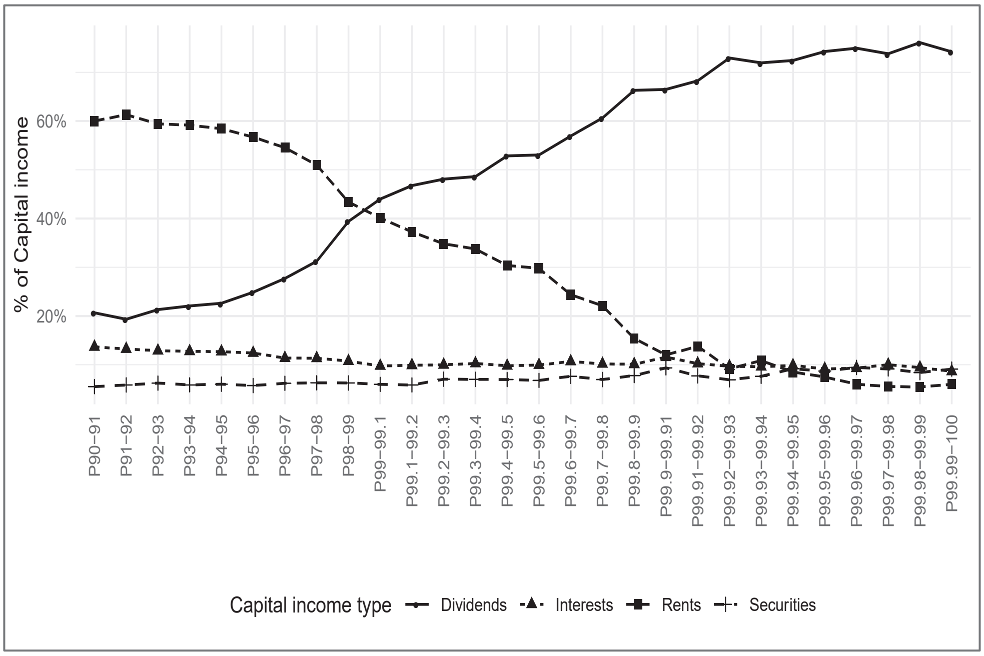
Notes: The figure presents average income shares of the top percentile for OECD countries between 2008 and 2017. Data for OECD countries excluding Israel are taken from the World Inequality Database, 2021. Income shares are ranked and calculated using total income excluding capital gains. Average income shares are calculated from 2008 to the latest available year or 2017. The OECD average is the simple average of the presented countries. Some OECD countries are not presented due to lack of data (Canada, Colombia, Costa Rica, France, Japan, South Korea and Mexico). Detailed estimates are reported in Appendix Table 1. The latest year is 2015 for Chile and 2016 for Turkey.

Figure 3
Income Composition across Income Groups (2018)



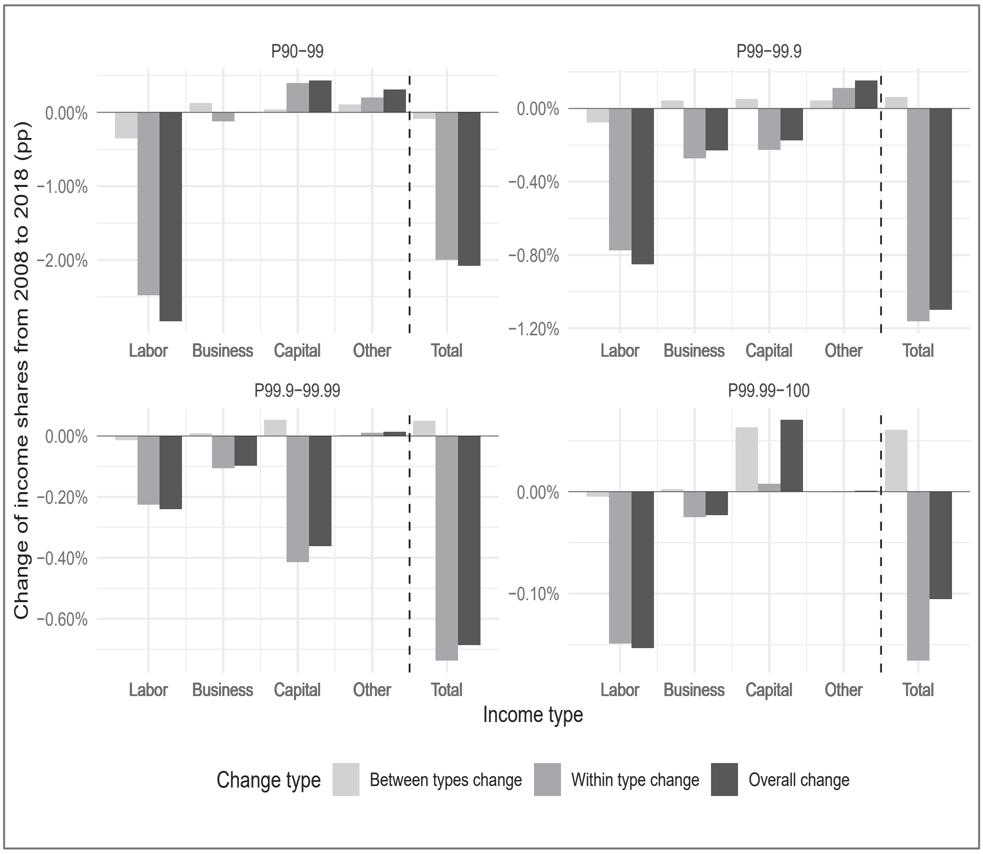
Notes: The figure illustrates the composition of income sources for different income groups in the year 2018. Income sources include labor income, business income, capital income and other incomes. The area of each income source represents the percentage of that income from total income excluding capital gains, for each group. Income groups are ranked according to total income excluding capital gains. The evolution of income composition over time is reported for selected income groups in Appendix Table 2.

Figure 4
Capital Income Composition across Top Income Groups (2018)



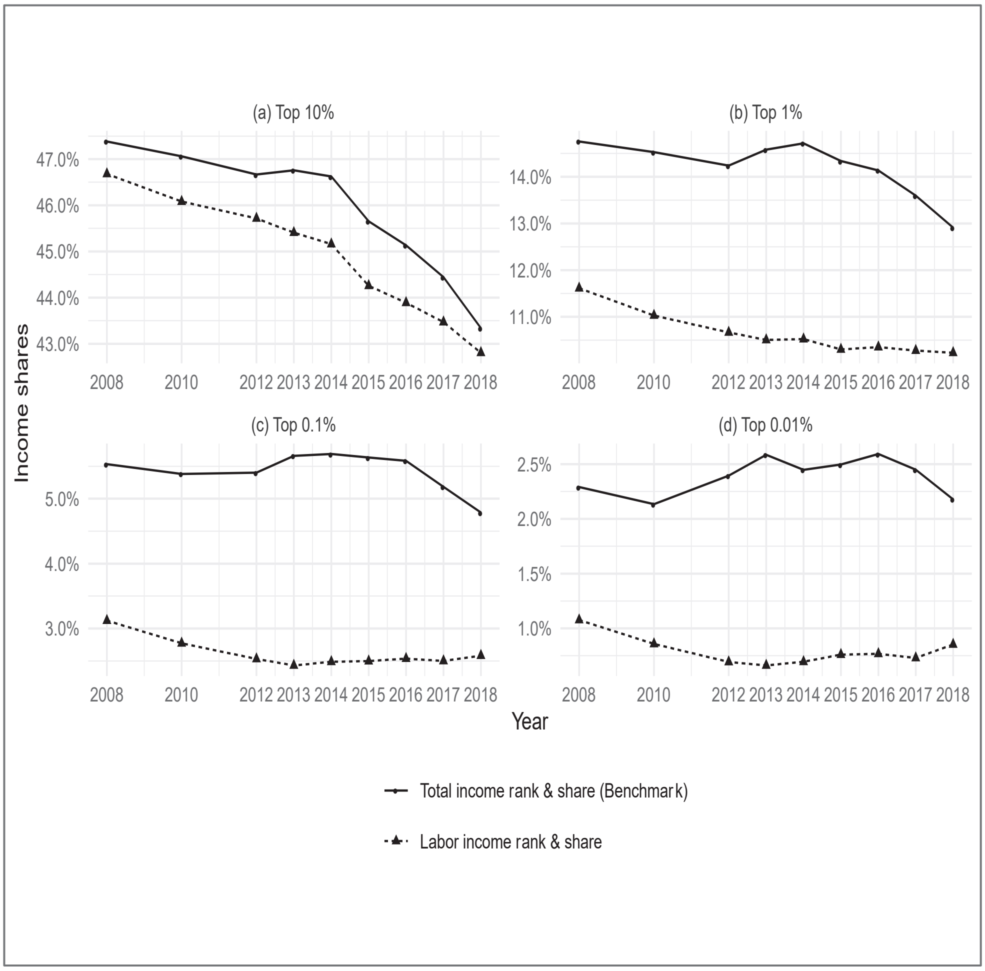
Notes: The figure presents the composition of subtypes of capital income for the top income groups in the year 2018. Capital income subtypes include dividends, rents, interest and interest on securities. For each subtype, we report its share (in percentages) of total capital income for each income group. Incomes from gambling, patents, and other types of capital incomes were not included due to their negligible proportions. The income groups on the horizontal axis are ranked by total income excluding capital gains. The classification of capital income into subtypes is further discussed in Appendix A.1.

Figure 5
Decomposing the Change in Top Income Shares by Income Types



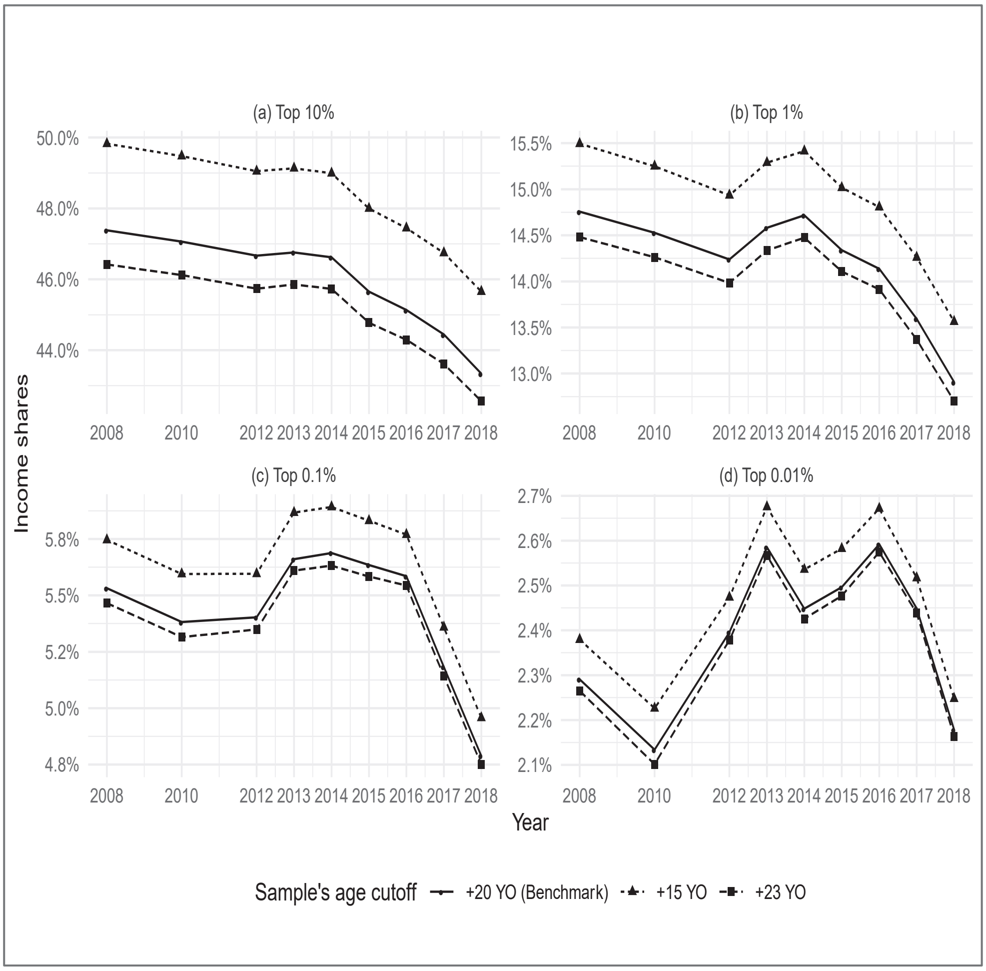
Notes: The figure presents changes in income shares between the years 2008 and 2018 (vertical axis), disaggregated by income type (horizontal axis) and by type of change (colors). Each subfigure represents a different income group, indicated in the title. The total change represents the change in income shares between 2008 and 2018, in percentage points. It is composed of two types of changes: changes between income types, and changes within income types. For further details see Subsection 4.2. Income groups and income shares are calculated based on total income excluding capital gains.

Figure 6
Comparing Top Income Share Using Labor vs. Total Income



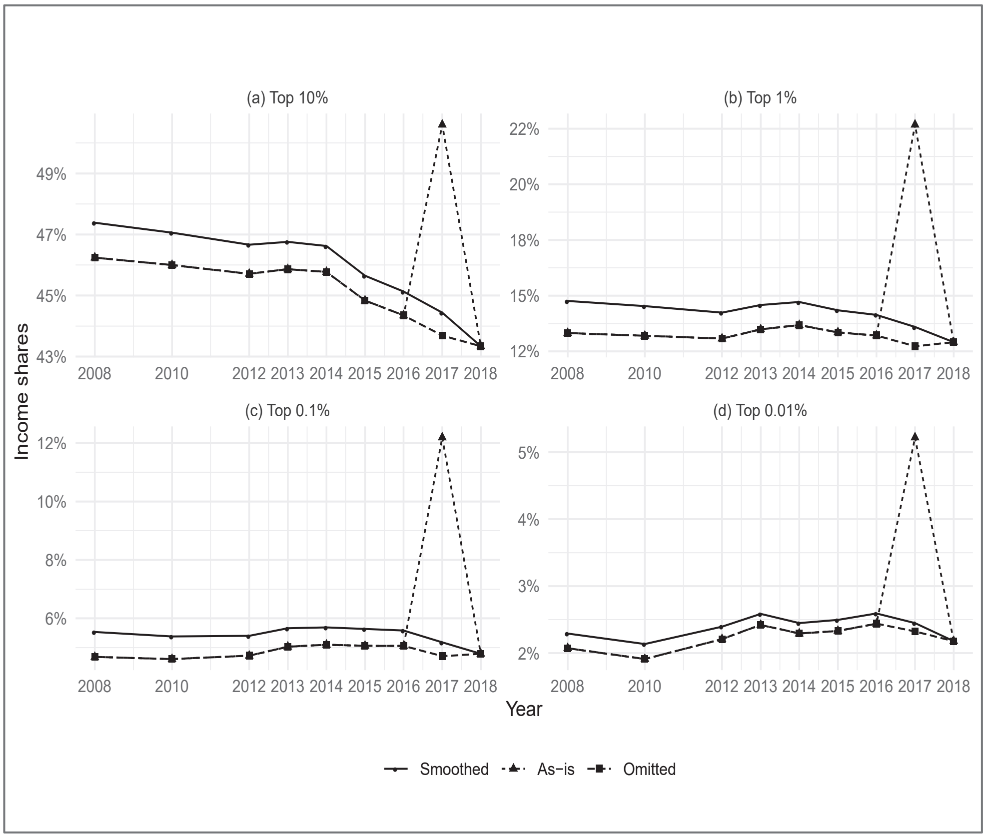
Notes: This figure shows the top income shares for selected top income groups under two different specifications: the circles with solid lines represent the top income shares in our main specification (ranking and shares based on total income excluding capital gains), and the triangles with dashed lines represent the top income shares from labor income only, with the ranking of income groups also based solely on labor income. Both specifications include individuals aged 20 and above. The numerical values are reported in Appendix Table 6.

Figure 7
Top Income Shares by Age Thresholds



Notes: The figure shows the top income shares for selected top income groups across three different specifications: our main specification with an age threshold of 20+ (circles with solid lines), a specification with an age threshold of 15+ (triangles with long dashed lines), and a specification with an age threshold of 23+ (squares with short dashed lines). The numerical values are reported in Appendix Table 7.

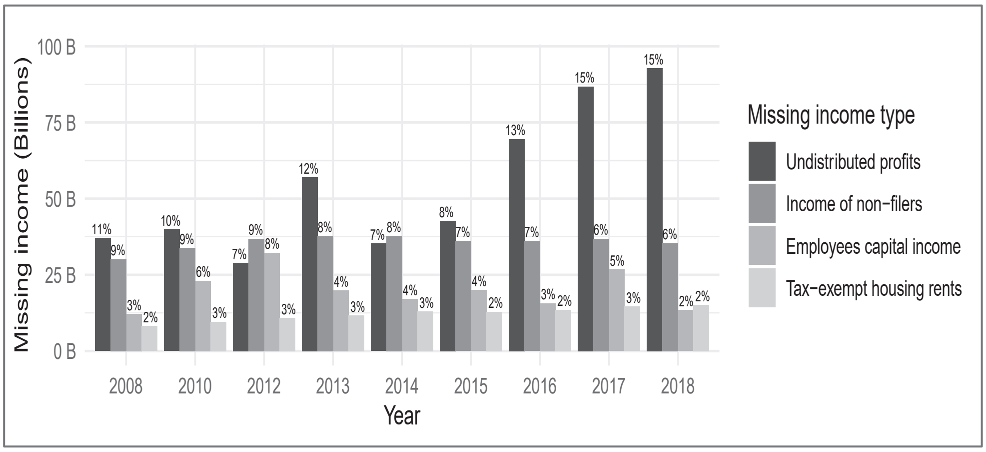
Figure 8
Top Income Shares by Approach to Including 2017 Tax-Cut Dividends



Notes: The figure shows the top income shares for selected top income groups using three different approaches of attributing the tax-cut dividends of 2017: our main specification, which allocates the tax-cut dividends of 2017 evenly over 2008-2017 ("smoothed", circles with solid lines); a specification that leaves the tax-cut dividend income as-is ("as-is", triangles with long dashed lines); a specification that omits the dividends altogether ("omitted", squares with short dashed lines). The numerical values are reported in Appendix Table 6.

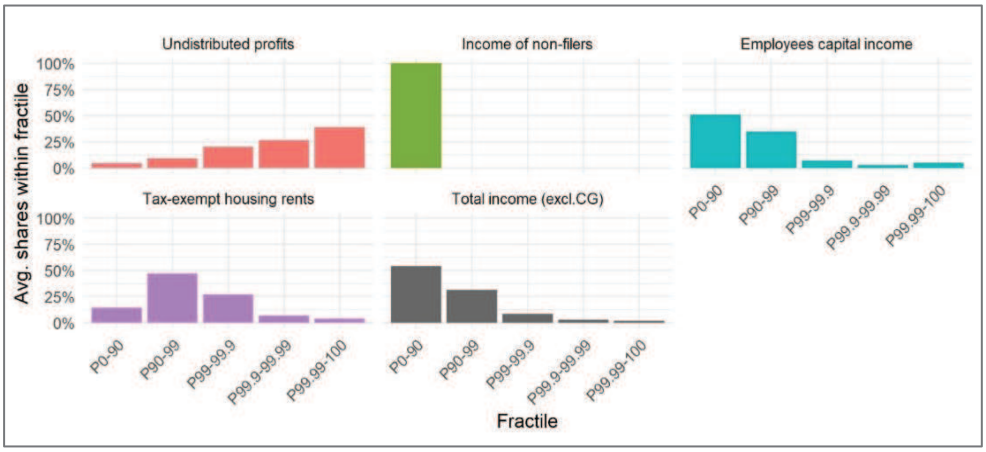
Figure 9
Missing Incomes Sums and Distributions

(A) Sums of Missing Incomes



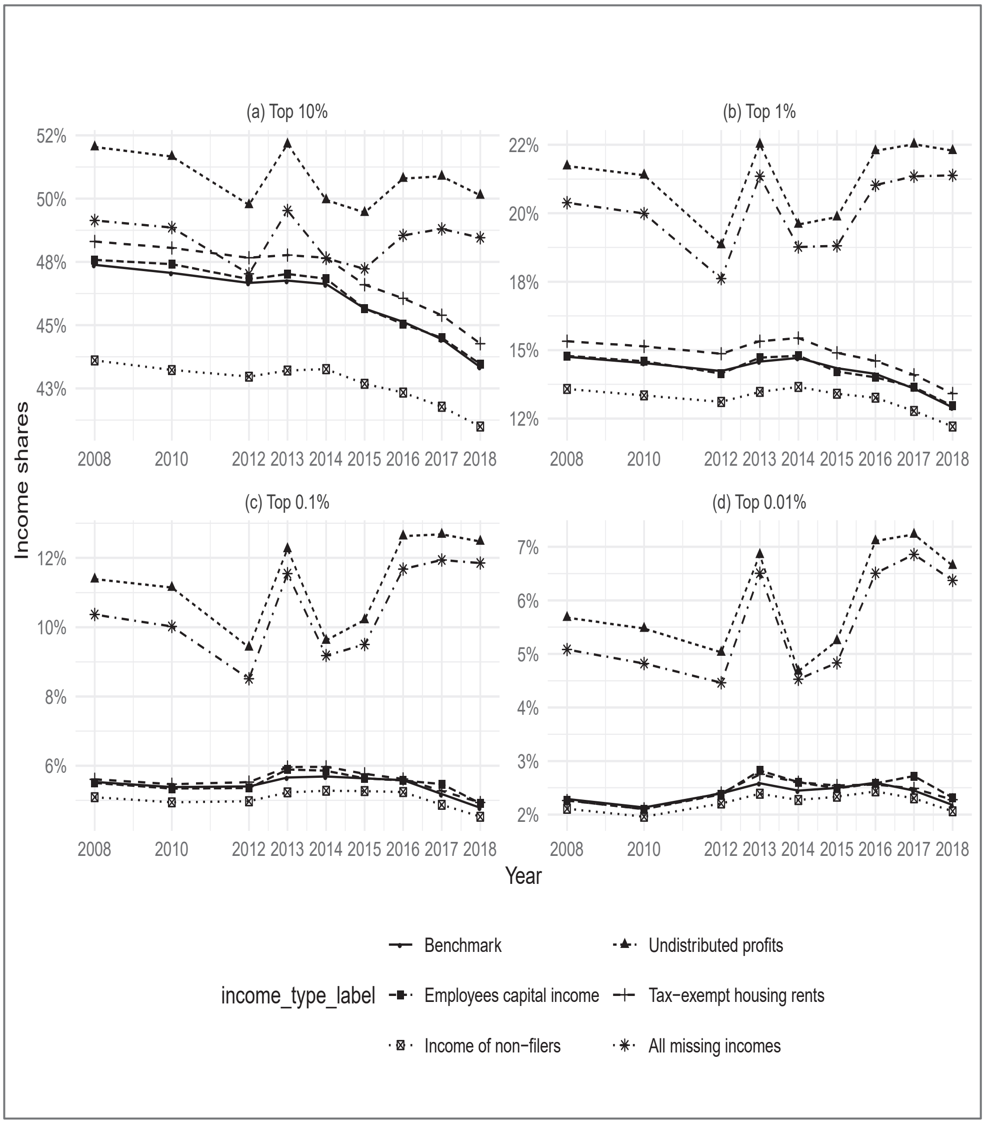
Notes: The figure presents the amount of missing income for years 2008–18, in NIS billion in nominal terms. At the top of each column, we report the percentage out of the total observed income excluding capital gains in our main specification. Appendix A.4 discusses the method for calculating the sum of each missing income.

(B) Distributions of Missing Incomes



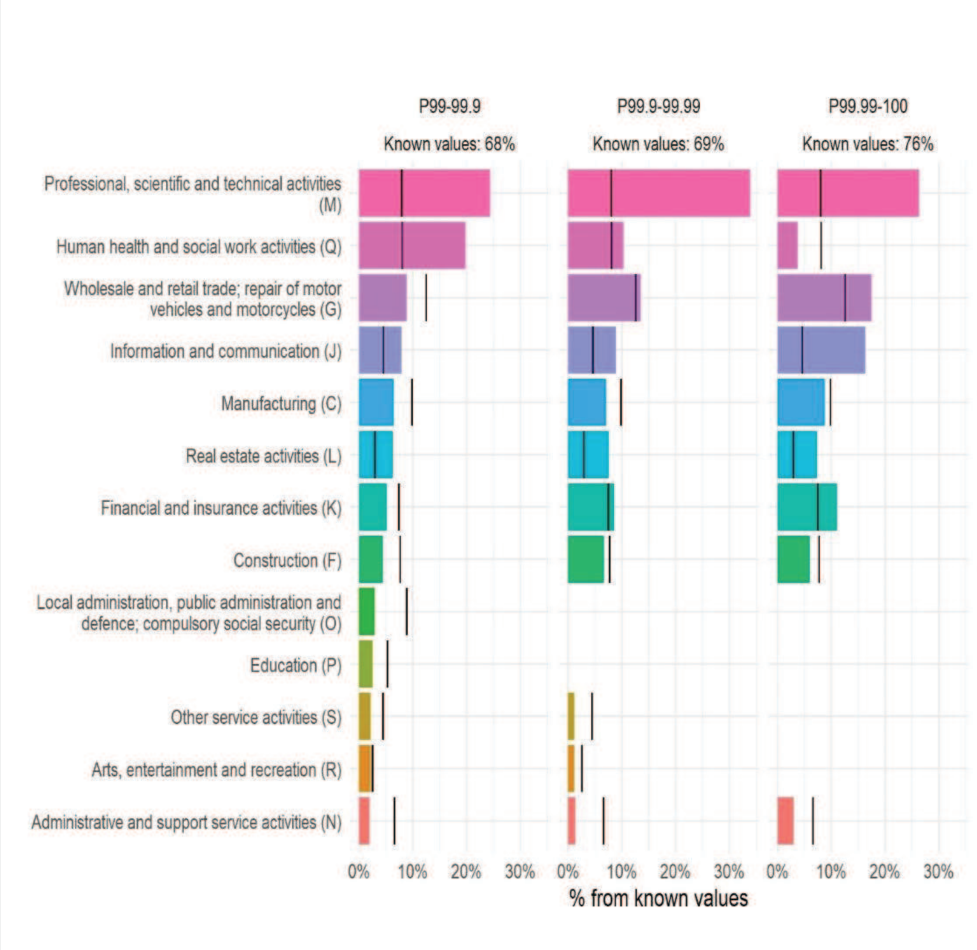
Notes: The figure presents the average distribution (vertical axis) of various missing incomes across selected top income groups (horizontal axis). The type of missing income is written in the title of each subfigure. For comparison, the average distribution of total income is shown in the bottom-middle subfigure. The distributions are averaged over the observed period (2008-2018). Individuals are ranked using our main specification. A detailed description of the imputation methods and sources is provided in Appendix A.4.

Figure 10
Top Income Shares After Adding Missing Incomes



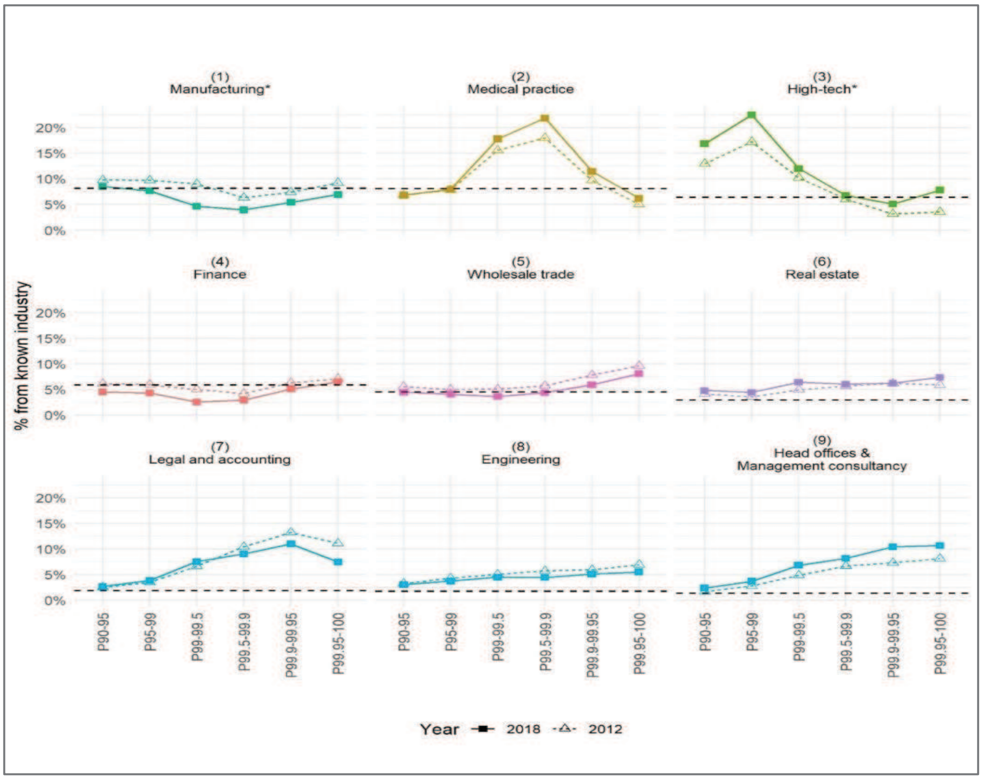
Notes: The figure shows the top income shares for selected top income groups after adding the missing incomes. The different shapes and lines represent which missing income has been added, as shown in the legend. We also show a specification where all missing incomes are added, and our main specification ("benchmark") for ease of comparison. The ranking is based on our main specification, and the imputation methods are discussed in Appendix A.4.

Figure 11
Broadest Industry Sectors Distribution Within the Top 1% (2018)



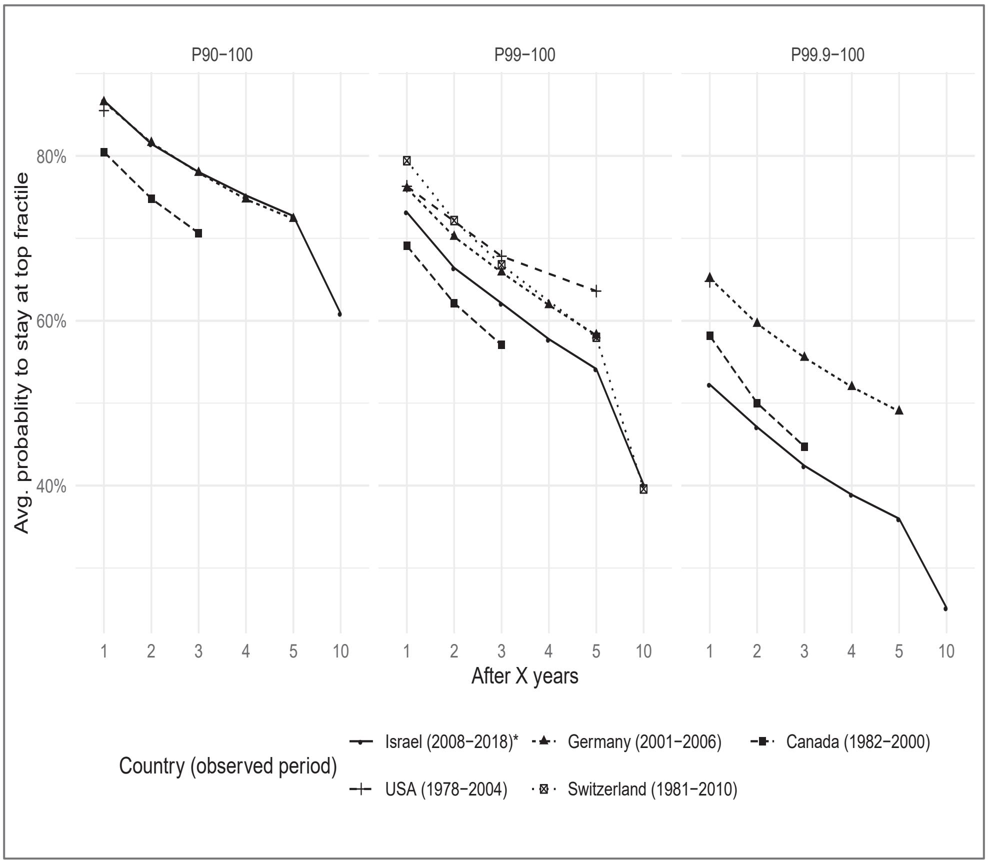
Notes: The figure shows the distribution of individuals according to industry sectors, using the broadest classification (letters), within top income groups in 2018. Each column shows the percentage of individuals in each of the 13 industry sectors (sorted by the percentages for P99-99.9). The percentage of individuals is calculated from the total number of individuals with known industry classification in the respective income group, with the total percent of individuals with a known industry is reported at the top of each column. Income rankings are calculated using our main specification. Eight industry sectors are omitted due to negligible percentages among the top 1% (codes A, B, D, E, H, I, T and U). The percentage of individuals for each industry sector for the entire population is presented by black vertical lines.

Figure 12
Selected Industry Sectors Distribution (2012 vs 2018)



Notes: The figure shows the percentage of individuals working in an economic sector (vertical axis) out of all individuals in the same income group (horizontal axis) for nine selected sectors that are common in the top 1%. The filled squares represents 2018 and the empty triangles represent 2012. In selecting the nine common sectors, we use the broadest classification (letters) as well as less coarse classifications (two-digit codes and three-digit codes). Additionally, we combine several sectors using three-digit classification to represent the high-tech sector, following the Central Bureau of Statistics (2015), since it is of particular interest in research on the Israeli economy. We exclude the sectors included in the high-tech classifcation from other categories. Income rankings are calculated using our main specification. Percentages are calculated from all individuals in the same income group with a known industry. The nine sectors, according to the ISIC4 codes, are: (1) Manufacturing – sector C excluding two-digit codes 21 and 26; (2) Medical Practice – sector Q; (3) High tech – two-digit codes 21, 26, 61 and 62, and three-digit codes 303, 631, 720 and 721; (4) Finance – two-digit code 64; (5) Wholesale trade – two-digit code 46; (6) Real estate – sector L; (7) Legal and accounting – two-digit code 69; (8) Engineering – two-digit code 71; (9) Head offices and Management consultancy – two-digit code 70.

Figure 13
International Comparison of Top Income Group Survival Rates



Notes: The figure presents the survival rates of individuals in selected top income groups for various countries. Survival rate is defined as the probability that an individual in a specific income group remains in the income group over the defined period. The vertical axis represents the survival rate, and the horizontal axis represents the time frames. Shown survival rates are averages over the observed period for each country, reported in the parentheses in the legend. Income rankings are calculated using our main specification. Not all countries have survival rates for all income groups—a detailed description of each country is provided in Appendix Table 9. The estimates for Israel exclude 2009, 2011 and 2017.

A. APPENDICES

A.1. Dataset Construction

This appendix outlines the process of constructing the dataset on which the findings of this study are based.[31] The raw datasets are derived from tax records of salaried employees and individuals who directly file their taxes to the ITA. We begin by presenting the raw datasets, continue with describing the process of merging the raw datasets into a unified dataset, and conclude with a discussion on the data cleaning process.

The income data from the ITA consists of four raw datasets: two identically structured datasets for salaried employees, one for men and one for women, and two datasets for direct filers, one for the individual reporting directly to the ITA and one for their spouse. The datasets for employees include information on wages, pensions, tax-exempt work income, and capital gains received through employers. In contrast, the datasets for direct filers and their spouses are more comprehensive, covering wages, pensions, business income (sometimes referred to as income from self-employment), capital gains, and income from various capital sources. All datasets also contain demographic variables: gender, year of birth, marital status (verified through the population registry), place of residence, and economic sector, defined as the sector where the individuals earns the majority of their income.

The data for direct filers include separate variables for different sources of income, encoded according to the reporting of direct filers to the ITA on Form 1301. The capital income variables distinguish between income sources with different tax bases. However, they may aggregate various types of capital income under the same variable if they are subject to the same tax rate. For example, in 2018, income from securities, bond yields, and dividends from preferred stocks were all taxed at the same rate of 15%. Therefore the sum of these three income sources is reported as a single variable. Consequently, we cannot classify the amount of capital income based on the type of investment, such as dividends, interest and rents, without further assumptions using only the observed data.

This feature of the dataset, which aggregates multiple income types into a single variable, complicates the characterization of capital income by type. To facilitate discussion on the differences between various types of capital income, we make a simplifying assumption that all types of capital income are equally distributed within a specific variable, dividing its total among the different types of capital income that comprise it. For example, when considering the variable we discussed above, we will equally divide its total income among securities, bonds, and dividends. An exception to this rule is the data from 2008, where all variables of capital income are combined under one variable without differentiation by tax rates, rendering allocation to different types of capital income impossible. Since there were no

[31] All estimates reported in this study are based on at least ten individuals, due to privacy constraints. The data was compiled by Dor Leventer during his employment at the Chief Economist's Office in the Ministry of Finance.

significant changes in capital gains tax rates between 2008 and 2010, we use the distribution of capital income types from 2010 for the 2008 data. Finally, income from assets acquired after marriage is reported within the primary filer's capital income, while for the spouse only income from assets that were acquired before marriage is reported.

We merged the raw datasets described above into a single dataset. First, we combined the datasets of employees into a single dataset, and also combined the datasets of direct filers and their spouses into a single dataset. As expected, there is some overlap between the two datasets: approximately 15% of individuals appear in both datasets (Appendix Table 10), meaning they are reported to the ITA both by their employers and by themselves. For these individuals, we used the data from the direct filers dataset exclusively, following previous research by the CBS (Frohman, 2007), assuming that an individual's direct report is more accurate and comprehensive than their employer's indirect report. To validate this assumption, we examined the difference in labor income of the same individual as observed in both datasets, as depicted in Appendix Figure 6. We found that, on average over all observed years, 86% of individuals included in both datasets had a labor income difference of less than 5% between the two datasets, and for 63% of individuals the reported labor income was equivalent in both datasets.

Our final dataset disregards instances of negative income. We removed all negative incomes from labor (salary and pensions), capital gains, and other income (tax-exempt income for individuals with disabilities). Negative incomes in these categories typically result from specific tax arrangements in previous years (for labor and other income) or investment losses (for capital gains). These phenomena are excluded from our income definition in the main specification, which does not include capital gains and focuses solely on gross income. Appendix Table 11 columns (2)-(10) shows the number of individuals with negative income, and its share of the total income for each type. We found that these adjustments apply to less than 0.2% (at most) of the entire population and involve negligible amounts compared to the total observed income. Accordingly, these adjustments are expected to have a minimal impact on our estimates.

A.2 Control Totals for Population and Income

In this appendix we present the external data sources and imputation methods used to estimate the control totals.

A.2.1. Control Total for Population

The control total for population is derived from official statistics by the CBS, which divides the entire Israeli population into age groups.[32] Appendix Table 12 shows the population coverage rates of the ITA data by age group over the years. At the bottom of the table, the

[32] The Central Bureau of Statistics (2021c) Table 2.19 for 2008-2010 and table 2.3 for 2012-2018.

percentage of individuals with missing age data is reported. This percentage is relatively small, ranging from 0.2% to 1.1%, depending on the year.

A.2.2. Control Total for Income

Unlike the data sources used to establish the control total for population, imputing the control total for income is a more complex task that requires a variety of data sources and imputation methods. Appendix Table 13 reports the different income components we used to impute our control total (row 13) from the net national income (row 1), and highlights several types of income not observed in our data. Decisions regarding these income types and their calculation were based on two sources. The calculation process from net national income to household primary income (rows 1 to 9) was derived from Blanchet et al. (2021). Subsequently, the calculations from household primary net income to declared taxable income of filers (rows 10 to 23) were based on Atkinson (2007). Throughout this subsection of the appendix, we use terms from the 2008 System of National Accounts. Therefore, when we refer to income as "primary", we mean before taxes (as opposed to "secondary"), and when we refer to income as "net", we mean income after depreciation.

We begin with net national income (row 1). To derive the household primary net income (row 9), we subtract from the net national income the income of the government sector (row 2), the undistributed profits of the corporate sector[33] (row 5), corporate taxes paid to the government (row 6), and the income of nonprofit institutions serving households (row 8). Our concept of income is defined as cash flow income, meaning it is fully available for consumption, savings, or investment by the income recipient. Therefore, we exclude from household primary net income two components that do not fall under this definition: employer-paid social security contributions (row 11), which are not fully controllable incomes as they are saved by the social security system, and imputed rental income (row 12), which is not cash-flow income received by the owners. Ultimately, we arrive at our control total for income, termed household actual primary net income (row 13). In row 24 of Appendix Table 13, we report the total initial income in the ITA dataset. From this data we exclude individuals below the age of 20 (row 25). We report the income total in our main specification, which is based on individuals aged 20 and above, in line 26.

A.3. Data Coverage

In this appendix, we discuss the coverage of the ITA dataset and the discrepancies between the ITA data and our control totals for population and income.

A.3.1 Income Coverage

In row 27 of Appendix Table 13, we report the coverage rate of income of individuals aged 20 and above, derived from the control total (row 26 divided by row 13). Over time, there is

[33] For the calculation of undistributed profits of corporates see Appendix A.4.1.

a positive trend in the coverage rate, increasing from 75% in 2008 to 81% in 2018. This raises the question of the source of the gap between the total income in our main specification and the control total for income. This discrepancy arises partly due to the nature of our data source, which includes only individuals' reported income. Therefore, income not reported at the individual level to the ITA is absent from our data, as well as income reported to the ITA in aggregate form across multiple individuals. Additionally, we do not account for income that is illegally not reported to the ITA, sometimes referred to as the "black market". However, black market income does not affect our data coverage, as it is also absent from our control total for income.[34]

We identify three major types of income included in our income control total that are not observed in our data. First, our dataset does not include rental income exempt from taxes, as individuals receiving this income are also exempt from reporting it. Second, we do not observe employee income from capital which is deducted at source and reported in aggregate by financial institutions, such as banks. Finally, we do not observe taxable income below the declaration threshold, which we refer to as income from individuals who do not report income. For each of these missing income types, we calculate the sum of income using external data sources, as discussed in Appendix A.4. When we subtract these unobserved income amounts from the control total, the coverage rate increases by an average of 10 percentage points (Appendix Table 13 row 28), ranged from 82% to 92% over the years. This indicates a gap of 8-18 percentage points between the control total and the observable income in the ITA data that is not likely attributed to these three unobserved incomes. This gap may be due to the use of different calculation methods, income definitions, and data sources in macroeconomic aggregate estimates compared to those used in micro level data (Atkinson, 2007). Other studies on top income shares in various countries have found similar coverage gaps (Piketty & Saez, 2003; Dell, 2005; Saez & Veall, 2005).

A.3.2. Population Coverage

The coverage rate of the control total for population in the ITA data is reported in Appendix Table 14. The population coverage rate increases over time, from 78% in 2008 to 84% in 2018. There are two main reasons for the absence of individuals from the ITA data. First, when all their income comes from sources not observed in the data. Second, some individuals may have zero annual income according to our income definition and sustain themselves through government transfers, family transfers, etc.

To determine the reason for the absence of individuals from our data, we closely examine the missing population by age groups. The ITA's population coverage is relatively low for very young individuals and very old people, as reported in Appendix Table 12. It is likely that young individuals (e.g., the 15-17 age group) are missing from the data because they are still in school and have zero annual income. Regarding older individuals, if they receive a

[34] Our control total for income is a subset of national net income, which does not include untaxed income. For more details on the income control total, see Appendix A.2.

pension, then they are recording in the ITA data. However, there is an older population that does not receive a pension and relies solely on government transfers. Income survey data from the CBS shows that on average 44% of individuals over the age of 65 did not have a primary income (including pensions) during the observed period. For immigrants from later years (1990 onward), this rate rises to 64% on average.

Finally, we find that the positive trend in population coverage is mainly due to an increase in coverage among individuals aged 65 and above. This increase has become more pronounced as the proportion of this age group within the total population has grown over time. Furthermore, it is likely that the rise in population coverage has contributed to the increase in total income coverage, as a significant portion of the unobserved income in our data is the income of individuals who do not report income.

A.4. Calculating Missing Income

In this appendix, we describe the calculation of the missing income sums and the method of their allocation within our data, which serve as the basis for the robustness tests in Section 5.

A.4.1. Undistributed Profits

To calculate the aggregate amounts of undistributed profits for each year, we used the corporate data from the ITA for all companies paying corporate taxes in Israel. These datasets provide us with the total amount of profits. From this total, we subtracted the distributed dividends as well as the corporate taxes paid. Additionally, we subtracted the dividends withdrawn due to the 2017 dividend tax reform smoothed over ten years, consistent with our main specification. Subsection 5.2 contains further details on the 2017 tax reform and our smoothing method.

We allocate the distribution of undistributed profits according to the empirical distribution of dividends in our data (distributed profits). Finally, we use the distribution of distributed profits from 2010 to allocate the distribution of undistributed profits in 2008. We do this because in 2008 capital income data are aggregated in a way that makes it impossible to separate the types of capital income, and thus the shares of dividends cannot be estimated.

A.4.2. Capital Income of Employees

As stated in Appendix A.3, while for direct filers capital income is reported directly to the ITA, there are also capital income earnings by employees that are withheld at the source by financial institutions. These institutions report collectively to the ITA the capital income they withhold without breaking it down to the individual level.

To the best of our knowledge, the sum of this missing income is unavailable in a public data source or in ITA data that were available to us. To estimate this sum, we utilize the income tax collected from the financial institutions that withheld such income, extracted from national accounts and reported in Appendix Table 16, column (4). To derive the income from the sum of tax, we divide the tax sum by the tax rate. However, the tax on capital varies for different types of capital income, with further different rates within categories. Thus, we compute an average tax rate for each type of capital income, weighted by the empirical distribution of capital tax rates in our data, reported in Appendix Table 16 column (3). Utilizing these weighted tax rates to calculate the sum of capital income for employees assumes that the distribution of capital income for each of these tax rates for employees is equal to the observed distribution of capital income of direct filers.

Another source of uncertainty is the issue of double reporting of capital income by direct filers. Certain types of capital income may be reported by direct filers and also withheld at the source, potentially distorting the estimated amount of unobservable capital income we derive. Since we cannot ascertain which income is reported twice, we create two extreme estimates. The first estimate assumes only employee capital income is withheld at the source, presented in column (6) in Appendix Table 16. The second estimate assumes all direct filers' income is also withheld at source. Based on this assumption, to calculate the employees' capital income withheld at source we subtract from the sum of capital withheld at source the observable income of direct filers, presented in column (7) in Appendix Table 16.[35] Since we lack data from which to infer which assumption is more reasonable, our final estimate of employees' capital income that is withheld at the source is the average between these two extreme estimates, reported in columns (8)-(9) in Appendix Table 16.

Subsequently, we attribute the distribution of unobserved employee capital income by income groups using the observed distribution of capital income of direct filers by income group. There are differences in the distribution of employees and direct filers across income groups. Accordingly, to derive the distribution of employees' capital income, we divide the observed distribution of capital income by the marginal distribution of direct filers, and then multiply by the marginal distribution of employees. Using this distribution to allocate the missing income from capital among employees assumes that the distribution of income from capital is identical for employees and direct filers. In this calculation, we also use the 2010 capital income distribution for the year 2008 for the same reasons discussed above.

To clarify the imputation method, we formulate a formula for attributing the missing capital income of employees. For an income group $\boldsymbol{A}$, such as P90-99, we calculate the proportion of employees in this group out of all employees, denoted $\boldsymbol{f_{EMP}(A)}$. Similarly, we denote $\boldsymbol{f_{DF}(A)}$ the proportion of direct filers in group $\boldsymbol{A}$ out of all direct filers. Let $\boldsymbol{SUM_{EMP}}$ represent the total capital income of employees and let $\boldsymbol{g_{CAP|DF}(A)}$ represent the share of capital income for group $\boldsymbol{A}$ out of all capital income of direct filers. Then, the imputation of the missing employee capital income for $\boldsymbol{A}$ is

$$\boldsymbol{MISS(A) = SUM_{EMP} \times g_{CAP|DF} \times \frac{f_{EMP}(A)}{f_{DF}(A)}}$$

[35] It should be noted that dividend income that is withheld at source is lower in some years than dividend income of direct filers, which creates a negative sum. This implies that not all direct filers report twice, at least for this income type and in those years.

A.4.3 Tax-Exempt Rent

We do not observe tax-exempt incomes (except for income of individuals with disabilities). One type of tax-exempt income is rental income, which is exempt from tax below a certain threshold.

To calculate the aggregate income from tax-exempt rental payments, we use data from the CBS household expenditure survey (2021a). There are two possible measures to compute the rental income: the expenditure measure, which aggregates rent paid by households, and the income measure, which aggregates rent received by households from renting out their housing properties to other households. There are discrepancies in the distribution of rental income between these two measures. These discrepancies can be explained by the way rental income is recorded in each approach in the CBS surveys. When a household reports rental income, it reports the total amount received across all properties. In contrast, a household's report of rental expenditure pertains to a single property. Consequentially, rental income as measured via the expenditure approach is more likely to be below the tax threshold and thus marked as tax-exempt, whereas rental income measured by the income approach is likely to be higher and therefore marked as non-exempt. Additionally, the tax system taxes rental income on an aggregate basis across all individuals' properties. This discussion highlights that the income approach is more reliable.

Another factor contributing to the discrepancy between the two measurement approaches is the underrepresentation of very wealthy households in CBS surveys. We know from the distribution of rental income reported in the ITA data that property owners are concentrated in top income groups, which are typically underrepresented in the income and expenditure surveys. This implies that the amount of tax-exempt rental income is likely underestimated when estimation is based on survey data. This discussion actually presents the income approach as less reliable. Therefore, we combine both approaches to create our estimate for the missing income, presented in Appendix Table 17.

For each household, we calculated whether its rental income was tax-exempt based on the threshold for that year. The threshold for each year is reported in Appendix Table 17 column (2). The total amount of tax-exempt rental income (columns (6)-(7)) is calculated by inflating the income and expenditure measures according to the household survey weights. The final amount of tax-exempt rental income used in our analysis is the average of the two measures, reported for each year in column (8). For comparison, we present the total taxable rental income (total rental income minus tax-exempt rental income), using the CBS surveys in columns (3)-(4), and using the ITA data in column (5).

For the years 2008 and 2010 there is no rental income data in the CBS surveys. To estimate the amounts of tax-exempt rental income for these years, we impute the missing values using data from subsequent years (2012–18). We employ linear regressions where the dependent variable is the rental income (as reported in Appendix Table 17), and the explanatory variables are the specifications used to calculate each amount: expenditure or income approaches, and taxable or tax-exempt, as well as survey year. Specifically, we estimate the following model using least squares:

$$\boldsymbol{THR = \alpha + \beta_1 Year + \beta_2 IA + \beta_3 Taxed + \beta_4 IA \times Taxed + \epsilon}$$

Where $\boldsymbol{THR}$ is the amount of rental income in the CBS survey, $\boldsymbol{Year}$ represents the survey year, $\boldsymbol{IA}$ is a dummy variable equal to one if the rental income is calculated using the income approach and zero if calculated using the expenditure approach, and $\boldsymbol{Taxed}$ is a dummy variable equal to one if the rental income is taxable, and equal to zero if it is tax-exempt. We then predict the amounts for 2008 and 2010 for each combination of income or expenditure approach and taxable or tax-exempt rental income. The results reported in Appendix Table 17 for these years are the predictions from this model.

Finally, we allocate the tax-exempt rental income using the distribution of taxable rental income observed in the data. This method assumes that taxable and tax-exempt rental incomes are distributed similarly across income levels. However, it is more likely that these distributions differ, with households earning lower rental incomes, and thus being tax-exempt, are not distributed in the same manner as households earning higher, and hence taxable, rental income. Therefore, this imputation might bias the top income shares upward.

A.4.4 Income of Nonfilers

We turn to the imputation of income for individuals who do not appear in the ITA data, and hence have no reported income. For this missing income, there is no specific income amount that needs to be completed in our data. Instead, there are various assumptions regarding the magnitude of income to impute for individuals not appearing in the tax data. As described in Subsection 2.2, when we inflate the population size to match the total population size, we add individuals (who do not report income) with zero income. We can also make a more lenient assumption that these individuals have some minimal positive income.

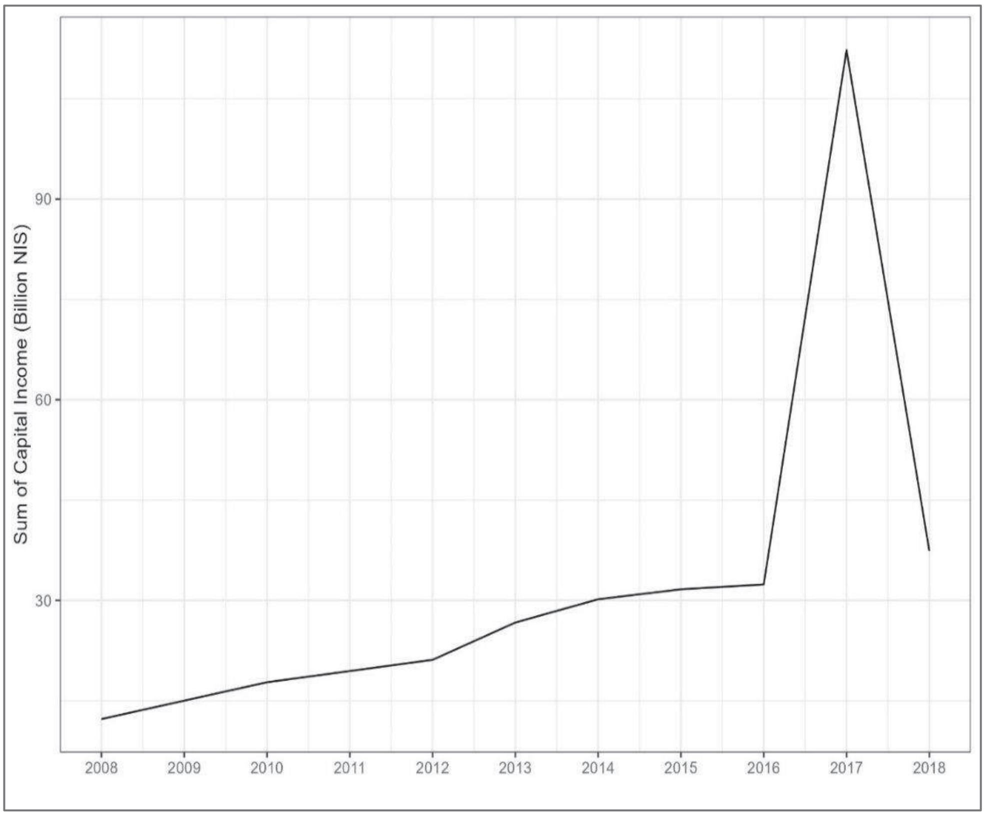
As stated by Atkinson (2007), two different approaches can be used to impute the income of nonfilers: the bottom-up approach, where a certain percentage of the average income is allocated, and the top-down approach, where the difference between a benchmark income statistic (e.g., the Control Total for Income) and the observed total income is calculated and then allocated to nonfilers. According to the top-down approach, it would be necessary to allocate to each nonfiler an income equal to 70% of the average income in our data. This allocation is too high as individuals in such cases would have been required to declare their income to the ITA. Therefore, we operate according to the bottom-up approach.

We assume that the average income of nonfilers is significantly lower than the observed average income of the population. Specifically, we define the income level of nonreporting individuals to be 30% of the unadjusted average income, following Piketty & Saez (2003). The sum of this allocation is reported in Appendix Table 18.

For the computation of missing income for the Control Total for Income we also estimated the income of nonfilers of individuals aged 15-19, which are missing from our benchmark sample (Appendix Table 13, row 21). However, we know this age group population has lower workforce participation rates, and they usually earn lower incomes. Therefore, we set their imputed income to be 10% of the observed average income level.[36]

B. APPENDIX FIGURES AND TABLES

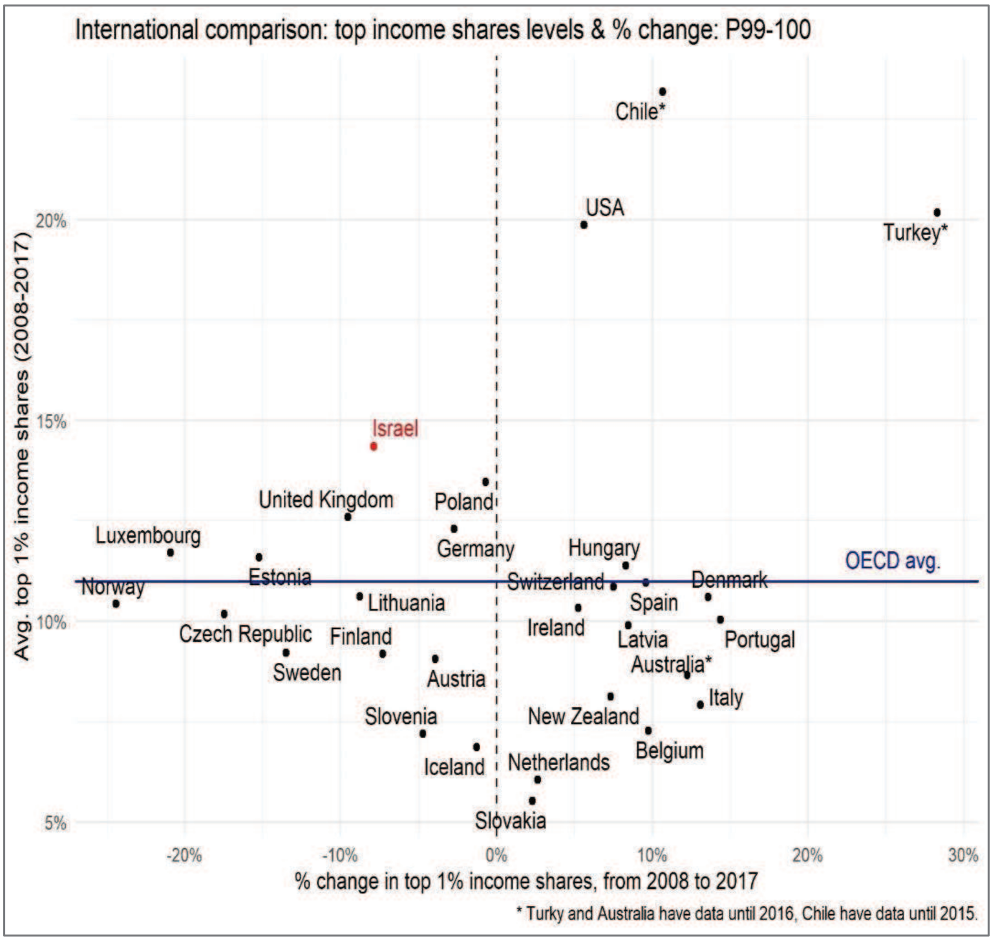
Appendix Figure 1
Capital Income by Year



Notes: The figure presents the sum of capital income by year for individuals aged 20 and over, without smoothing of tax-cut dividends of 2017. Years 2009 and 2011 are missing.

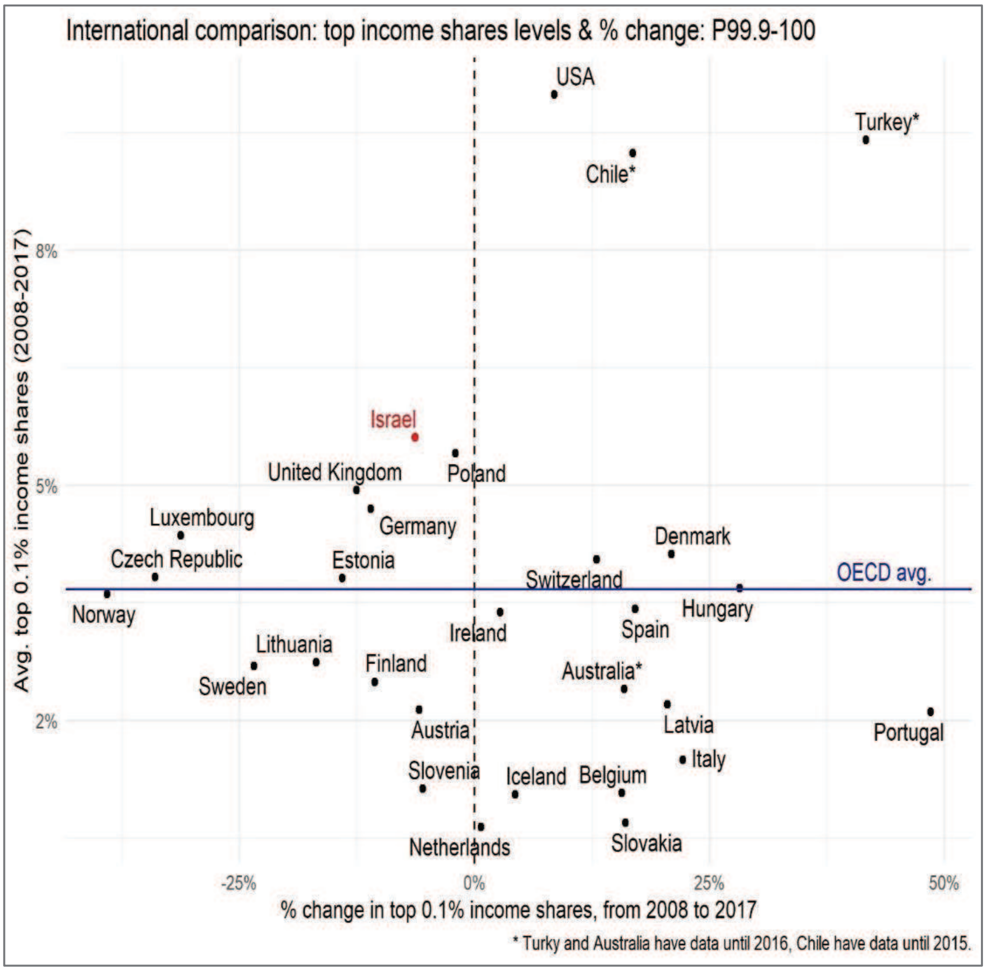
[36] The average income was computed using a non-inflated sample of individuals aged 15 and over with smoothed 2017 tax-cut dividends.

Appendix Figure 2
International Comparison of Value vs. Change for Top 1%



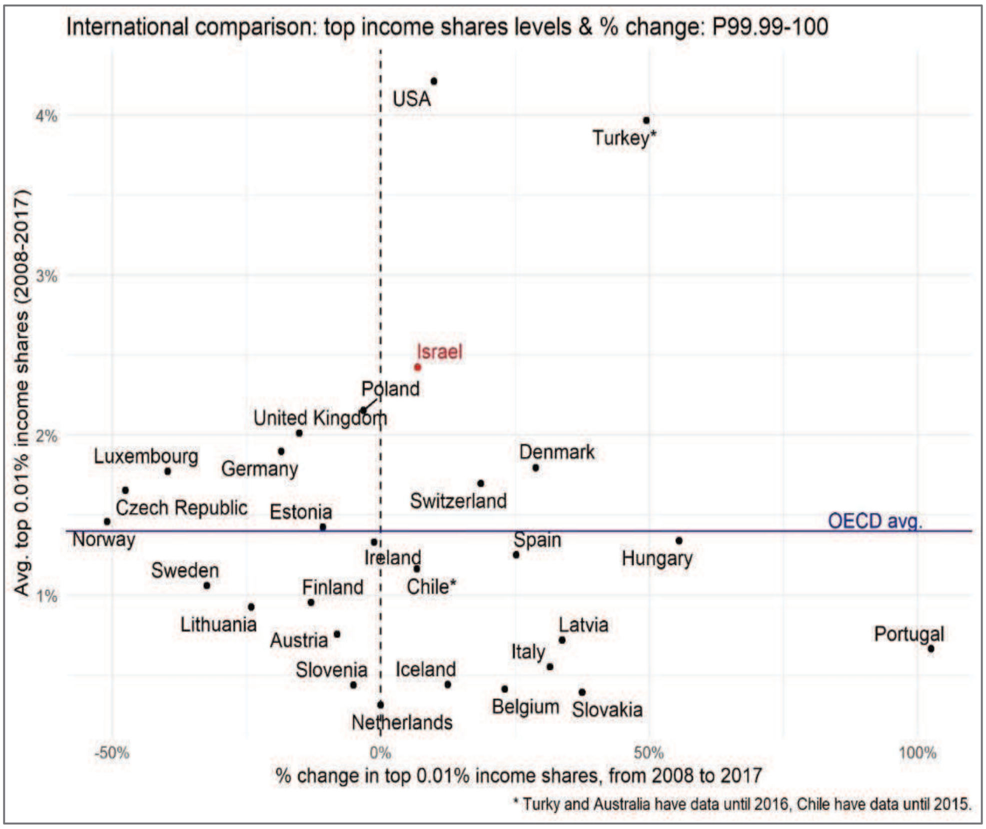
Notes: The figure presents the relative change in top income shares between the years 2008–2017 (horizontal axis) compared to the average of the income share over the same period (vertical axis) in OECD countries. Data for OECD countries, excluding Israel, are taken from the World Inequality Database (2021). Income shares are ranked and computed for total income excluding capital gains. Percent change is calculated as the income share in 2017 divided by the income for 2008. Average income shares are computed from 2008 to the most recent year available up to 2017. The blue line represents average top income shares across the countries in the figure (including Israel). Some OECD countries are not including due to lack of data: Canada, Colombia, Costa Rica, France, Japan, South Korea and Mexico. Detailed estimates are provided in Appendix Table 1.

Appendix Figure 3
International Comparison of Value vs. Change for Top 0.1%



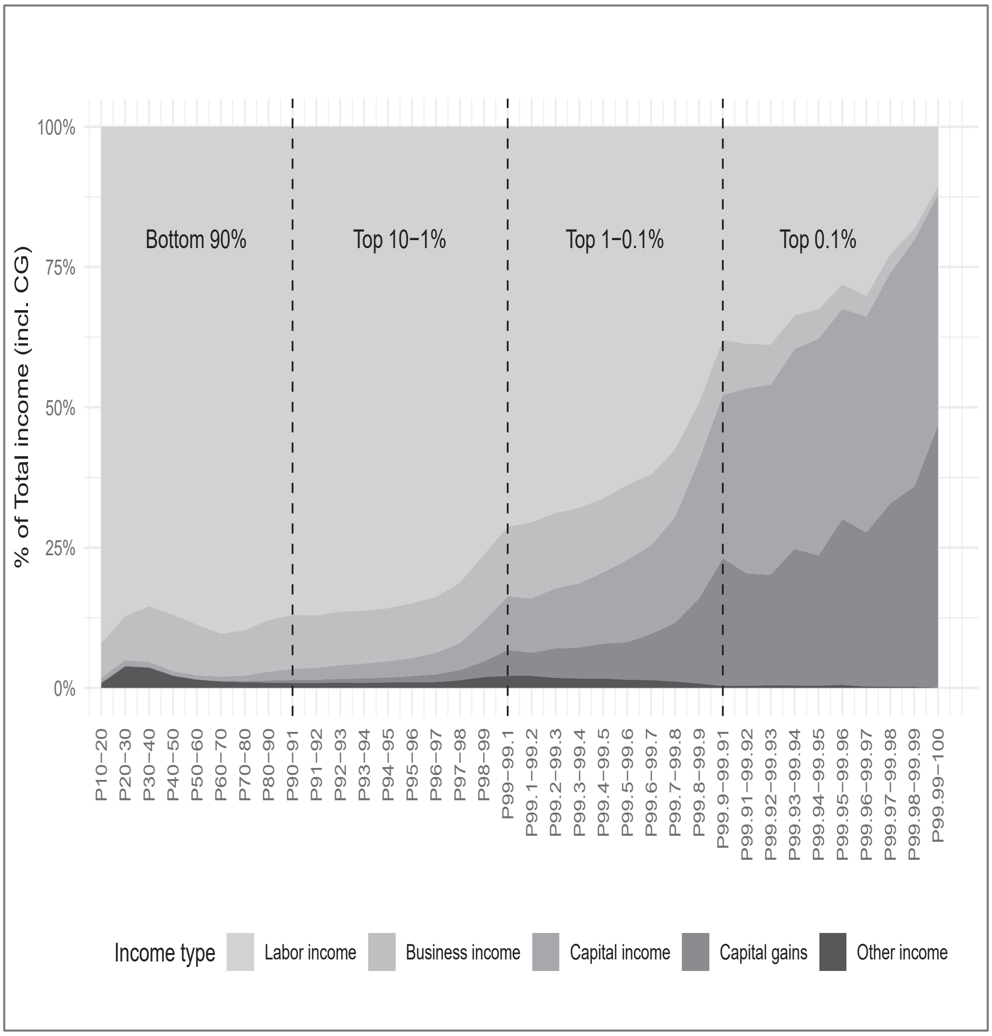
Notes: See notes of Appendix Figure 2.

Appendix Figure 4
International Comparison of Value vs. Change for Top 0.01%



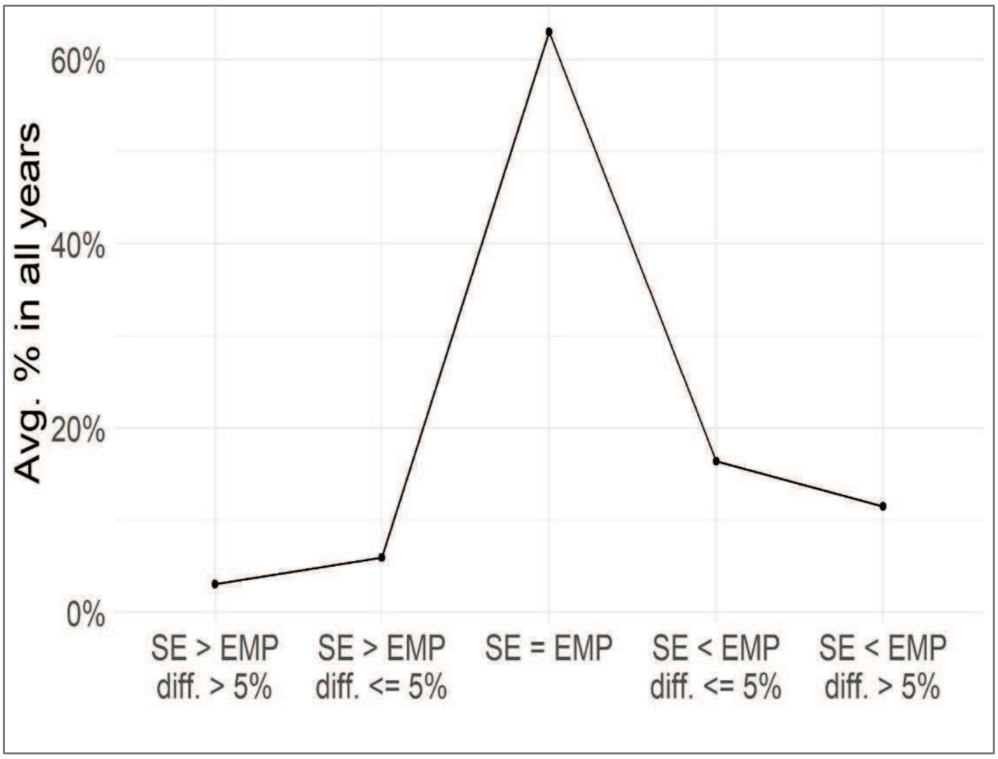
Notes: See notes of Appendix Figure 2.

Appendix Figure 5
Income Composition across Income Groups (2018) – Including Capital Gains



Notes: The figure presents the composition of income sources for different income levels in 2018, including capital gains. Income sources include labor, business, capital, capital gains and other incomes, where the area represents the percentage out of total income, including capital gains. The ranking of the income groups (horizontal axis) is based on an income definition which includes capital gains.

Appendix Figure 6
Descriptive Statistics of Raw Data



Notes: The figure presents the distribution of differences in income between the employee datasets and the direct filer datasets. Each data is an average over all years.

Appendix Table 1
International Comparison of Top Income Shares

Country	P99-100		P99.9-100		P99.99-100		Last Year Observed
	Average Income Shares	% Change	Average Income Shares	% Change	Average Income Shares	% Change	
Chile	23.18%	11%	8.53%	17%	1.16%	7%	2015
Turkey	20.18%	28%	8.67%	42%	3.97%	49%	2016
USA	19.87%	6%	9.15%	8%	4.21%	10%	2017
Israel	14.36%	-8%	5.51%	-6%	2.42%	7%	2017
Poland	13.47%	-1%	5.34%	-2%	2.15%	-3%	2017
UK	12.59%	-10%	4.95%	-13%	2.01%	-15%	2017
Germany	12.30%	-3%	4.75%	-11%	1.90%	-18%	2017
Luxembourg	11.71%	-21%	4.46%	-31%	1.77%	-40%	2017
Estonia	11.59%	-15%	4.01%	-14%	1.43%	-11%	2017
Hungary	11.39%	8%	3.90%	28%	1.34%	56%	2017
Spain	10.97%	10%	3.68%	17%	1.25%	25%	2017
Switzerland	10.86%	8%	4.21%	13%	1.70%	19%	2017
Lithuania	10.62%	-9%	3.12%	-17%	0.93%	-24%	2017
Denmark	10.60%	14%	4.27%	21%	1.80%	29%	2017
Norway	10.43%	-24%	3.84%	-39%	1.46%	-51%	2017
Ireland	10.34%	5%	3.65%	3%	1.33%	-1%	2017
Czech Republic	10.18%	-17%	4.02%	-34%	1.65%	-48%	2017
Portugal	10.04%	14%	2.59%	49%	0.66%	102%	2017
Latvia	9.89%	8%	2.67%	21%	0.72%	34%	2017
Sweden	9.21%	-14%	3.08%	-23%	1.06%	-32%	2017
Finland	9.19%	-7%	2.91%	-11%	0.95%	-13%	2017
Austria	9.06%	-4%	2.62%	-6%	0.75%	-8%	2017
Australia	8.66%	12%	2.83%	16%			2016
New Zealand	8.13%	7%					2017
Italy	7.92%	13%	2.08%	22%	0.55%	31%	2017
Belgium	7.28%	10%	1.73%	16%	0.41%	23%	2017
Slovenia	7.20%	-5%	1.77%	-6%	0.44%	-5%	2017
Iceland	6.86%	-1%	1.71%	4%	0.44%	13%	2017
Netherlands	6.06%	3%	1.37%	1%	0.31%	0%	2017
Slovakia	5.53%	2%	1.41%	16%	0.39%	37%	2017

Notes: The table presents average income shares and their relative changes over the observed period, for top income groups (columns) and OECD countries (rows). Average income shares are computed from 2008 to the most recent available year up to 2017. Percent change is calculated as the top income share in the most recent year divided by the top income share in 2018, marked green for positive and red for negative changes. Some OECD countries are not included due to lack of data: Canada, Colombia, Costa Rica, France, Japan, South Korea and

Appendix Table 2
Income Composition of Top Income Groups

Year	Whole Population				P90-99				P99-99.9				P99.9-99.99				P99.99-100			
	L	B	C	CG	L	B	C	CG	L	B	C	CG	L	B	C	CG	L	B	C	CG
2008	84%	9%	6%	2%	88%	10%	3%	2%	70%	14%	15%	5%	43%	9%	48%	11%	26%	4%	70%	8%
2010	83%	9%	7%	3%	87%	9%	3%	3%	68%	12%	19%	7%	37%	7%	56%	13%	20%	2%	78%	10%
2012	83%	9%	7%	2%	87%	9%	3%	1%	69%	12%	18%	6%	40%	6%	54%	10%	12%	2%	87%	12%
2013	83%	9%	8%	3%	86%	10%	4%	2%	67%	12%	20%	7%	34%	6%	60%	15%	10%	2%	88%	9%
2014	82%	9%	8%	3%	86%	9%	4%	3%	66%	11%	22%	7%	32%	5%	62%	16%	11%	2%	87%	18%
2015	82%	9%	8%	4%	86%	10%	4%	3%	65%	12%	21%	8%	34%	6%	60%	19%	12%	1%	87%	19%
2016	82%	9%	7%	4%	85%	10%	4%	2%	66%	13%	19%	9%	37%	7%	56%	19%	12%	1%	87%	31%
2017	82%	10%	7%	6%	84%	10%	4%	3%	67%	13%	18%	9%	41%	8%	51%	20%	14%	1%	85%	48%
2018	83%	10%	6%	4%	85%	10%	4%	3%	69%	14%	16%	8%	43%	8%	49%	17%	20%	3%	77%	24%

Notes: The table presents the income composition for the whole population and selected top income groups. The columns make use of the following abbreviations: L for labor, B for business, C for capital and CG for capital gains. The shares for labor (L), business (B) and capital (C) were calculated using our main specification (which excludes capital gains), and sum up to 100% within each year and income group. In contrast, the values for capital gains (CG) were calculated using an income definition that includes capital income. In all specifications, individuals were ranked using the main specification.

Appendix Table 3
Labor Income Shares (2018)

Income	N	Lower Income Threshold	Avg. Labor Income	% Wages	Income Composition		
					Labor	Business	Capital
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
P0-100	5,676,000	0	90,651	91%	83%	9%	6%
P90-95	283,800	200,000	262,831	93%	93%	1%	5%
P95-99	227,040	300,000	409,721	93%	91%	1%	8%
P99-99.5	28,380	600,000	651,150	93%	87%	2%	11%
P99.5-99.9	22,704	750,000	918,773	92%	88%	2%	10%
P99.9-99.95	2,838	1,300,000	1,434,617	92%	86%	1%	13%
P99.95-99.99	2,270	1,600,000	2,128,169	94%	76%	1%	23%
P99.99-100	568	3,300,000	7,718,825	98%	81%	0%	18%

Notes: The table describes the characteristics of the top labor income groups in 2018, created by ranking individuals based solely on their labor income. Incomes are in nominal prices for the base year 2018. Lower income thresholds are rounded to NIS 50,000 up to the 0.1%, and to NIS 100,000 within the top 0.1%. Column (5) presents the share of wages in income from labor (other incomes for labor being pensions). Columns (6)-(8) depict the composition of total income excluding capital gains, in a specification that is ranked using labor income.

Appendix Table 4

Different Age Threshold Specifications

Year	+15				+20				+23			
	Population	Coverage	Lower Threshold Top 1%	Income (Billions)	Population	Coverage	Lower Threshold Top 1%	Income (Billions)	Population	Coverage	Lower Threshold Top 1%	Income (Billions)
(1)	(2)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
2008	5234	74%	500000	343	4646	78%	526000	340	4301	78%	543000	334
2010	5491	73%	519000	377	4892	77%	544000	374	4544	78%	562000	367
2012	5683	74%	553000	423	5070	78%	579000	420	4713	78%	596000	413
2013	5786	75%	581000	454	5162	78%	609000	450	4801	79%	627000	442
2014	5896	75%	603000	482	5258	79%	633000	478	4894	80%	653000	470
2015	6012	77%	613000	515	5359	81%	643000	511	4992	82%	663000	503
2016	6130	78%	629000	542	5461	82%	660000	538	5089	83%	680000	529
2017	6250	79%	648000	574	5567	82%	679000	569	5188	83%	700000	559
2018	6375	80%	664000	624	5676	84%	695000	619	5288	85%	715000	607

Notes: The table provides a breakdown of models with different age brackets – 15+, 20+ (benchmark), 23+ – structured as follows: columns (2), (5) and (10) represent control totals of population, in thousands, according to the respective age threshold. Columns (3), (7) and (11) are coverage rates of the ITA population size compared to the control total by age threshold. Columns (4), (8) and (12) denote total income excluding capital gains in specifications by age threshold, in billions of nominal NIS.

Appendix Table 5
Robustness Tests Summary – Changes in Top Income Shares

	P90-100		P99-100		P99.9-100		P99.99-100	
Income Share (Main Specification)	45.9 (1.3)		14.2 (0.6)		5.4 (0.3)		2.4 (0.2)	
Labor Income								
Ranking Only	-3.92 (0.3)	-9% (1%)	-3.45 (0.4)	-24% (3%)	-2.61 (0.32)	-48% (4%)	-1.56 (0.23)	-65% (6%)
Ranking and Shares	-1.07 (0.32)	-2% (1%)	-3.59 (0.49)	-25% (3%)	-2.82 (0.37)	-52% (5%)	-1.61 (0.26)	-67% (7%)
Age Threshold								
15+	2.36 (0.05)	5% (0%)	0.69 (0.03)	5% (0%)	0.2 (0.02)	4% (0%)	0.08 (0.01)	3% (0%)
23+	-0.88 (0.06)	-2% (0%)	-0.24 (0.02)	-2% (0%)	-0.05 (0.01)	-1% (0%)	-0.02 (0.01)	-1% (0%)
2017 Tax-Cut Dividends								
As-is	-0.04 (2.35)	0% (5%)	0.12 (3.39)	1% (25%)	0.26 (2.54)	6% (49%)	0.17 (0.98)	7% (40%)
Omitted	-0.81 (0.33)	-2% (1%)	-0.98 (0.41)	-7% (3%)	-0.57 (0.24)	-10% (4%)	-0.15 (0.07)	-6% (3%)
Missing Incomes								
Undistributed Profits	4.86 (1.32)	11% (3%)	7.02 (1.73)	50% (14%)	5.89 (1.45)	110% (31%)	3.6 (0.94)	151% (40%)
Employee Capital Income	0.14 (0.13)	0% (0%)	0.01 (0.1)	0% (1%)	0.08 (0.13)	1% (2%)	0.08 (0.12)	3% (5%)
Tax-Exempt Rent	0.97 (0.04)	2% (0%)	0.59 (0.1)	4% (1%)	0.14 (0.09)	3% (2%)	0.05 (0.08)	2% (3%)
Unreported Income	-3.22 (0.54)	-7% (1%)	-1.00 (0.17)	-7% (1%)	-0.38 (0.06)	-7% (1%)	-0.17 (0.02)	-7% (1%)
All Missing Incomes	2.46 (1.58)	5% (4%)	5.87 (1.73)	42% (14%)	5.08 (1.44)	95% (31%)	3.16 (0.95)	132% (40%)

Notes: The table presents differences in top income share estimates between our main specification, presented in the first row for ease of comparison, and all robustness tests discussed in Section 5. Values represent averages of estimate for the years 2008-2018, with standard deviation in parentheses. For each income group, the columns on the left display the mean income share difference between the main specification and the respective robustness test. And, within each income group the columns on the right show the relative difference in income shares between the main specification and the robustness tests.

Appendix Table 6

Robustness Tests Summary – Top Income Shares

Income Group	Year	Main	Labor Income		Age Threshold		Tax-Cut Dividends		Missing Incomes				
			Ranking	Ranking and Shares	15+	23+	As-is	Omitted	Undis. Profits	Emp. Capital	Tax-Ex. Rent	Non-Filers	Sum
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
P90-100	2008	47.40%	43.90%	46.70%	49.80%	46.40%	46.20%	46.20%	52.00%	47.60%	48.30%	43.60%	49.10%
	2010	47.10%	43.40%	46.10%	49.50%	46.10%	46.00%	46.00%	51.70%	47.40%	48.10%	43.20%	48.90%
	2012	46.70%	43.20%	45.70%	49.10%	45.70%	45.70%	45.70%	49.80%	46.80%	47.70%	43.00%	47.00%
	2013	46.80%	42.70%	45.40%	49.10%	45.90%	45.90%	45.90%	52.20%	47.00%	47.80%	43.20%	49.50%
	2014	46.60%	42.30%	45.20%	49.00%	45.70%	45.80%	45.80%	49.90%	46.80%	47.70%	43.30%	47.60%
	2015	45.70%	41.50%	44.30%	48.00%	44.80%	44.80%	44.80%	49.40%	45.70%	46.60%	42.70%	47.20%
	2016	45.10%	41.00%	43.90%	47.40%	44.30%	44.30%	44.30%	50.80%	45.00%	46.10%	42.30%	48.50%
	2017	44.40%	40.30%	43.50%	46.70%	43.60%	50.60%	43.70%	50.90%	44.50%	45.40%	41.80%	48.80%
	2018	43.30%	39.50%	42.80%	45.70%	42.60%	43.30%	43.30%	50.10%	43.50%	44.30%	41.00%	48.50%
P99-100	2008	14.80%	11.80%	11.60%	15.50%	14.50%	13.30%	13.30%	21.70%	14.80%	15.30%	13.60%	20.40%
	2010	14.50%	11.40%	11.00%	15.20%	14.30%	13.20%	13.20%	21.40%	14.60%	15.10%	13.30%	20.00%
	2012	14.20%	11.10%	10.70%	14.90%	14.00%	13.10%	13.10%	18.80%	14.10%	14.90%	13.10%	17.60%
	2013	14.60%	10.70%	10.50%	15.30%	14.30%	13.50%	13.50%	22.50%	14.70%	15.30%	13.50%	21.40%
	2014	14.70%	10.70%	10.50%	15.40%	14.50%	13.70%	13.70%	19.60%	14.80%	15.40%	13.70%	18.80%
	2015	14.30%	10.60%	10.30%	15.00%	14.10%	13.30%	13.30%	19.90%	14.20%	14.90%	13.40%	18.80%
	2016	14.10%	10.40%	10.30%	14.80%	13.90%	13.20%	13.20%	22.30%	14.00%	14.60%	13.30%	21.00%
	2017	13.60%	10.00%	10.30%	14.30%	13.40%	22.70%	12.70%	22.50%	13.60%	14.10%	12.80%	21.30%
	2018	12.90%	9.90%	10.20%	13.60%	12.70%	12.90%	12.90%	22.30%	13.00%	13.40%	12.20%	21.40%

Appendix Table 6 (continued)

Income Group	Year	Main	Labor Income		Age Threshold		Tax-Cut Dividends		Missing Incomes				
			Ranking	Ranking and Shares	15+	23+	As-is	Omitted	Undis. Profits	Emp. Capital	Tax-Ex. Rent	Non-Filers	Sum
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
P99.9-100	2008	5.50%	3.30%	3.10%	5.70%	5.50%	4.70%	4.70%	11.40%	5.50%	5.60%	5.10%	10.40%
	2010	5.40%	3.10%	2.80%	5.60%	5.30%	4.60%	4.60%	11.10%	5.30%	5.50%	4.90%	10.00%
	2012	5.40%	2.80%	2.50%	5.60%	5.30%	4.70%	4.70%	9.40%	5.40%	5.50%	5.00%	8.50%
	2013	5.70%	2.70%	2.40%	5.90%	5.60%	5.00%	5.00%	12.30%	5.90%	6.00%	5.20%	11.50%
	2014	5.70%	2.70%	2.50%	5.90%	5.60%	5.10%	5.10%	9.60%	5.90%	6.00%	5.30%	9.20%
	2015	5.60%	2.80%	2.50%	5.80%	5.60%	5.10%	5.10%	10.20%	5.60%	5.80%	5.30%	9.50%
	2016	5.60%	2.80%	2.50%	5.80%	5.50%	5.10%	5.10%	12.60%	5.60%	5.60%	5.20%	11.70%
	2017	5.20%	2.60%	2.50%	5.40%	5.10%	12.20%	4.70%	12.70%	5.50%	5.30%	4.90%	11.90%
	2018	4.80%	2.70%	2.60%	5.00%	4.80%	4.80%	4.80%	12.50%	4.90%	4.90%	4.50%	11.90%
P99.99-100	2008	2.3%	1.0%	1.1%	2.4%	2.3%	2.1%	2.1%	5.7%	2.3%	2.3%	2.1%	5.1%
	2010	2.1%	0.9%	0.9%	2.2%	2.1%	1.9%	1.9%	5.5%	2.1%	2.1%	2.0%	4.8%
	2012	2.4%	0.7%	0.7%	2.5%	2.4%	2.2%	2.2%	5.0%	2.4%	2.4%	2.2%	4.5%
	2013	2.6%	0.8%	0.7%	2.7%	2.6%	2.4%	2.4%	6.9%	2.8%	2.7%	2.4%	6.5%
	2014	2.4%	0.8%	0.7%	2.5%	2.4%	2.3%	2.3%	4.7%	2.6%	2.6%	2.3%	4.5%
	2015	2.5%	0.8%	0.8%	2.6%	2.5%	2.3%	2.3%	5.2%	2.5%	2.5%	2.3%	4.8%
	2016	2.6%	0.8%	0.8%	2.7%	2.6%	2.4%	2.4%	7.1%	2.6%	2.6%	2.4%	6.5%
	2017	2.4%	0.8%	0.7%	2.5%	2.4%	5.2%	2.3%	7.2%	2.7%	2.5%	2.3%	6.9%
	2018	2.2%	0.9%	0.9%	2.2%	2.2%	2.2%	2.2%	6.6%	2.3%	2.3%	2.1%	6.4%

Notes: The table presents estimates of the top income shares by robustness tests (columns) for select top income groups by year (rows). Column (3) presents the top income shares in our main specification. The methodology used the reported values can be found in the following sections: labor income in Subsection 4.3, age threshold in Subsection 5.1, for tax-cut dividends in Subsection 5.2, and for missing incomes in Subsection 5.3.

Appendix Table 7
Demographic Composition of Top Income Groups (2018)

Variable	Value	Pop. Share	P90-99	P99-99.5	P99.5-99.9	P99.9-99.95	P99.95-100
Sex	Female	49%	28%	18%	15%	13%	13%
	Male	51%	72%	82%	85%	87%	87%
	Known %	100%	100%	100%	100%	100%	100%
Age Group	18-24	11%	0%	0%	0%	0%	0%
	25-29	12%	2%	0%	0%	0%	0%
	30-34	11%	8%	2%	2%	0%	1%
	35-39	11%	13%	7%	5%	3%	4%
	40-44	11%	16%	14%	12%	11%	9%
	45-49	9%	16%	18%	17%	18%	15%
	50-54	8%	12%	15%	16%	16%	15%
	55-59	6%	11%	14%	15%	15%	14%
	60-64	6%	9%	12%	14%	14%	14%
	65-69	6%	6%	9%	10%	11%	12%
	70-74	4%	3%	4%	5%	6%	9%
	+75	5%	2%	3%	4%	7%	7%
	Known %	100%	100%	99%	100%	96%	97%
Marital Status	Divorced	9%	9%	8%	9%	9%	9%
	Married	66%	80%	84%	85%	88%	87%
	Single	21%	9%	5%	4%	3%	5%
	Widows	4%	2%	2%	2%	1%	0%
	Known %	100%	100%	100%	100%	97%	96%
Residence District	Haifa	12%	12%	12%	11%	10%	9%
	Jerusalem	10%	7%	7%	7%	9%	8%
	Judea and Samaria	4%	4%	2%	2%	1%	0%
	Tel Aviv	18%	23%	29%	33%	43%	48%
	The Center	26%	34%	35%	34%	32%	30%
	The North	16%	10%	8%	7%	4%	2%
	The South	14%	11%	8%	6%	2%	3%
	Known %	97%	100%	100%	99%	95%	96%

Notes: The table presents the distribution of demographic variables within the overall population and for individuals in top income groups for the year 2018. The overall population includes all individuals in the ITA data without inflating the population size to match the Control Total of population. Each demographic category percentage is calculated from the total number of individuals in that category with known values. The proportion of individuals with known values is reported in the "Known %" row for each variable by income group.

Appendix Table 8
Survival Rates of Top Income Groups

Year	P90-100					P95-100					P99-100					P99.5-100					P99.9-100				
	T+1	T+2	T+3	T+4	T+5	T+1	T+2	T+3	T+4	T+5	T+1	T+2	T+3	T+4	T+5	T+1	T+2	T+3	T+4	T+5	T+1	T+2	T+3	T+4	T+5
2008		81.5		75.4	73.1		77.9		71	68.7		65.3		57	53.9		59.1		50.8	46.6		49.3		40	35.6
2010		81.1	78.4	75.6	73.3		77.7	74.8	71.7	68.8		66.9	62.7	58.2	54.5		61.6	56.2	51.5	48.1		48.9	42.2	38.6	36.5
2012	86.9	81.9	78.5	75.8		84.2	78.5	74.6	71.8		73.8	66.5	62.1	58.8		68	60.4	56.7	53.1		53.2	45.5	43.1	40.1	
2013	86.8	82.1	78.7		71.7	83.9	78.7	74.8		67.7	73	66.8	62.5		54.1	66.7	61.1	56.5		48.5	51.5	47.5	43.1		35.9
2014	86.9	81.6		74		83.9	78.1		70.1		72.6	66.7		57		66.4	60.3		51.1		51.1	45.2		36.9	
2015	86.2		76.7			83.1		73.1			73.3		61.1			68.1		55.6			53.2		41.2		
2016		80.4					77.3					66.3					60.5					46.1			

Notes: The table presents estimates of survival rates, i.e., the probability of remaining in the same income group, for selected top income groups and time frames (columns) and years)rows(. The length of the time frame over which survival rate is calculated is presented by the "T + …" columns. All values are expressed as percentages. Individuals are ranked according to total income excluding capital gains, and differently from the main specification, without smoothing dividends from 2017.

Appendix Table 9
International Comparison of Survival Rates

Country	T + …	Average Survival Rates for T + …					Study	Period	Ages
		P90-100	P95-100	P99-100	P99.5-100	P99.9-100			
Canada	1	80.46%	75.80%	69.08%	66.67%	58.18%	Saez& Veall (2005)	1982-2000	20+
	2	74.82%	69.41%	62.14%	59.42%	50.00%			
	3	70.64%	64.70%	57.05%	54.16%	44.73%			
Germany	1	86.53%	83.29%	76.07%		65.17%	Jenderny (2016)	2001-2006	-
	2	81.59%	77.82%	70.19%		59.64%			
	3	77.95%	73.84%	65.86%		55.52%			
	4	74.73%	70.46%	61.90%		51.97%			
	5	72.36%	67.56%	58.25%		49.00%			
Israel	1	86.71%	83.78%	73.17%	67.29%	52.26%	Our estimates	2008-2018	20+
	2	81.45%	78.05%	66.42%	60.50%	47.09%			
	3	78.04%	74.33%	62.10%	56.22%	42.40%			
	4	75.20%	71.15%	57.76%	51.61%	38.88%			
	5	72.71%	68.40%	54.14%	47.74%	35.98%			
	10	60.87%	55.78%	40.12%	34.28%	25.16%			
US	1	85.49%		76.31%		64.78%	Kopezuk et al., (2010)	1978-2004	25-60
	3			67.82%					
	5			63.60%					
Sweden	1			79.41%			Martinez (2018)	1981-2010	20-65
	2			72.15%					
	3			66.77%					
	5			57.99%					
	10			39.58%					

Notes: The table presents details regarding the international comparison of survival rates, based on Table 1 from Martinez (2018). Column (2) shows the length of the time frame over which survival rates were calculated. Columns (3)-(7) display the survival rates by country and time frame, for selected top income groups (blank spaces indicate survival rate were not estimated for the respective time frame or income group). Columns (8)-(10) report the study from which the estimates were taken, the observable time period in the data, and the age range of the individuals in the data, respectively, for each country.

Appendix Table 10
Number of Observations in Raw ITA Datasets

Year	N (Thousands)			
(1)	Only Employees (2)	Only Direct Filers (3)	In Both Datasets (4)	Combined (5)
2008	3,023	370	484	3,877
2010	3,128	384	522	4,033
2012	3,227	415	570	4,211
2013	3,310	422	602	4,334
2014	3,384	432	642	4,458
2015	3,484	439	730	4,653
2016	3,567	460	775	4,803
2017	3,630	477	821	4,929
2018	3,755	484	876	5,115

Notes: The table presents the number of observations in the raw ITA datasets in thousands. Column (2) reports the number of individuals that only appear in the employee datasets, column (3) reports the number of individuals that appear in the direct-filers datasets, and column (4) reports the number of individuals who appear in both employee and direct-filers datasets. Column (5) reports the sum of (2)-(4), which is the number of individuals who appear at least once in any dataset.

Appendix Table 11
Negative Income Correction

Year	Labor Income			Capital Gains Income			Other Income		
	N	Sum Corrected (Millions)	% Total	N	Sum Corrected (Millions)	% Total	N	Sum Corrected (Millions)	% Total
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
2008	6915	22.67	0.01%	0	0	0.00%	19	0.14	0.00%
2010	3554	25.82	0.01%	0	0	0.00%	8415	13.55	0.29%
2012	2020	26.62	0.01%	0	0	0.00%	129	5.21	0.11%
2013	2078	35.26	0.01%	144	1.13	0.01%	157	2.27	0.05%
2014	2075	36.98	0.01%	248	0.96	0.01%	146	1.72	0.03%
2015	2384	40.56	0.01%	426	3.02	0.01%	623	2.64	0.04%
2016	2391	39.98	0.01%	4010	1.58	0.01%	3138	1.8	0.03%
2017	2716	51.95	0.01%	154	1.81	0.01%	181	2.27	0.03%
2018	2535	54.94	0.01%	242	1.46	0.01%	68	1.47	0.02%

Notes: The table presents the descriptive statistics on negative income corrections for the raw ITA datasets. Columns titled "N" – (2), (5) and (8) – refer to the number of individuals for which we corrected negative incomes. Columns titled "Sum Corrected)" – (3), (6), and (9) – refer to amount of income we adjusted to zero in nominal prices, in million NIS. Columns titled "% Total" – (4), (7) and (10) – refer to the share of the adjusted income out of the total income within the respective income type, as reported in the top row.

Appendix Table 12
Population Coverage in ITA Data by Age Groups

Age	2008	2010	2012	2013	2014	2015	2016	2017	2018
15-17	29% (360)	27% (360)	30% (370)	31% (380)	29% (390)	31% (400)	33% (410)	32% (420)	32% (430)
18-19	62% (230)	60% (240)	63% (240)	65% (240)	65% (250)	67% (250)	69% (260)	69% (270)	70% (270)
20-22	67% (340)	67% (350)	68% (360)	69% (360)	70% (360)	71% (370)	72% (370)	72% (380)	76% (390)
23-24	79% (230)	80% (230)	81% (230)	82% (240)	82% (240)	83% (240)	84% (240)	85% (250)	87% (250)
25-29	83% (550)	83% (570)	85% (580)	86% (580)	87% (590)	88% (590)	89% (600)	90% (600)	92% (610)
30-34	84% (540)	84% (550)	85% (560)	86% (560)	87% (570)	88% (580)	89% (580)	90% (590)	92% (590)
35-39	86% (480)	85% (520)	86% (540)	87% (550)	87% (550)	87% (560)	87% (560)	88% (560)	89% (570)
40-44	86% (400)	85% (440)	87% (470)	87% (490)	88% (500)	89% (520)	89% (530)	89% (540)	90% (550)
45-49	84% (380)	82% (400)	84% (410)	86% (410)	86% (420)	88% (440)	89% (450)	90% (470)	90% (490)
50-54	82% (370)	81% (390)	82% (390)	83% (390)	83% (400)	84% (400)	85% (400)	86% (410)	87% (420)
55-59	80% (360)	78% (370)	78% (370)	79% (380)	80% (380)	82% (380)	82% (390)	82% (390)	83% (390)
60-64	76% (280)	76% (330)	74% (350)	75% (350)	75% (360)	78% (370)	78% (370)	78% (370)	79% (370)
65-69	62% (190)	61% (200)	70% (250)	70% (280)	70% (300)	75% (320)	74% (340)	74% (340)	75% (350)
70-74	50% (180)	51% (190)	52% (190)	54% (180)	52% (180)	66% (190)	56% (210)	65% (230)	72% (260)
+75	51% (340)	52% (360)	48% (380)	47% (390)	50% (400)	56% (410)	59% (420)	58% (420)	60% (430)
% Unknown Age	1.10%	1.00%	0.30%	0.20%	0.50%	0.30%	0.90%	0.80%	0.50%

Notes: The table presents data coverage and control totals for the ITA data by age group (rows) and years (columns). The percentages represent the coverage rate within each age group by year, while the numbers in parentheses indicate the Control Total of population of the age group by year in thousands. Percentages are calculated using individuals with known values only. Rates of individuals with unknown ages out of the total number of individuals in the ITA data is reported in the last row. Control Totals for population values by age group were taken from CBS statistics (Central Bureau of Statistics, 2021c).

Appendix Table 13

Constructing the Control Total for Income

	Aggregate Income	Sum Aggregate Income (NIS Million)									Source	Notes
		2008	2010	2012	2013	2014	2015	2016	2017	2018		
1	**Net national income**	649	740	832	897	956	1003	1055	1094	1154	Central Bureau of Statistics (2021b)	
2	Minus: Government primary net income	75	97	110	117	137	146	149	146	148	Central Bureau of Statistics (2021b)	
3	**Equal to: Private primary net income**	574	643	722	780	818	858	906	948	1006		
4	Minus: Corporation primary net income	70	71	64	102	78	85	115	137	136		Sum of rows 4 and 5
5	*Of which: Undistributed profits*	45	48	37	65	43	51	78	95	93	ITA Corporate datasets	Without tax-cut dividend smoothing
6	*Of which: Corporation taxes*	25	23	27	37	35	35	38	42	43	Central Bureau of Statistics (2021c)	
7	**Equal to: Personal primary net income**	504	572	658	678	740	772	791	811	870		
8	Minus: NPISH primary net income	0.66	0.64	0.51	0.49	0.51	0.5	0.55	0.61	0.61	World Inequality Database (2021)	
9	**Equal to: Household primary net income**	503	571	658	678	739	772	790	811	870		

Appendix Table 13 (continued)

10	Minus: Items not included in tax base (non-HH income)	49	64	74	79	85	90	96	101	106		Sum of rows 11 and 12
11	*Of which: Employers SS contributions*	0	0	0	0	0	0	0.01	0.01	0.01	Central Bureau of Statistics (2021b)	
12	*Of which: Imputed rents*	49	64	74	79	85	90	96	101	106	Central Bureau of Statistics (2021b)	
13	**Equal to: Household actual primary net income**	454	506	583	599	654	682	694	710	764		
14	Minus: Items not included in tax base (HH income)	11	11	12	13	15	15	16	18	19		Sum of rows 15 and 16
15	*Of which: Tax-exempt rent*	8	10	11	12	13	13	14	15	15	Household Expenditure Surveys	Appendix A.4.3
16	*Of which: Declared tax-exempt income of filers*	2.3	1.2	1.5	1.7	1.9	2.3	2.8	3.1	3.4	ITA Individuals datasets	
17	**Equal to: Household taxable income**	444	496	571	585	639	667	678	692	745		
18	Minus: Undeclared income	45	60	73	61	59	60	56	68	53		Sum of rows 19 and 20
19	*Of which: Employee Cap. Inc. Deducted at source*	12	23	32	20	17	20	16	27	13	Central Bureau of Statistics (2021b)	Appendix A.4.2

Appendix Table 13 (continued)

20	*Of which: Income of nonfilers*	33	37	40	41	42	40	40	41	40		Sum of rows 21 and 22
21	*Of which: Income of nonfilers aged 15-19*	3	3.3	3.6	3.7	4	4	4	4.2	4.4		Appendix A.4.4
22	*Of which: Income of nonfilers aged 20+*	30	34	37	38	38	36	36	37	35		
23	**Equal to: Declared taxable income of filers**	399	435	498	524	580	607	622	624	692		
24	**ITA total income of filers**	343	377	423	454	482	515	542	574	624		
25	Minus: Income of individuals aged 15-19	2.9	2.8	3.3	3.5	3.5	3.9	4.4	4.8	5.1		
26	**Equal to: ITA total income of filers aged 20+**	340	374	420	450	478	511	538	569	619		
27	Coverage from Control Total	75%	74%	72%	75%	73%	75%	77%	80%	81%	= row 26 / row 13	
28	Coverage from Control Total Including unobserved incomes	85%	86%	84%	86%	82%	84%	86%	91%	89%	= row 26 / row 23	

Notes: The table presents the calculation of the control total for income, as well as amounts of sums of missing incomes and income coverage. The table's structure and definitions are based on Table 2.2 from Blanchet et al. (2021) for rows 1-7 and on Atkinson (2007) for rows 7-23. The calculation methods for row 15 and 19-23 can be found in Appendix A.4. All values are in NIS billion at nominal prices. The total income in the ITA data is reported in row 24-27 excluding capital gains and tax-reduced dividends for 2017.

Appendix Table 14
Control Totals Coverage

Year	N aged 20 and over (Thousands)			Total Income (in NIS billion, nominal prices)		
	Control Total	ITA data	Coverage	Control Total	ITA data	Coverage
2008	4,646	3,605	78%	454	340	75%
2010	4,892	3,776	77%	506	374	74%
2012	5,070	3,939	78%	583	420	72%
2013	5,161	4,052	78%	599	450	75%
2014	5,258	4,177	79%	654	478	73%
2015	5,359	4,350	81%	682	511	75%
2016	5,461	4,476	82%	694	538	77%
2017	5,566	4,590	82%	710	569	80%
2018	5,676	4,768	84%	764	619	81%

Notes: The table presents the control totals for population and income, as well as population and income sums and coverage of the ITA data. The target population is defined as the total number of individuals in Israel aged 20 and above. The control total for income refers to the total income of individuals in Israel in NIS billion at nominal prices, excluding tax-cut dividends of 2017 and capital gains. Similarly, the ITA data values are for individuals aged 20 and above and exclude the tax-cut dividends and capital gains. The coverage represents the ratio of the ITA data to the control total.

Appendix Table 15
Missing Income – Sums and Distributions

Missing Income	Year	Sum of Missing Income			Distribution of Missing Income					
		Sum (Billion NIS)	% Total Income	Source	P0-90	P90-99	P99-99.9	P99.9-99.99	P99.99 100-	Imputation Method
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Employee capital income deducted at source	*2008	12.14	3%	Income tax deducted at source (Central Bureau of Statistics, 2021b)	47%	38%	11%	3%	2%	Capital income of direct-filers
	2010	23.08	6%		47%	38%	11%	3%	2%	
	2012	32.31	8%		51%	36%	8%	3%	2%	
	2013	19.92	4%		47%	35%	7%	3%	8%	
	2014	17.1	4%		47%	36%	6%	4%	7%	
	2015	19.98	4%		54%	35%	5%	3%	2%	
	2016	15.66	3%		58%	32%	4%	3%	2%	
	2017	26.76	5%		54%	31%	3%	3%	9%	
	2018	13.41	2%		51%	34%	5%	2%	9%	
Income of non-filers	2008	30.13	9%	30% Average Income	100%	0%	0%	0%	0%	No imputation
	2010	33.85	9%		100%	0%	0%	0%	0%	
	2012	36.87	9%		100%	0%	0%	0%	0%	
	2013	37.65	8%		100%	0%	0%	0%	0%	
	2014	37.78	8%		100%	0%	0%	0%	0%	
	2015	36.11	7%		100%	0%	0%	0%	0%	
	2016	36.07	7%		100%	0%	0%	0%	0%	
	2017	36.84	6%		100%	0%	0%	0%	0%	
	2018	35.36	6%		100%	0%	0%	0%	0%	
Tax-exempt rents	**2008	8.16	2%	Household Expenditure Surveys (Central Bureau of Statistics, 2021a)	12%	48%	31%	8%	1%	Taxed rents
	**2010	9.57	3%		12%	48%	31%	8%	1%	
	2012	10.85	3%		13%	47%	29%	8%	3%	
	2013	11.69	3%		13%	43%	27%	9%	9%	
	2014	12.99	3%		14%	44%	26%	8%	8%	
	2015	12.89	2%		15%	47%	27%	7%	4%	
	2016	13.55	2%		17%	50%	27%	6%	1%	
	2017	14.58	3%		17%	49%	25%	5%	4%	
	2018	15.12	2%		18%	48%	23%	5%	6%	
Undistributed profits	2008	37.1	11%	Corporate ITA datasets	4%	9%	21%	29%	37%	Dividends (omitting 2017 tax-cut dividends)
	2010	39.88	10%		4%	9%	21%	29%	37%	
	2012	28.96	7%		5%	8%	18%	25%	44%	
	2013	57.03	12%		5%	9%	21%	24%	41%	
	2014	35.31	7%		4%	9%	23%	28%	35%	
	2015	42.6	8%		4%	9%	21%	27%	39%	
	2016	69.6	13%		5%	9%	18%	25%	43%	
	2017	86.78	15%		6%	12%	19%	24%	39%	
	2018	92.82	15%		5%	11%	21%	27%	36%	

Notes: The table presents the amounts of unobserved income and their distribution for all observed years. Column (3) reports sums in NIS billion at nominal prices. Column (4) reports the percentage of the missing income sums out of the total income in the main specification. Column (5) describes the data sources used to calculate the sums of the missing incomes. Columns (6)-(10) present the distribution of the missing incomes across top income groups. Column (11) shows the observable variable with which the distribution of the missing income was imputed. * Calculation based on capital income for 2010, see Appendix A.4. ** Predicted using linear regression, see Appendix A.4.

Appendix Table 16
Employee Capital Income – Computation and Estimates

Year	Capital Income Type	Weighted Income Tax	Taxes Deducted at Source (NIS billion)	Taxes in ITA data (NIS billion)	Missing Income (Billion NIS): Employee Only	Missing Income (Billion NIS): Both Employees And Direct-Filers	Average (6)-(7): By Type	Average (6)-(7): Sum
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2008	Dividend	24.70%	1.4	0.71	5.67	2.97	4.32	12.14
	Interest	21.70%	1.51	0.73	6.93	4.08	5.51	
	Bonds	20.40%	0.67	0.48	3.28	1.36	2.32	
2010	Dividend	24.70%	4.14	2.44	16.78	6.88	11.83	23.08
	Interest	21.70%	0.73	0.66	3.35	0.33	1.84	
	Bonds	20.40%	2.07	0.29	10.12	8.69	9.41	
2012	Dividend	27.60%	7.74	3.11	28.11	16.8	22.46	32.31
	Interest	20.30%	1.56	0.75	7.67	3.99	5.83	
	Bonds	17.70%	0.85	0.28	4.82	3.22	4.02	
2013	Dividend	27.80%	4.21	3.76	15.14	1.63	8.38	19.92
	Interest	23.30%	1.94	0.9	8.33	4.49	6.41	
	Bonds	21.00%	1.38	0.6	6.57	3.7	5.13	
2014	Dividend	28.10%	3.31	4.45	11.79	-4.06	3.87	17.1
	Interest	24.70%	1.66	1.03	6.73	2.58	4.66	
	Bonds	22.70%	2.29	0.69	10.09	7.06	8.57	
2015	Dividend	28.10%	4.41	4.89	15.69	-1.71	6.99	19.98
	Interest	25.70%	1.88	1.03	7.31	3.29	5.3	
	Bonds	23.50%	2.11	0.62	9	6.37	7.69	
2016	Dividend	27.20%	4.31	4.64	15.87	-1.19	7.34	15.66
	Interest	24.60%	1.59	0.99	6.43	2.42	4.43	
	Bonds	22.90%	1.23	0.67	5.36	2.42	3.89	
2017	Dividend	25.20%	15.57	23.78	61.85	-32.62	14.61	26.76
	Interest	24.60%	1.74	1.18	7.07	2.29	4.68	
	Bonds	24.40%	2.32	1	9.53	5.41	7.47	
2018	Dividend	27.30%	3.03	5.78	11.11	-10.05	0.53	13.41
	Interest	26.00%	1.82	1.07	7.02	2.89	4.95	
	Bonds	24.40%	2.29	0.71	9.38	6.49	7.93	

Notes: The table presents the calculation process used to generate the missing income for employees from capital income deducted at source. Column (3) reports the average tax rates for each type of capital income, weighted by the distribution of tax rates within capital income type. Tax rates for 2008 are determined using 2010, since in 2008 capital income is aggregated. Columns (4)-(9) are in NIS billion at nominal prices. Column (4) reports sum of taxes from national accounts, while column (5) reports sum of imposed taxes using the ITA direct-filers data. Columns (6)-(7) present two separate estimates for the capital income deducted at source. No direct-filer doubly reports income, reported in column (6) and calculated as (6) = (4) / (3). Or, all direct-filers doubly report income, reported in column (7) and calculated as (7) = ((4) - (5)) / (3). We average these two estimates in column (8) = ((7) + (6)) / 2 for each income type and report the sum over types in column (9), which is our final estimate of missing capital income for employees. See Appendix A.4.2 for further discussion.

Appendix Table 17
Taxed and Tax-Exempt Housing Rents

Year	Income Threshold (Monthly)	Taxable Rents (Billion NIS)			Tax-Exempt Rents (Billion NIS)		
		Expenditure (CBS)	Income (CBS)	Income (ITA)	Expenditure (CBS)	Income (CBS)	Average
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2008	4,320	*1.36*	*1.31*	-	*14.03*	*2.3*	*8.16*
2010	4,680	*2.77*	*2.72*	2.03	*15.44*	*3.71*	*9.57*
2012	4,910	4.1	4.35	2.89	16.03	5.67	10.85
2013	4,980	4.72	4.89	3.78	17.12	6.26	11.69
2014	5,080	5.45	5.77	4.41	18.67	7.31	12.99
2015	5,070	6.21	6.58	4.86	18.35	7.43	12.89
2016	5,030	6.81	5.87	5.35	19.66	7.43	13.55
2017	5,010	7.32	7.97	5.99	21.44	7.71	14.58
2018	5,030	9.45	8.27	6.84	21.46	8.78	15.12

Notes: The table presents details regarding the imputation of the total amount of tax-exempt rents. Column (2) reports the threshold from which monthly rent incomes below this value are exempt from tax, in NIS at nominal prices. Columns (3)-(5) represent the sum of taxable rents by approach and data source, where columns (3)-(4) present values for the expenditure and income approaches using the household expenditure surveys, respectively, while column (5) presents the income approach using the ITA data. Columns (6) and (7) represent the sum of tax-exempt rents calculated using the expenditure and income approaches, respectively, based on the household expenditure surveys. Column (8) reports the average of columns (6) and (7). Columns (3)-(8) are in NIS billion at nominal prices. Estimates for 2008 and 2010 based on the household expenditure surveys, in italics, were estimated using linear regression, discussed in Appendix A.4.3.

Appendix Table 18
Income of Nonfilers

Year	N (Thousands)	Average Income	Sum Imputed Income (NIS Billion)
2008	1,041	96,508	30.13
2010	1,116	101,111	33.85
2012	1,131	108,666	36.87
2013	1,110	113,081	37.65
2014	1,081	116,474	37.78
2015	1,009	119,320	36.11
2016	985	121,998	36.07
2017	976	125,754	36.84
2018	908	129,754	35.36

Notes: The table provides a breakdown of the imputation method for missing income of non-filers. Column (2) represents the number of individuals aged 20 and over that do not appear in the ITA data, in thousands. Column (3) reports the average annual income, in NIS at nominal prices, in our main specification prior to inflating the population to match the Control Total for population. Column (4) reports the sum of income that is added to nonfilers, in NIS billion at nominal prices, calculated as (4) = (0.3 x (3)) x (2).