Methodological note: State of Tax Justice 2023

Tax Justice Network, August 2023

The purpose of this methodological note is to describe the methodology of new estimates of corporate tax abuse of multinational corporations and of offshore wealth tax abuse by private individuals, as presented in the State of Tax Justice 2023 report published by the Tax Justice Network in July 2023 and the correction published in August 2023.

1 Corporate tax abuse by multinational corporations

For the purposes of the State of Tax Justice 2023 report, we analyse aggregate country by country reporting (CBCR) data for the year 2018 as published by the OECD in November 2022. The dataset contains information on the activities of the multinational corporations (MNCs) headquartered in 45 countries.[1] We use these data to measure misaligned profits (high profits in jurisdictions with low economic activity). We then estimate the tax loss suffered by countries due to these misaligned multinational profits/shifted profits. This section of the State of Tax Justice Report is largely based on the methodology developed by García Bernardo and Janský (2021).

1.1 Data

The methodology exploits CBCR data which include information on MNCs' economic activity in jurisdictions where subsidiaries are located. The dataset was provided thanks to a CBCR regulation which stems from OECD Base Erosion and Profit Shifting (BEPS) Action 13 on CBCR. The regulation requires all large MNCs to report how much economic activity they have, how much profit they generate, and how much tax they pay in every individual country they operate in, including tax havens. The regulation impacts MNCs with consolidated group revenues of at least EUR 750 million, headquartered in any country which has adopted the CBCR regulation. As the main data source for our analysis, we use the CBCR data for large MNCs published by the OECD within the fourth edition of the Corporate Tax Statistics. The data for 2018 contains information for 45 headquarter countries (see Table 1) and was published in November 2022.

[1] The 2016 and 2017 data also contain data on Chinese MNCs. However, they are not part of the 2018 dataset.

Table 1: Countries reporting at least some CBCR data in the OECD database

Argentina	Finland	Latvia	Saudi Arabia
Australia	France	Lithuania	Singapore
Austria	Germany	Luxembourg	Slovenia
Belgium	Greece	Malaysia	South Africa
Bermuda	Hong Kong	Mexico	South Korea
Brazil	Hungary	Netherlands	Spain
Canada	India	New Zealand	Sweden
Cayman Islands	Indonesia	Norway	Switzerland
Chile	Ireland	Panama	United Kingdom
China*	Isle of Man	Peru	United States
Czechia	Italy	Poland	
Denmark	Japan	Romania	

Source: Authors.

*Note: *China does not have available data in this dataset for 2018 but does for 2016 and 2017.*

Existing research compared the US CBCR data with other sources (Clausing 2020a; Garcia-Bernardo, Janský, and Tørsløv forthcoming) and established a good correlation between various types of data sources. Moreover, the CBCR data is outstanding in several dimensions:

One of the most obvious advantages of CBCR data over other data sources is its much more substantial country coverage. This is especially relevant for low- and middle-income countries and for selected parts of the world. For example, US CBCR data includes information on taxes and profits for 25 African countries while the frequently used data from the Bureau of Economic Analysis of the United States Department of Commerce only covers three. CBCR data includes data on large MNCs' profits and tax payments in, for example, up to 169 (Switzerland) and 164 (Germany) jurisdictions in the full data set – 166 and 163 jurisdictions respectively for the data set limited to firms with positive profits (see Table 3; the two data sets are discussed below). The exceptional data coverage provided by the OECD’s CBCR data thus enables us to collect evidence of profit shifting for many countries with low and middle per capita incomes. The superior coverage is one reason why UNODC and UNCTAD (2020) proposed to use this CBCR data for the Sustainable Development Goals indicator of illicit financial flows, likely in a similar way that we implement the profit misalignment method outlined below (Cobham and Janský 2020).

Notwithstanding the better country coverage compared to other data sources, the OECD’s CBCR data is far from complete. As shown in Table 2, in most reporting countries, the OECD’s CBCR data entails significantly fewer reporting MNCs than expected based on Bureau van Dijk’s Orbis ownership database. Interestingly, however, the number of MNCs in some jurisdictions, notably the Cayman Islands and Ireland, is higher in the CBCR data than in Orbis. This could be due to the lack of transparency of Caymans or Ireland based MNCs, that will be cautious to reveal their existence and are not covered in Orbis, as a consequence. However, these MNCs might still be forced to provide a country by country report and therefore appear in the CBCR data.

The imperfect company coverage revealed in Table 2 gives an indication of the level of uncertainty surrounding our estimates. We hope for a steady improvement of the data provided by the OECD to consistently improve our estimates.

Table 2: Number of reporting companies expected (according to Orbis) versus observed in the CBCR data

Country	# Expected (Orbis)	# Observed (CBCR)	Ratio	Country	# Expected (Orbis)	# Observed (CBCR)	Ratio
Panama	185	2	92.81	Mexico	310	69	4.5
Hungary	204	5	40.82	Sweden	447	103	4.34
Lithuania	128	4	32.05	Austria	340	82	4.15
Romania	128	4	32.05	Australia	454	132	3.45
Slovenia	161	6	26.96	Spain	441	132	3.35
Saudi Arabia	323	18	17.95	Italy	455	142	3.21
Greece	289	19	15.23	India	476	151	3.16
New Zealand	283	19	14.91	Switzerland	415	138	3.01
Chile	334	32	10.44	Netherlands	451	165	2.74
Argentina	219	21	10.44	Luxembourg	340	147	2.32
Poland	314	31	10.15	Canada	487	220	2.22
Indonesia	252	27	9.36	South Korea	518	245	2.11
Finland	380	52	7.32	France	479	232	2.07
Peru	185	26	7.14	Hong Kong	337	167	2.02
Malaysia	378	60	6.31	United Kingdom	526	387	1.36
Norway	374	61	6.14	Germany	517	387	1.34
Belgium	346	58	5.98	Japan	623	861	0.72
Denmark	401	69	5.82	United States	666	1641	0.41
Bermuda	393	70	5.62	South Africa	394	1136	0.35
Singapore	372	79	4.71	Cayman Islands	473	1535	0.31
Brazil	376	81	4.65	Ireland	378	1505	0.25

Source: Authors.

A second advantage of CBCR data is that profits and taxes are defined consistently with the concepts of corporate profits and taxes (with some limitations, in particular the potential double counting of dividends, see below). By contrast, this is not the case with e.g. Bureau of Economic Analysis data where profits are imputed from a combination of net profits, intra-group dividends, interest paid, and other variables, as recently discussed by Blouin and Robinson (2020), Garcia-Bernardo, Janský, and Tørsløv (2021), Clausing (2020a), and Clausing (2020b). Since CBCR data offers the best available information on MNCs' tax payments for many countries, it provides us with the first such dataset suitable for a high-quality cross-country comparison (for example, until now various proxies for profits were used, e.g. by Haberly and Wójcik (2015), Bolwijn, Casella, and Rigo (2018) or Damgaard, Elkjaer, and Johannesen (2019)).

Third, CBCR data are provided in two separate data sets, for all large MNCs ("All Sub-Groups") as well as for those large MNCs that have reported positive profits and so not losses in a given year ("Sub-Groups with Positive Profit"). The latter dataset is useful to estimate effective tax rates (ETRs). Though ETRs are not central to our analysis (see below), this data structure allows us to calculate them based on the data set for MNCs that have positive profits only, at the expense of a decrease in country coverage. By using the data with positive profits only, we avoid offsetting firms with losses and firms with profits and we can thus estimate ETRs more precisely. By contrast, data sets which include both profits and losses likely understate profits (since losses are included) and overstate ETRs (since taxes are paid by companies earning profits, typically, though losses are also included in the denominator). We use the dataset including all MNCs (both the ones that have reported profits and the ones that have reported losses) for the misalignment method since for these purposes we prefer to have information on real economic activities of MNCs regardless of whether these MNCs are profit- or loss-making. The dataset including all MNCs is also more suitable for comparison with other datasets (e.g. from the Bureau of Economic Analysis). Unfortunately, both datasets might be affected by a practice where MNCs prefer to report losses in countries with high taxes while locating their profits in countries with low taxes.

Table 3: Number of jurisdictions available per country

	CHE	**DEU**	**CYM**	**ROU**	**USA**	**JPN**	**PER**	**ESP**	**HKG**	**DNK**
All sub-groups	169	164	150	147	147	140	129	121	120	116
Sub-groups with positive profits	166	163	124	133	101	118	112	80	94	119
	ITA	**BMU**	**IND**	**FRA**	**LUX**	**AUS**	**MEX**	**NOR**	**SAU**	**IDN**
All sub-groups	108	104	95	94	91	83	75	65	61	43
Sub-groups with positive profits	81	77	94	33	90	42	63	49	41	31
	ZAF	**BRA**	**SGP**	**PAN**	**MYS**	**ARG**	**BEL**	**LVA**	**CAN**	**NLD**
All sub-groups	41	40	35	35	29	24	21	16	15	10
Sub-groups with positive profits	35	31	42	0	23	19	21	0	15	29
	CHL	**GBR**	**LTU**	**SVN**	**SWE**	**GRC**	**IMN**	**POL**	**AUT**	**HUN**
All sub-groups	10	7	7	7	7	6	6	6	6	2
Sub-groups with positive profits	10	6	6	6	7	6	6	0	6	0
	NZL	**KOR**	**IRL**	**FIN**	**CZE**					
All sub-groups	2	2	2	2	2					
Sub-groups with positive profits	2	2	2	2	0					

Source: Authors.

While these advantages of CBCR data open new avenues for research, several challenges associated with the data remain. First, unfortunately, the data contain a certain extent of double counting in profit due to intercompany dividends – MNCs are instructed not to double count intercompany dividends in revenue but not so explicitly in profit. This potential double counting has been explored recently for US data by Horst and Curatolo (2020). We correct explicitly for double counting of dividends (see Section 1.3.1), and exclude stateless income, another potential source of double counting. Second, some countries are aggregated in country groups (like “Other Africa” or “Other Europe”) and these groups are not defined consistently. Section

1.3.2 explains how we handle this problem. Third, data of reporting countries are sometimes incomplete, an issue we take care of as detailed in Section 1.3.3.

Further limitations of the CBCR data (e.g revenues unavailable according to the location of the final customer) are discussed by the OECD, which published the data with an "Important disclaimer regarding the limitations of the country by country report statistics", and by Garcia-Bernardo, Janský, and Tørsløv (2021) and Clausing (2020a).

1.2 Misalignment method

We estimate profit shifting based on profit misalignment. The misalignment method starts from the notion that profits should accrue where the economic activity takes place. Profit misalignment therefore measures shifted profits by the mismatch between reported profit (π) and theoretical profits (p), i.e. profits we would expect given the observed economic activity. We multiply shifted profits by the applicable corporate income tax rates (CITs) to obtain an estimate for tax revenue losses. The following section details our approach.

We start by **calculating theoretical profits**. In principle, a jurisdiction's theoretical profits can be estimated based on a combination of labour, capital and revenue the MNC has in this jurisdiction. In the State of Tax Justice, we calculate theoretical profits by allocating 50% of the weight to employees (E), and 50% of the weight to wages (W). We base theoretical profits on employment related variables as these are hard to manipulate and data quality is relatively high in the CBCR data. While the number of employees represents an estimate for the workforce located in a given country, the wage component accounts for potential differences in labour productivity. Alternative formulas, e.g., based on sales or assets or a combination of all factors, yield similar results and are presented in Section 0.

Formally, for each country i in which MNCs from parent jurisdiction j operate, we calculate the theoretical profits j's MNCs generate in i as follows. Note that MNCs from parent jurisdiction j operate in countries $i = 1$, $i=2$, …, $i = I$.

$$p_{ij} = \sum_{i=1}^{I} \pi_{ij} \times \left(0.5 \times \frac{W_{ij}}{\sum_{i=1}^{I} W_{ij}} + 0.5 \times \frac{E_{ij}}{\sum_{i=1}^{I} E_{ij}}\right)$$

For instance, if 10% of Indian MNCs' employees were located in Bangladesh and 10% of Indian MNCs' payroll was paid in Bangladesh, theoretical profits in Bangladesh should be 10% of all profits generated by Indian MNCs. Importantly, since MNCs can report zero or negative profits in a country with the goal of avoiding taxes, we use the data on all sub-groups for this calculation.

In a second step, we **estimate profit shifting on a bilateral level**. Profit shifted into country i or out of country i by MNCs from parent jurisdiction j (S_{ij}) is calculated as the difference between profits reported by MNCs from parent jurisdiction j in country i (π_{ij}) and theoretical profits in that country (p_{ij}):

$$S_{ij} = \pi_{ij} - p_{ij}$$

S_{ij} is negative if less profits are reported in country *i* than we would expect, given the economic activity. A negative S_{ij} thus indicates that profit is shifted out of jurisdiction *i*. S_{ij} is positive if more profits are reported in country *i* than we would expect, given the economic activity. A positive S_{ij} thus indicates that profit is shifted *into* jurisdiction *i*.

As we only aim to capture misaligned profits which are due to tax considerations, we set S_{ij} to zero whenever the ETR of the destination country of shifted profits is higher than 15%. We thereby assume that MNCs only involve in tax induced profit shifting if they can realize an ETR below 15% in the destination of profit shifting.

In a third step, we **obtain the total profit shifted into and/or out of a country**. We aggregate all misalignment estimates of country *i*, i.e. misalignment generated by MNCs from all parent jurisdictions *j = 1, j=2,…,j=J* that report activity in country *i*. We do so separately for positive and negative misalignment values to allow for the possibility that a country might suffer from profit shifting but act as a destination for shifted profits at the same time. Total profit shifting estimates for jurisdiction *i* are consequently calculated as:

$$Profit\ shifted\ out\ of\ country_i = \sum_{j=1}^{J} S_{ij}^{-}$$

$$Profit\ shifted\ into\ country_i = \sum_{j=1}^{J} S_{ij}^{+}$$

In a final step, we **translate profits shifted into or out of a country in tax revenue losses**. We calculate tax revenue losses suffered by country *i* by multiplying profits shifted out of the country by the country's CIT (CIT_i).

$$Tax\ loss\ incurred_i = \ Profit\ shifted\ out\ of\ country_i \times \ CIT_i$$

Reversely, we calculate tax revenue losses inflicted on other countries by multiplying profits shifted to country *i* by the average CIT of those countries that these profits are shifted away from. In particular, we calculate the average CIT_j by taking the weighted average of the CITs of all countries experiencing outward profit shifting by MNCs from parent jurisdiction *j*, weighted by their amount of outward shifted profits:

$$Tax\ loss\ inflicted_i = \sum_{j=1}^{J} S_{ij}^{+} \times CIT_j$$

Unlike in previous versions of the State of Tax Justice, where we used ETRs to calculate these losses, we use statutory rates. We prefer statutory rates as countries have actively decided that corporates should pay these rates, in the best case as a result of a democratic process. As such, these rates that should be applied on profits by MNCs who choose to operate in the country.

1.3 Accounting for shortcomings of the OECD's CBCR data

As outlined previously, the OECD's aggregated CBCR data comes with a number of shortcomings. To obtain as trustworthy estimates as possible, we diligently clean the data. In the following section, we first describe our approach to correct for the double counting of dividends. We then explain how we deal with aggregated country groups and missing data.

1.3.1 Correcting for the double counting of dividends

CBCR data double-count profits as several companies include tax-exempt dividends flowing across subsidiaries as profit. We use a highly conservative correction applied independently to the domestic operations and foreign operations of MNCs.

We correct the domestic profits of multinational corporations based on reports provided by the governments and – when such reports are unavailable – based on the academic literature. In particular, we remove 60.69 per cent of domestic profits for Sweden and 50% of domestic profits for Italy based on the analyses published by the two countries.[2] For the Netherlands and the United Kingdom, we use the adjusted values that the countries publish.[3] We correct the data for the United States (where 74 per cent of domestic profits are double counted) based on the analysis by Garcia-Bernardo, Janský, and Zucman (2022). For Belgium, Isle of Man and Singapore, countries with very low ETRs, we remove 50 per cent of all domestic profits. For all other countries, we remove 35 per cent of domestic profits, except for Mexico and Slovenia, where double counting does not seem to be an issue since domestic ETRs are higher than foreign ETRs and except for Ireland, the Cayman Islands, and Luxembourg, where total profits are negative in 2018.

We correct the foreign operations of multinational corporations using the analysis by Garcia-Bernardo, Janský, and Zucman (2022) on US multinational corporations, reducing foreign profits by 39%. For tax havens, we remove 10 per cent of foreign profits.

As a result of our correction, the effective tax rates faced by foreign multinational corporations in a country are similar to the effective tax rates faced by domestic multinational corporations (see Figure 1). This is not the case in the original data, where domestic ETRs are consistently smaller than foreign ETR, indicating that our correction is useful.

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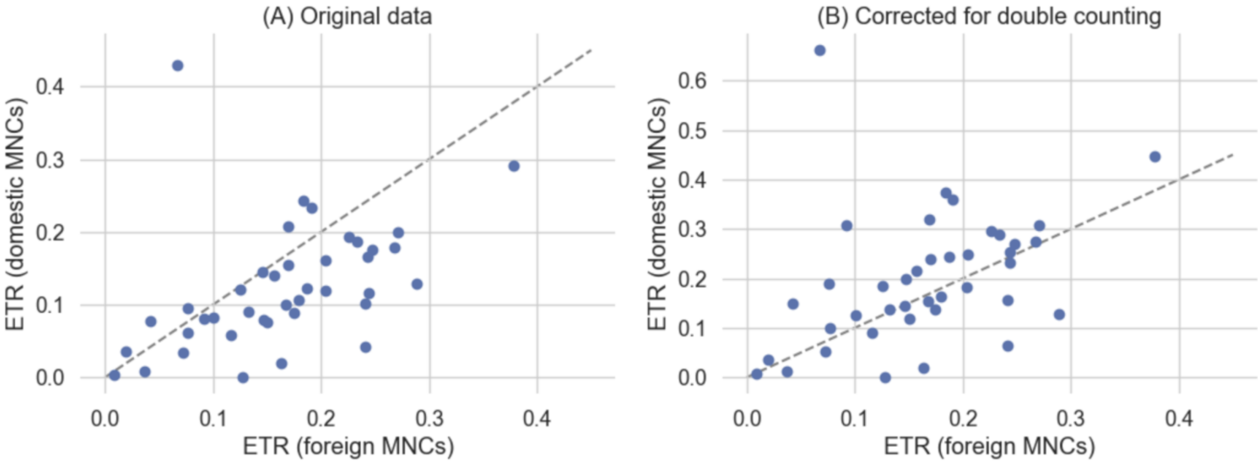
[2] See https://www.oecd.org/tax/tax-policy/sweden-cbcr-country-specific-analysis.pdf and https://www.oecd.org/tax/tax-policy/italy-cbcr-country-specific-analysis.pdf.

[3] See https://www.oecd.org/tax/tax-policy/netherlands-cbcr-country-specific-analysis.pdf and https://www.oecd.org/tax/tax-policy/united-kingdom-cbcr-country-specific-analysis.pdf.

Figure 1: Effective tax rate for domestic and foreign multinational in the (A) original data (B) corrected data. Each point corresponds to a different reporting country



Source: Authors.

1.3.2 Dealing with aggregated country groups

The second important data limitation concerns the combinations of countries in aggregated categories (e.g. "Other Africa" or "Other Europe"). The aggregation criterion is different for different countries. While, for example, India and South Africa do not seem to aggregate data, the United States aggregates countries with a low number of reporting MNCs. This is problematic as aggregation affects particularly low- and middle-income countries and low tax jurisdictions. For instance, only three countries report information on Zambia and only two countries report on the Isle of Man. The other countries aggregate information on Zambia and the Isle of Man in larger categories such as "Other Africa" and "Other Europe". If we decided to ignore these grouped data, we would be missing a significant part of the operations in those countries, leading to an underestimation of the extent of profit shifting.

We address these biases by modelling the location of employees and sales for each pair of countries using the Histogram-based Gradient Boosting Regression Tree, a type of gradient boosting based on decision trees which frequently outperforms other machine learning algorithms while offering some interpretability on the most relevant variables (Ke et al. 2017; Friedman 2001). Specifically, we use the Python implementation in scikit-learn (Pedregosa et al. 2011). Another of its advantages is that it offers native support for missing values, and as such is able to use the full available information without data imputation. We train the location of profits, employees and sales using variables from the gravity data set of CEPII, imports and exports from UN Comtrade, and foreign direct investment from the World Bank as well as from other sources. We obtain a median out-of-sample R-square of 0.75, 0.45 and 0.52 respectively for employees, sales and profits.

We use the model to estimate the total number of employees and unrelated party sales for each pair of countries in the world. For reporting countries, we then adjust the estimated values, so their sum corresponds to the aggregated sum in CBCR, and assign the "Other" categories to specific countries, accordingly. We illustrate our procedure by the following example: French MNCs have 10,000 employees in “Other America”, and “Other America” comprises Paraguay and Suriname – we can establish this by checking which countries are missing from the CBCR data of France. If our model estimates 6,000 employees in Paraguay and 5,000 employees in Suriname (so 11,000 in total), we calculate the number of employees in Paraguay and Suriname to be $\frac{6,000}{\frac{10,000}{11,000}} = 5,455$ and $\frac{5,000}{\frac{10,000}{11,000}} = 4,545$, respectively. For each country, we compare the sums of those estimated values with values observed in the CBCR data. We then use the lowest of the two ratios (estimated vs reported employees and sales) to adjust the profits shifted to correct for the combination of small countries in aggregated groups. While this step typically increases total shifted profits by approximately 20%, it is key with respect to accounting for missing data in countries underrepresented in the sample, i.e. typically low- and middle-income countries. Without this step, we would redistribute too little profits to those countries.

1.3.3 Estimating missing data

The third limitation of the OECD’s CBCR data concerns the lack of reporting by some countries. This is partially addressed in the previous step, where financial information for all pairs of countries is estimated, even for non-reporting countries. However, especially for large countries, domestic information on MNC activity is important. This is addressed by estimating the number of domestic employees and revenue for all non-reporting countries. We do so by using a linear model based on the number of expected companies in each country, its GDP, population, the ETRs and the total consolidated banking claims on an immediate counterparty basis (Table B4 of the BIS data) (with R-squared of 0.96 and 0.93 for employees and sales, respectively). We only use this information to redistribute profits back to the home countries but not to calculate profit shifted. This is a conservative strategy since domestic profits of companies in non-reporting countries with low tax rates (e.g. the British Virgin Islands) are not included in the estimate.

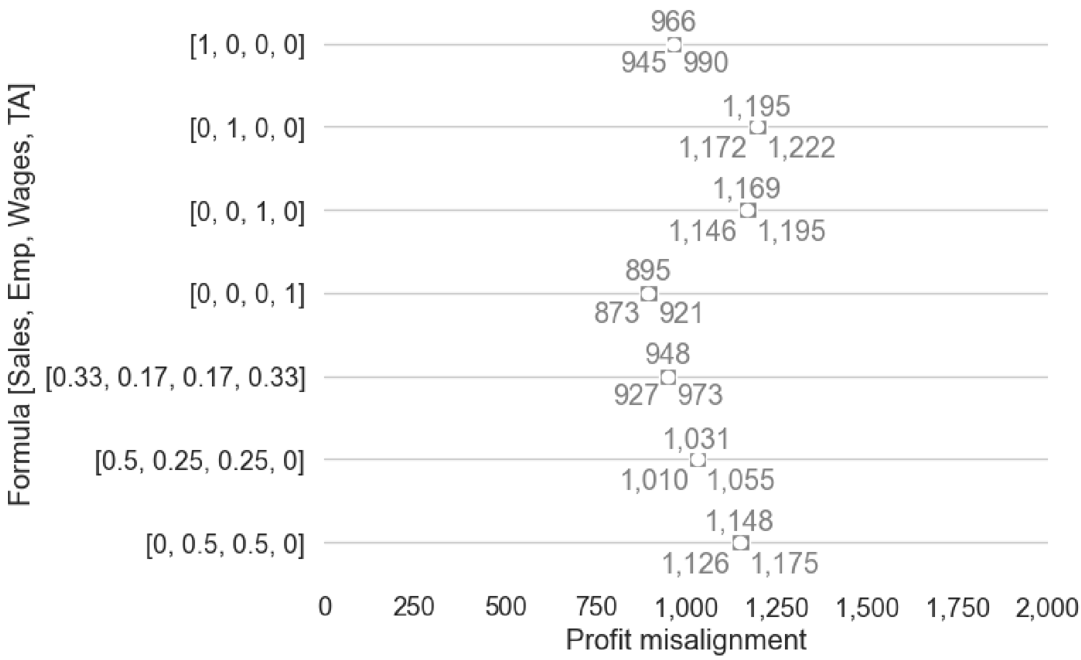
Given the high amount of estimated data, we assess our results' sensitivity to the estimation of missing information. To do so, we train the models 1,000 times using bootstrapped samples of the data (i.e. the gradient boosting ensemble to address the second limitation and the linear regression to address the third limitation) and record the impact in our results. Since the sampling randomly removes information, samples without important dyads (e.g. USA–Netherlands, or China–Hong Kong) will be heavily affected. We thus offer a conservative strategy allowing us to partially understand how our results depend on methodological choices. In the end, we use the median value for our point estimates.

1.4 Robustness tests: Using different formulas to calculate profit shifting

To make sure that our results are not disproportionally affected by our calculation of theoretical profits (based on 50% employees and 50% wages, see Section 1.2), we rerun our analysis for different formulas gauging economic activity. Figure 2 reports the results.

Total global profit shifting with our formula is US$1,148 billion, a medium estimate compared with the results for other formulas, as shown in Figure 2. Generally, the estimates of overall global profit shifting are slightly lower when employees and wages are left out of the formula.

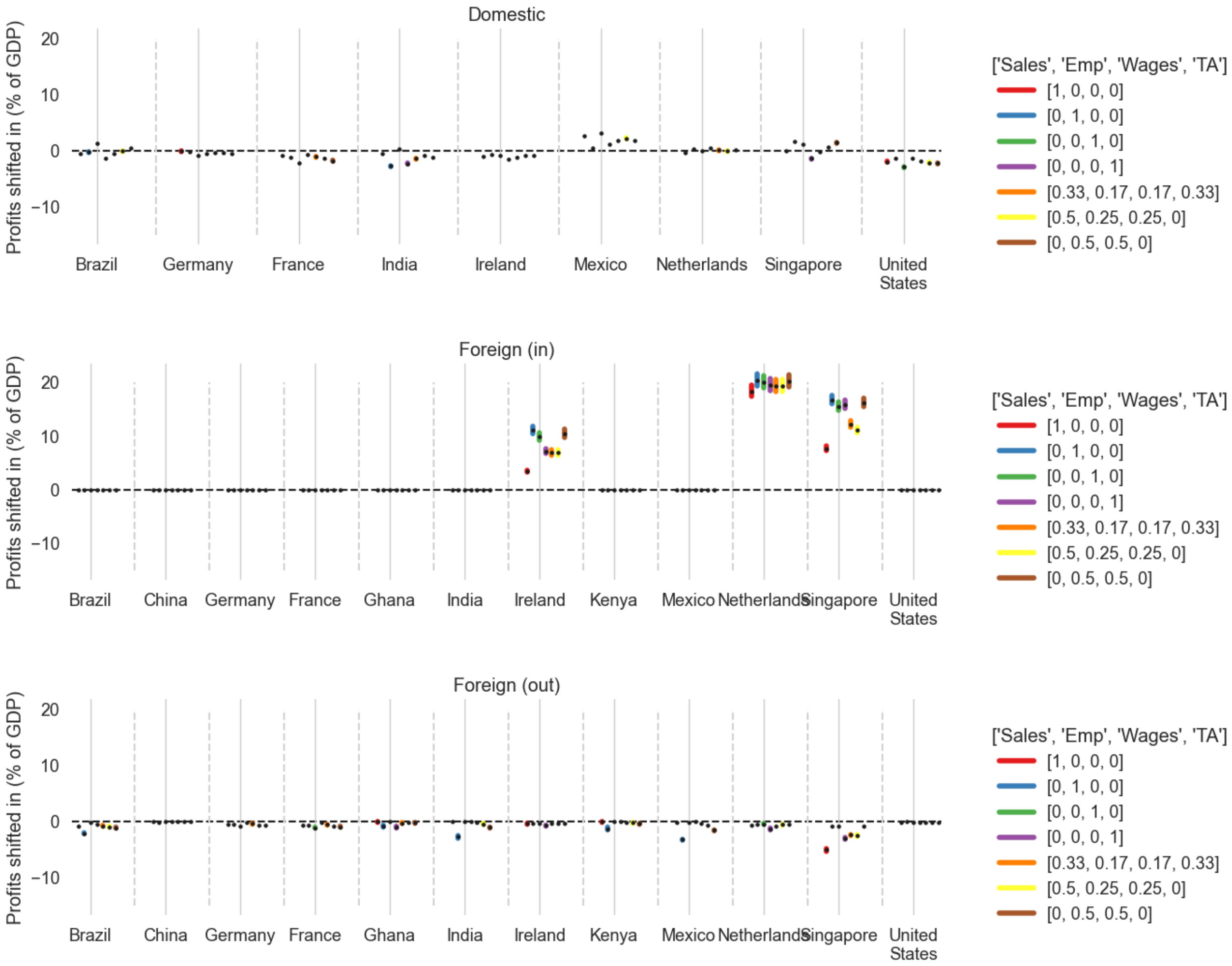
Figure 2: Total global profit shifting using alternative formulas to calculate the share of economic activity



Source: Authors.

Like depicted in Figure 3, the choice of a certain formula has also a relatively small influence in the estimation of profit shifting at the country level for domestic operations of MNCs, foreign MNCs shifting profits in, and foreign MNCs shifting profits out.

Figure 3: Alternative formulas - results for selected countries.



Source: Authors.

Note: TA = tanglible assets, Emp = employees.

2 Offshore wealth tax abuse

Our country-level estimates of offshore wealth tax abuse are based on existing estimates for total wealth that is hidden offshore. This hidden wealth – estimated at US$9.9 trillion for the year 2018[4] – has been identified by ECORYS (2021) based on Zucman (2013). Zucman's method uses portfolio data of countries to identify hidden wealth as the difference between reported cross-border liabilities and cross-border assets. This method identifies hidden wealth as wealth that exists, according to official statistics of the country where the wealth is located, but no one owns it, according to official statistics of all other countries. In the State of Tax Justice, we identify the probable location of this hidden wealth and assign it to owners all over the world.

2.1 Data

The primary source of data that we use to estimate the distribution of offshore financial wealth is the Locational Banking Statistics (LBS) from the Bank for International Settlements (BIS). Many offshore financial centres have been reporting information on the owners of deposits in their banks to the BIS for many years, however, only in 2016 did they authorize the BIS to publish this data as part of the LBS. In the State of Tax Justice 2023, we focus on data for the year 2018 to stay consistent with the corporate tax abuse estimates.

2.2 Methodology and results

Our approach to distribute wealth hidden offshore to owners in different countries can be summarized in four steps. First, we identify where the hidden wealth is located by 'abnormal' deposits in highly secretive financial centres – deposits that we would not expect to see in highly secretive countries based simply on the size of their economies. Second, we follow Alstadsaeter, Johannesen, and Zucman's (2018) approach to attribute these abnormal deposits to their origin countries. Third, we combine these country shares with the existing estimates of *total* global offshore financial wealth to derive the value of total offshore wealth originating from each individual country. Finally, we derive the tax revenue losses resulting from income earned on this wealth, building on the established approaches of Henry (2012) and Zucman (2015). A more detailed explanation follows.

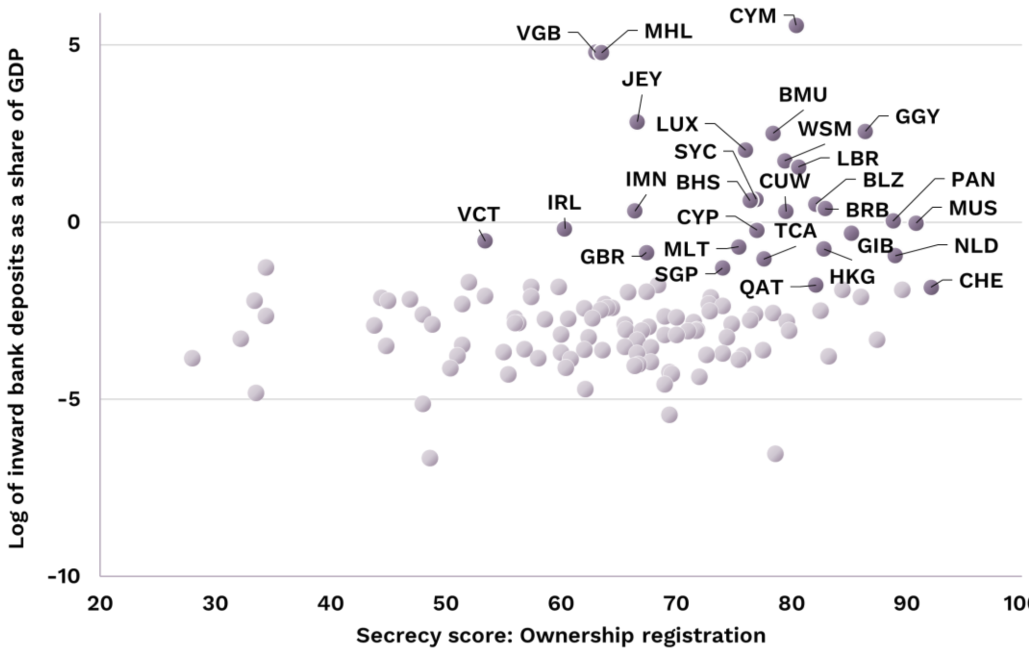
In the first step, we identify the location of hidden wealth by what we call "abnormal deposits". We start by identifying jurisdictions that (a) attract amounts of bank deposits that are disproportionally large in comparison to the size of their economy and (b) offer strong bank secrecy laws. For our purposes, we define

[4] The US$ 9.9 trillion figure differs slightly from the 9.8 trillion figure reported by ECORYS as we include more countries than ECORYS (2021). We adjust our total estimate based on the % of GDP estimate provided by ECORYS.

these jurisdictions as those that have high Secrecy Scores on the Financial Secrecy Index 2020[5] for the category of ownership registration. Combining these two indicators (i.e. high score on financial secrecy and high intensity of inward bank deposits), we identify jurisdictions with significant abnormal deposits due to secrecy as follows: countries with an inward bank deposit intensity of 30 per cent of GDP and a secrecy score of more than 50, and those with an inward bank deposit intensity of 15 per cent of GDP and a secrecy score of more than 70. These countries are highlighted in Figure 4. In the banks of these jurisdictions, foreign deposits are significantly higher than would be expected based on the size of the jurisdictions' economies, and at the same time, these countries offer high financial secrecy.

The list of these countries contains most of the important offshore financial centres. The full list is as follows: Bahamas, Barbados, Belize, Bermuda, British Virgin Islands, Cayman Islands, Cyprus, Curaçao, Gibraltar, Guernsey, Hong Kong, Ireland, Isle of Man, Jamaica, Jersey, Liberia, Luxembourg, Malta, Marshall Islands, Mauritius, Netherlands, Panama, Qatar, Saint Vincent and the Grenadines, Seychelles, Singapore, Switzerland, Turks and Caicos Islands, United Kingdom, United States Virgin Islands, and Western Samoa.

Figure 4: Bank deposits and financial secrecy



Source: Authors.

Note: Secrecy scores on the horizontal axis are constructed as the arithmetic average of the first five secrecy indicators in the Financial Secrecy Index 2020. Data on inward bank deposits are for 2018.

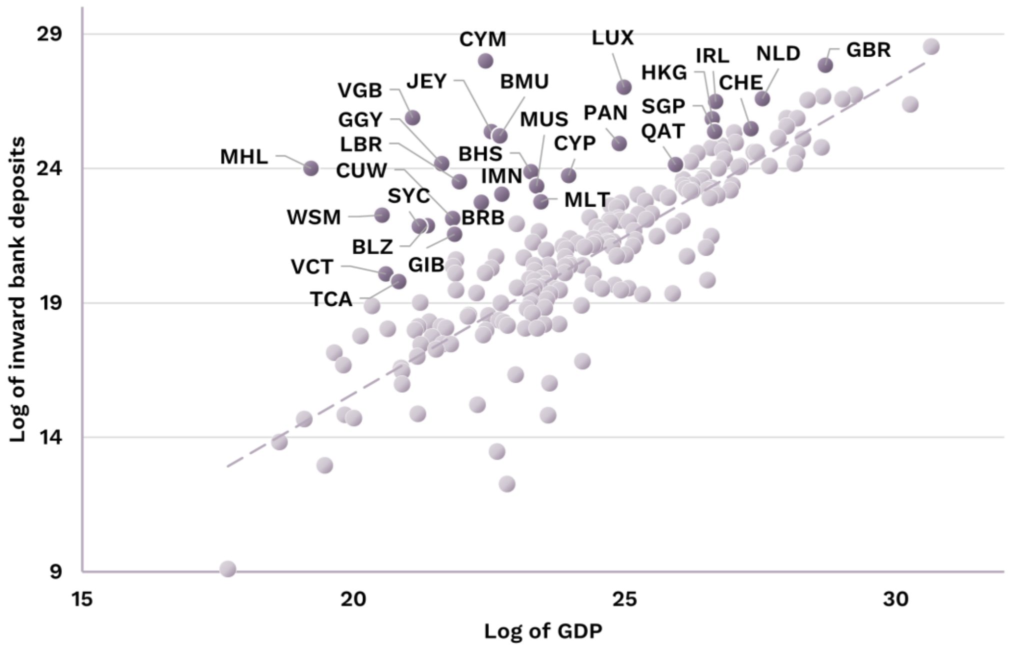
[5] We use the 2020 edition of the Financial Secrecy Index in this step, rather than the more recent 2022 edition, to be in line with the data used in this analysis, which comes from the end of 2018. The 2020 edition of the Financial Secrecy Index had a cut-off date on September 30, 2019, and thus is the closest edition to the data.

Excluding these jurisdictions, we seek to establish a 'normal' relationship between inward deposits and GDP. Using a sample of the remaining countries i and data for 2018, we estimate the following model:

$$Log\ inward\ bank\ deposits_i = \beta_0 + \beta_1 * log\ GDP_i + \epsilon$$

Figure 5 shows the resulting relationship between (log) GDP and (log) inward bank deposits. In total, the regression is carried out using a sample of 192 remaining countries which represent 92.9% of the world GDP. There is a strong positive relationship between GDP and inward bank deposits in these countries: the R-squared for the regression is 0.789. Labelled individually and highlighted are those jurisdictions excluded from the regression.

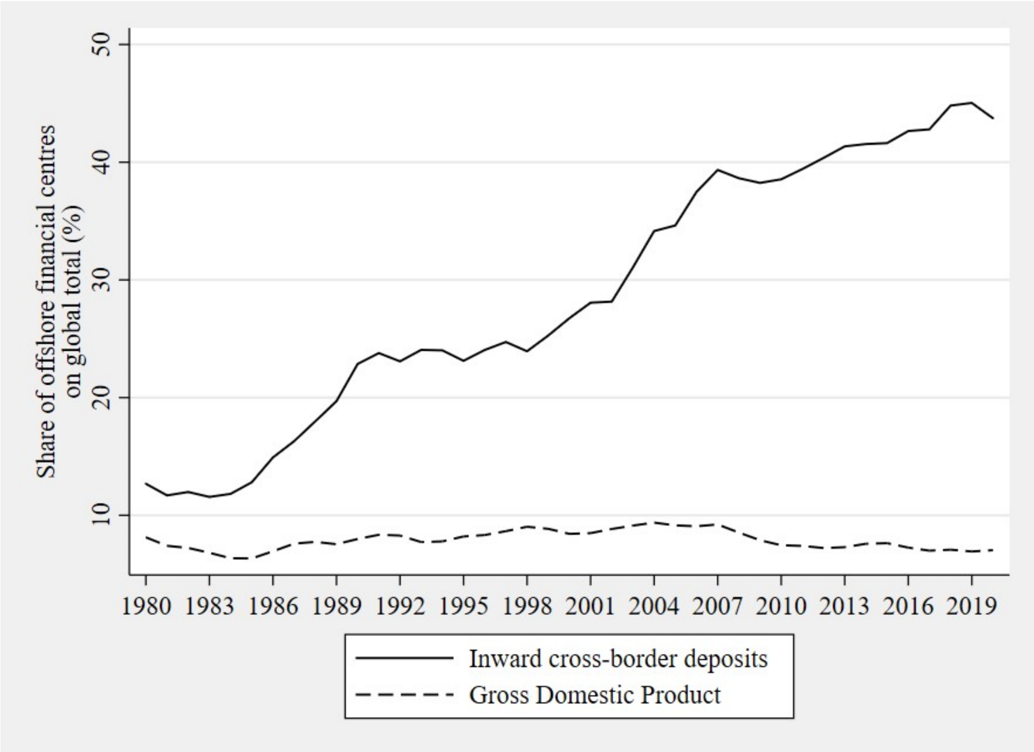
Figure 5: Inward bank deposits and GDP; 2018



Source: Authors.

The disproportionate amount of inward bank deposits (compared to GDP) in these 30 jurisdictions is further examined in Figure 6, where we present the development of the share of cross-border deposits in these jurisdictions of the global total. We observe that while they account for only 7.03% of global GDP, a share which has remained relatively stable over time, they collectively host over 40% of global cross-border deposits in 2018, a share that has steadily risen from just around 13% in the year 1980.

Figure 6: Share of offshore financial centres' inward bank deposits and GDP on the global total, over time



Source: Authors.

The level of "abnormal deposits" in each jurisdiction is then defined as the difference between actual, observed deposits, and the expected deposits as predicted by the regression coefficient. The assumption is that these deposits are located here precisely due to the fact that these jurisdictions provide some form of financial secrecy.

We find that 49.9% of global bank deposits can be considered abnormal as per our definition, meaning that they are located in individual jurisdictions in quantities that are higher than would be expected based on the size of these jurisdictions' economies. Note that this includes additional jurisdictions to the 30 pre-identified: that is, jurisdictions within the regression sample can also be identified as holding abnormal deposits, where the levels exceed that predicted. For each jurisdiction, our approach allows us to quantify how much money is considered to represent abnormal bank deposits and how large a share of each jurisdiction's total bank deposits these abnormal deposits represent. Table 4 provides an overview of each jurisdiction's value of abnormal deposits.

While some of the jurisdictions that appear in Table 4 are not routinely considered to be important destinations of offshore wealth (such as Italy or Spain) and their secrecy scores on Ownership registration (column 2) are correspondingly relatively low, we choose not to exclude these countries from our consideration as destinations of offshore wealth. For such countries, the large abnormal deposits could be explained by other factors than financial secrecy offered by the destination country – such as unusually intense cross-border economic activity – but we do not see a way accurately to estimate the size of these effects. In the light of this caveat, our estimates of inflicted loss by countries with low secrecy scores may be somewhat overstated, while those by countries with high secrecy scores are likely to be understated.

Table 4: Countries with abnormal deposits

Country	Secrecy score: Ownership registration	Total deposits (US$ bn)	Abnormal deposits (US$ bn)	Abnormal deposits (share of total)	BIS reporting
Cayman Islands	80.4	1431.8	1431.4	99.97%	No
United Kingdom	67.4	1231.1	975.1	79.21%	Yes
United States	86.0	2477.5	666.4	26.90%	Yes
Luxembourg	76.0	543.9	537.6	98.84%	Yes
Ireland	60.3	319.8	285.8	89.38%	Yes
Netherlands	89.0	356.2	275.6	77.36%	Yes
British Virgin Islands	63.0	175.0	174.9	99.93%	No
Italy	57.4	334.4	149.8	44.81%	Yes
France	65.8	385.6	139.3	36.14%	Yes
Hong Kong	82.8	169.4	137.5	81.16%	Yes
Jersey	66.6	104.7	104.1	99.48%	Yes
Bermuda	78.4	89.1	88.4	99.28%	No
Singapore	74.0	103.5	70.2	67.85%	No
Panama	88.8	67.1	61.3	91.46%	No
Switzerland	92.1	117.0	52.1	44.54%	Yes
Belgium	52.0	99.8	51.9	51.96%	Yes
Spain	57.4	171.7	46.3	26.99%	Yes
Guernsey	86.4	31.9	31.7	99.32%	Yes
Marshall Islands	63.5	26.5	26.5	99.93%	No
Denmark	59.8	57.1	25.7	44.90%	Yes
United Arab Emirates	84.4	62.8	25.5	40.64%	No
Bahamas	76.4	23.6	22.5	95.23%	No
Finland	68.4	46.6	22.3	47.83%	Yes
Sweden	53.4	69.6	20.6	29.58%	Yes
Canada	72.8	171.1	18.9	11.04%	Yes
Cyprus	77.0	20.4	18.1	88.95%	No
Liberia	80.6	16.2	15.9	98.14%	No
Qatar	82.1	30.9	14.7	47.64%	No
Norway	44.4	51.3	12.7	24.84%	No
Portugal	67.4	34.0	12.6	37.14%	No
Mauritius	90.8	13.9	12.6	90.97%	No
Isle of Man	66.4	10.2	9.6	93.55%	Yes
Barbados	82.9	7.5	7.0	94.00%	No
Malta	75.4	7.6	6.3	82.28%	No
Samoa	79.4	4.6	4.6	98.44%	No
Curacao	79.5	4.1	3.8	93.49%	No
Belize	82.1	3.2	3.0	94.72%	No
Seychelles	76.9	3.1	3.0	95.37%	No
New Caledonia		3.4	2.5	74.40%	No

Gibraltar	85.2	2.3	2.0	87.97%	No
Oman		9.9	1.9	18.86%	No
Macao	73.0	6.6	1.8	26.49%	Yes
Ghana	33.4	7.3	1.4	19.14%	No
Mozambique		2.5	1.2	48.59%	No
Bahrain	46.9	4.3	0.9	21.72%	No
Croatia	51.4	6.2	0.7	11.45%	No
Andorra	34.4	0.9	0.6	68.53%	No
Mongolia		1.7	0.5	31.97%	No
St. Vincent and the Grenadines	53.4	0.5	0.4	85.06%	No
Greenland		0.7	0.4	60.77%	No
Liechtenstein	89.6	1.0	0.4	40.61%	No
Australia	64.0	126.4	0.4	0.32%	Yes
Turks and Caicos Islands	77.6	0.4	0.3	75.03%	No
Faroe Islands		0.5	0.3	47.71%	No
French Polynesia		0.6	0.1	16.42%	No
Bonaire, Sint Eustatius and Saba		0.2	0.1	62.12%	No
Montenegro	63.8	0.5	0.1	10.44%	No
San Marino	45.0	0.2	0.0	19.43%	No
Dominica	74.0	0.1	0.0	5.63%	No

Source: Authors.

In the second step of our approach, we attribute these abnormal deposits to their origin countries. To do so, we broadly follow Alstadsaeter, Johannesen, and Zucman's (2018) approach and again use the BIS Locational Banking Statistics. This dataset contains information on the origin of bank deposits in high-secrecy jurisdictions which report this data to the BIS: as indicated in the last column of Table 4, some of the most popular secrecy jurisdictions now report, including Luxembourg, Netherlands, Hong Kong, Switzerland, and the Channel Islands. On the other hand, some secrecy jurisdictions that are important for offshore wealth still do not report the relevant data at the level of disaggregation that we use in this analysis – most notably the Cayman Islands, British Virgin Islands, Bermuda, Singapore, Panama, and the Bahamas. In total, 62.97 per cent of the global abnormal deposits in 2018 are covered by the BIS data; if the six mentioned non-reporting jurisdictions published their data, this share would increase to 96.74 per cent. Until they do, we are left to make an assumption, similarly to Alstadsaeter, Johannesen, and Zucman (2018), that the distribution of origin countries for deposits stored in the BIS-reporting jurisdictions which have abnormal deposits also holds in the non-BIS-reporting jurisdictions.

The BIS data on bank deposits has one important drawback: it does not differentiate between households' deposits and corporate deposits. Therefore, the ultimate owner is not always attributed to the actual source country of the deposits. For example, if a German person sets up a shell company in Hong Kong and opens a bank account for this company in Switzerland, this will show up in the data as a Hong Kong-Swiss relationship, rather than a German-Swiss relationship. While this could be partially solved by only focusing on households, the BIS data does not offer a distinction between households' and corporations' deposits. In our approach, we thus assume that households' bank deposits are geographically distributed in a similar way as corporations' bank deposits. Also, even if there was such a distinction in the data, it would be questionable whether to use it: households can easily create shell corporations, and their wealth would thus be reported as corporate bank deposits.

In Table 5.2 in the State of Tax Justice 2023 report, the second column shows the share of global offshore wealth that is attributed to each country. We find that offshore wealth is relatively concentrated by origin country, with the United States and United Kingdom accounting for the largest shares at 20.64% and 12.68%, respectively. One consequence of the drawback of the BIS data that we discuss above is that important offshore financial centres appear to have a high share of global offshore wealth, because the shell corporations incorporated there hold deposits in other offshore financial centres. While this means that non-tax havens' estimated shares of global offshore wealth are likely to be understated by our approach, we do not see a good way to correct for this limitation of the data. For example, the share of global offshore wealth of Jersey (1.44%) is much larger than would be expected from an economy of Jersey's size (which only accounts for 0.0036% of the global GDP), because we are unable to differentiate between genuine deposits of the citizens of Jersey in offshore financial centres and deposits made by Jersey-incorporated shell companies owned by citizens of other countries. In future research, combining the BIS data with other sources, such as leaks of confidential documents, might shed light on the size of these effects and allow methods for correction to be developed.

In the third step, we combine existing estimates of total global offshore financial wealth with our estimated origin country shares, to derive the value of offshore wealth originating from each individual country. In particular, we use the 2018 estimate of global offshore financial wealth that uses the original methodology developed by Zucman (2013) and recently published by ECORYS (2021). The estimate suggests that the scale of offshore wealth amounts to 11.4% of global GDP (which is the number that we use here in combination with 2018 data on the distribution of bank deposits). It is important to note that this estimate only includes financial assets and not non-financial wealth, which is likely to exceed financial wealth in value by a factor of 3-4 (Henry 2012); and also does not capture the full breadth of financial assets. For these reasons, this exercise is likely to be highly conservative in the projected scale of offshore wealth-related tax evasion. The third column of Table 5.2 in the State of Tax Justice 2023 report translates the constructed shares of global offshore financial wealth into US dollars, and the fourth column expresses these amounts as shares of GDP of the individual countries.

In the fourth and final step, we derive the tax revenue losses resulting from financial wealth being stored in secrecy jurisdictions. Following Zucman (2015), we assume that all investments made in secrecy jurisdictions (including bank deposits, with likely lower yields, and other assets, such as securities and bonds, with likely higher yields) yield an average of a 5 per cent return. We then multiply these returns by the topbracket personal income tax (PIT) rates that would have been applied in the assets' origin countries, had these assets not been moved to secrecy jurisdictions.

While using PIT rates might be introducing an upward bias to our estimates (in the sense that governments would, in reality, likely tax the returns at lower rates, perhaps because some of this income would be subject to the capital gains tax (CGT)), we ultimately choose to use PIT rates due to two reasons. First, although in theory we are considering a full range of assets, in practice the numbers are driven by financial account holdings (to which PIT rather than CGT would generally apply). Second, there is an argument that if the returns were actually declared for PIT, individuals would have an incentive to lower the relevant tax rate (e.g. by structuring as capital gains rather than individual income) – however, we focus on the tax-evading element of the returns. Therefore, the income that is being evaded as things stand (without any avoidance response) would be subject to PIT rather than CGT.

The existence of cases such as Italy where a lower rate than the PIT would apply to income streams from declared offshore assets might suggest making more conservative adjustments on a country by country basis, and we will consider this for future work. We note, however, that even in such a case, the very existence of the offshore wealth is the result of an originally undeclared income stream. For that reason, applying the higher PIT rate to a hypothetical income stream generated by the offshore wealth – rather than to the original income stream that generate the offshore wealth itself – will anyways understate the total tax losses substantially.

The fifth column of Table 5.2 in the State of Tax Justice 2023 report shows the estimates of tax revenue loss for each country. Finally, in the sixth and seventh column, we show the estimated contribution of each country to the global tax losses due to offshore wealth as a share, and the respective tax loss in US dollars inflicted on other countries. Many of the countries with the biggest losses themselves, such as the USA, UK, Ireland and Luxembourg, also impose major losses on others. The Cayman Islands is responsible for the largest share on this metric, at 25.6 per cent of the global total, making it alone responsible for a tax revenue loss of US$43.3 billion globally.

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