Methodological note: State of Tax Justice 2020

Tax Justice Network, November 2020

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 2020 report published by the Tax Justice Network in November 2020.

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1 Corporate tax abuse by multinational corporations (Chapter 1 of the report)

We analyze the country-by-country reporting (CBCR) data published by the OECD on the activities of the multinational corporations headquartered in 26 countries (see Table 1.1). We use these data to measure misaligned profits (high profits in jurisdictions with low economic activity). We then filled data gaps using state-of-the-art machine learning algorithms using a large variety of data sources (e.g. bilateral FDI, corporate tax rates, bank deposits, distance between countries), assessing the robustness of our results.[1]

Table 1.1: Countries reporting some CBCR data (see the disaggregation in Table 1.3)

India	Singapore	Italy	Poland
France	Ireland	Australia	South Korea
Chile	South Africa	Slovenia	Denmark
Norway	Bermuda	Finland	Indonesia
United States	Canada	Mexico	Austria
Luxembourg	Sweden	Belgium	China
Japan	the Netherlands		

[1] This methodology note is a slightly modified excerpt from the working paper ``Profit Shifting by Multinational Corporations Worldwide: Evidence from Country by Country Reporting" by Javier Garcia-Bernardo and Petr Janský (version 2020/11/01, available upon request).

1.1 Data

The methodology exploits country by country reporting (CBCR) datasets which include information on MNCs which only became available recently and which is of heretofore unprecedented quality. The dataset was provided thanks to a CBCR regulation which stems from OECD Base Erosion and Profit Shifting (BEPS) Action 13 on CBCR and which requires all large MNCs to report how much tax they pay in individual countries, 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 2016 OECD CBCR data for large MNCs published by OECD for numerous headquarter countries in July 2020. In addition, instead of the 2016 data published by the OECD, we use 2017 US CBCR data published by the US Internal Revenue Service in December 2019; unlike the 2016 data, which included only 70% of the MNCs, this dataset is complete. Importantly, existing research compared these 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.

First, 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 141 (United States) and 163 (India) jurisdictions in the full data set – 93 and 134 jurisdictions respectively for the data set limited to firms with positive profits (the two data sets are discussed below). The exceptional data coverage provided by CBCR data thus enables us to collect evidence of profit shifting for many countries with low and middle per capita incomes. And this country 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).

Second, CBCR ensures that profits and taxes are defined consistently with the concepts of corporate profits and taxes. 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 forthcoming; Clausing 2020a; 2020b). Consequently, CBCR data excludes double-counting in revenue and likely in profit (with the exception of stateless entities dropped from our analysis and intercompany dividends, for which companies have neither instructions nor incentives). Furthermore, CBCR data is based on tax accounting and thus reflects how much MNCs in fact pay in taxes, rather than on financial accounting, which is the basis for most other datasets including Orbis and which has been shown to underestimate profit shifting (Bilicka 2019). Since CBCR data offers the best available information on MNCs' tax payments for many countries, it thus 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 positive profits and so not losses ("Sub-Groups with Positive Profit"). To estimate ETRs we prefer to use 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 this data set with all large MNCs 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. It is also more suitable for comparison with other datasets (e.g. from the Bureau of Economic Analysis). Furthermore, unfortunately both data sets 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.

While the substantial country coverage as well as the other advantages of CBCR data open new avenues for research, at least two challenges associated with the new data source remain (and we summarise them alongside the above discussed advantages in Table 1.2). First, unfortunately a certain extent of double counting in profit due to intercompany dividends is likely inevitable as 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). Significantly, there do not seem to be incentives for double counting profits in tax havens by MNCs (since they know this data is to be used for assessing transfer pricing risk). Furthermore, we exclude stateless income, another potential source of double counting. Consequently, the US CBCR data produce totals reassuringly consistent with other data sources (Clausing 2020a; Garcia-Bernardo, Janský, and Tørsløv forthcoming).

Table 1.2: Summary of selected advantages and disadvantages of the CBCR data

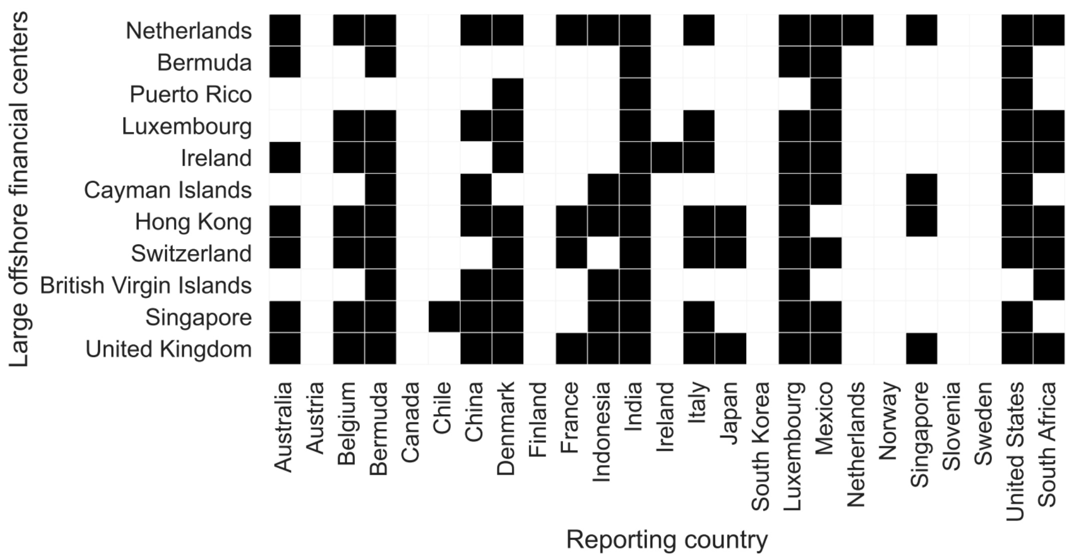
Selected advantages
Includes data on large MNCs' profits and tax payments in around 100 jurisdictions for at least five headquarter countries
Does not include double counting in revenue and likely not in profit.
Enables to use data on large MNCs and those with positive profit only (the latter estimates ETRs more precisely).
Selected disadvantages
Might include some double counting in profit due to intercompany dividends or stateless entities (which we drop).
Includes a sample of large MNCs for 2016 for some countries in aggregated and anonymised form (which we address).

Second, data from 2016, i.e. the only year for which we have data for most headquarter countries, does not provide complete coverage of all large MNCs for all countries. 2017 is thus the first year with complete data available, though only the United States has published its data thus far (OECD is to publish data from 2017 for other headquarter countries likely only in July 2021). In this paper, we therefore use both of the two years of data to make use of the best available data possible. While the CBCR regulation has been implemented by approximately 100 countries so far, only some of them agreed to share their data publicly in aggregated and anonymised form; moreover, some have chosen to aggregate data to a far greater extent than others. Of the 137 jurisdictions included in the Inclusive Framework on BEPS, 58 jurisdictions agreed on collecting CBCR, 35 received data from 20+ MNCs, 26 jurisdictions shared a limited amount of data, and only 10 jurisdictions disaggregated the data on more than 60 countries, with the United States and India (137 and 163 jurisdictions, respectively) leading the way (Table 1.3 and Fig. 1.1).

Table 1.3: Number of jurisdictions available per country (aggregates excluded). Jurisdictions with 1 observation only report on domestic activities of MNCs

	IND	USA	ZAF	ITA	MEX	DNK	CHN	FRA	LUX
All sub-groups	163	137	127	103	102	96	90	83	80
Sub-groups with positive profits	134	84	87	77	73	93	53	32	79
	BMU	AUS	BEL	IDN	JPN	CHL	SGP	CAN	SVN
All sub-groups	72	56	40	33	29	14	12	8	5
Sub-groups with positive profits	57	39	32	26	12	11	22	3	5
	POL	AUT	NLD	NOR	IRL	SWE	FIN	KOR	
All sub-groups	4	1	1	1	1	1	1	1	
Sub-groups with positive profits	0	1	1	1	1	1	1	1	

Figure 1.1: Country availability. Black squares mark the availability of data on large offshore financial centres for each reporting country.



We focus on the remaining challenges posed by this data in section 1.3, where we empirically deal with three additional issues: the lack of completeness in the data of reporting countries, the varying combinations of countries in the aggregated country categories and the lack of reporting by some countries. Other 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 (forthcoming) and Clausing (2020a). .

Table 1.4 shows the summary statistics of the CBCR data with positive profits for the countries in our sample. Table 1.4 distinguishes between domestic and foreign activities of MNCs - domestic one are those in the reporting (i.e. headquarter) countries, while foreign ones are those in all other countries (i.e. except for the domestic one). For most countries domestic profits and activities are higher than foreign ones. The exceptions are mainly Bermuda and Luxembourg, which are often considered tax havens, as well as Belgium. The observed balance between domestic and foreign activities provides a useful guidance for when we estimate missing data in Section 1.3.

Table 1.4: Summary statistics for a subsample of the countries.

Reporting country	Partner	Firm profits > 0	Profits, USD bn	Tax accrued, USD bn	Tax paid, USD bn	Employees, thousands	Revenue, USD bn	Assets, USD bn	ETR (%) accrued	ETR (%) cash
Australia	Domestic	94	69.8	13.9	10	949.9	365.2	340.7	19.9%	14.3%
	Foreign	758	26.5	3.1	2.7	335.3	124.2	92.9	11.6%	10.1%
Belgium	Domestic	43	18.7	1	0.8	146	88.4	90.8	5.4%	4.1%
	Foreign	52	82.2	7.1	8.5	499.3	167.5	101.2	8.7%	10.3%
Bermuda	Domestic	26	12.7	0	0	2.1	10.4	9.1	0.2%	0.1%
	Foreign	26	88.7	9.4	12.8	530.3	520.5	620.3	10.6%	14.5%
China	Domestic	77	391.8	65.5	77.9	11543.8	2785.2	5471.2	16.7%	19.9%
	Foreign	905	57.3	5.3	5.2	355.6	376.7	336.1	9.2%	9.1%
Denmark	Domestic	35	17	2.4	2.5	120.5	44.7	24	13.9%	14.5%
	Foreign	39	10	0.7	0.8	783.4	74.9	40.5	6.6%	7.7%
India	Domestic	146	74.8	18.4	22.2	3891.3	564.2	864	24.6%	29.7%
	Foreign	N/A	15	2.3	5.9	548.5	130.5	121.8	15.5%	39.6%
Italy	Domestic	104	48.3	6.6	7.4	630.5	340.7	209.1	13.6%	15.4%
	Foreign	130	44.9	5.7	6.4	612.8	263	148.2	12.6%	14.3%
Luxembourg	Domestic	52	8.2	0.1	0.1	8.8	8.6	18.4	1.4%	0.9%
	Foreign	119	34.3	2.4	2.8	1142.9	372.1	128.6	6.9%	8.1%
Mexico	Domestic	60	26.5	6.4	6.8	1228.6	139.3	100.6	23.9%	25.5%
	Foreign	334	9.8	2.3	2.3	340.9	114.2	79	23.1%	23.4%
United States	Domestic	1094	1310.5	257.9	209.6	19601.7	9426.7	4880.5	19.7%	16.0%
	Foreign	1548	873.6	102.5	100.5	10972	3338.4	1722.2	11.7%	11.5%
South Africa	Domestic	34	16.5	1.7	2.4	604.3	69.5	77	10.1%	14.6%
	Foreign	574	5.2	1.2	0.9	316.9	43.7	41.1	23.8%	18.1%

Note: Domestic indicate the financial reporting of MNCs in the reporting (i.e. headquarter) countries, while foreign in all other countries (i.e. except for the domestic, or headquarter, one). Note that since we are using ``Sub-Groups with positive profits", the number of firms included in the domestic section can be lower than the number of firms reporting on foreign operations.

1.2 Misalignment method

We estimate a profit misalignment method, which typically starts from a given relationship between real profit (p) and a combination of labour (measured using wages and employees), capital (often approximated with tangible assets) and revenue. Profit misalignment is then calculated as the difference between reported profits (π) and theoretical profits (p). In our version of this method, we allocate 25% of the weight to employees, 25% of the weight to wages, and 50% of the weight to unrelated party revenues.

$$\frac{\widehat{p_i}}{\sum_i \widehat{p_i}} = R_i \cdot \sum_i \pi_i$$

Importantly, since MNCs can report zero or negative profits in a country in order to avoid taxes, we use the data on all sub-groups. The ETRs (used to calculate tax revenue losses) are still calculated from the data on sub-groups with positive profit. For observations which were available in the data on all sub-groups but not in the data on sub-groups with positive profit we used the average country ETR if available and the statutory corporate income tax rate otherwise.

Profit shifting is calculated as the difference between booked profits and estimated profits:

$$\widehat{S_i} = \pi_i - \widehat{p_i}$$

In this case $\sum \widehat{S_i} = 0$ and $\Delta P_i = \widehat{S_i}$. However, we add one extra constraint. The profit misalignment of all foreign observations (pairs of reporting and investment countries where reporting and investment countries differ) with a tax rate higher than 25% was set to zero since we assumed that an MNC would not shift profits to a country with a tax rate over 25%. This corrects for extreme outliers such as high profits of Bermudian companies in Peru and high profits of MNCs in resource-rich countries.

1.3 Estimating missing data

The most important limitation of studies on profit shifting has been a lack of data completeness. While the availability of CBCR data constitutes a significant step forward and partially corrects this issue, as discussed in Section 1.1, three specific limitations remain to be addressed. The first limitation concerns the lack of completeness in the data of reporting countries. We address this limitation by comparing the number of companies in Orbis, a frequently used database covering over 300 million public and private firms worldwide, with the number of companies observed in CBCR (Table 1.5). While the number of countries observed is similar to the number of companies expected for most countries, we observe large differences in the case of some countries. We therefore multiplied all reported financial information by a ratio listed in Table 1.5 in case that ratio was above one, with the exception of two countries described below.

We address the lack of completeness in the data of two reporting countries, the United States and China, in a specific way. In the case of the United States, we expected 1,501 companies according to Orbis. Instead, we find 1,101 companies in the 2016 data. This is due to a lack of completeness of 2016 data in the United States. US Internal Revenue Service data for 2017 indicate that we should observe approximately 1,575 companies - 1,548 with profits in at least one jurisdiction. In order to correct for this disparity we use US data for 2017. In China, instead of the expected 583, only 82 companies reported satisfactory data to the OECD. However, those 82 companies reported \$2.9 tn of sales domestically, and \$0.45 tn abroad; for comparison, the numbers for the United States in 2016 were \$7.8 tn domestically and \$3.4 tn abroad. This indicates that the data is not as erratic as it may appear. Lacking a better heuristic, we multiply the financial information for China by a conservative factor of two.[2]

Table 1.5: Number of companies expected (according to Orbis) versus observed in the CBCR data

Country	# Expected (Orbis)	# Observed (CBCR)	Ratio	Country	# Expected (Orbis)	# Observed (CBCR)	Ratio
China	583	82	7.11	US (2017)	1501	1548	1.03
Denmark	69	39	1.77	AUS	111	110	1.01
Bermuda	60	39	1.54	India	158	165	0.96
Singapore	48	32	1.5	Norway	55	60	0.92
US (2016)	1,501	1,101	1.36	Chile	29	32	0.91
South Africa	58	44	1.32	Finland	48	54	0.89
Japan	891	715	1.25	Netherlands	136	155	0.88
Italy	151	130	1.16	Australia	64	73	0.88
Indonesia	22	19	1.16	Belgium	45	54	0.83
France	206	180	1.14	Poland	24	29	0.83
Canada	179	160	1.12	Slovenia	5	7	0.71
Korea	205	185	1.11	Mexico	40	74	0.54
Sweden	95	88	1.08	Luxembourg	30	120	0.25
Ireland	47	45	1.04				

The second limitation concerns the combinations of countries in aggregated categories (e.g. Other Africa, Europe). The aggregation criterion is different for different countries. While 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

[2] We run a robustness test in which the data of China was not adjusted. This increases total profit shifting by 5%, especially towards China and Macao, and away from the United States and the United Kingdom

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 0.49, 0.50 and 0.51 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. Let us demonstrate using the following model scenario: 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, we multiply the employees of those countries by 10,000 and 11,000 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 in order to correct for the combination of small countries in aggregated groups. While this step typically increases total shifted profits by approximately 30%, 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 few profits to those countries. Figure 1.2 shows the available information on CBCR, displaying how data coverage is especially worrisome in the case of low- and middle-income countries.

Figure 1.2: Available information on CBCR. Colour denotes increasing GDP per capita. Countries with availability below 10% are annotated.

The third limitation concerns the lack of reporting by some countries including e.g. Germany, Spain, and the United Kingdom. This is partially addressed in the previous step, where financial information for all pairs of countries is estimated even for non-reporting countries. However, domestic information is important, especially for large countries. 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) (R-square 0.91, 0.98 respectively for employees and sales. 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) do not counted towards the estimate.

Finally, 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.

2 Offshore wealth tax abuse (Chapter 4 of the report)

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.

2.2 Methodology and results

Our approach can be summarized in four steps. First, we use a simple approach to identify ‘abnormal’ deposits in financial centres, which we find to make up 39.3% of global bank deposits. Second, we follow Alstadsaeter, Johannesen, and Zucman's (2018) approach in order to attribute these abnormal deposits to their origin countries. Third, we combine these country shares with existing estimates of *total* global offshore financial wealth from Alstadsaeter, Johannesen, and Zucman (2018) to derive the value of total offshore wealth originating from each individual country (while recognising the estimate captures a somewhat narrow range of financial wealth, and that non-financial wealth may dominate in value by a factor of 3-4 (Henry 2012)),. 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 what we call “abnormal deposits”. We start by identifying jurisdictions that attract large amounts of bank deposits (compared to the size of their economy) and at the same time offer strong bank secrecy laws; for our purposes, we define these jurisdictions as those that score at least 20 (out of 100) on Banking Secrecy, the first Key Financial Secrecy Indicator of the Financial Secrecy Index 2018 (the relevant year from the Tax Justice Network’s biennial ranking of jurisdictions most complicit in financial secrecy, given the lag in publishing LBS data). In the banks of some of these jurisdictions, foreign deposits are significantly higher than would be expected based on the size of the jurisdictions’ economies: for our purposes, we consider jurisdictions that report foreign bank deposits with a value of more than 15 per cent of their GDP.

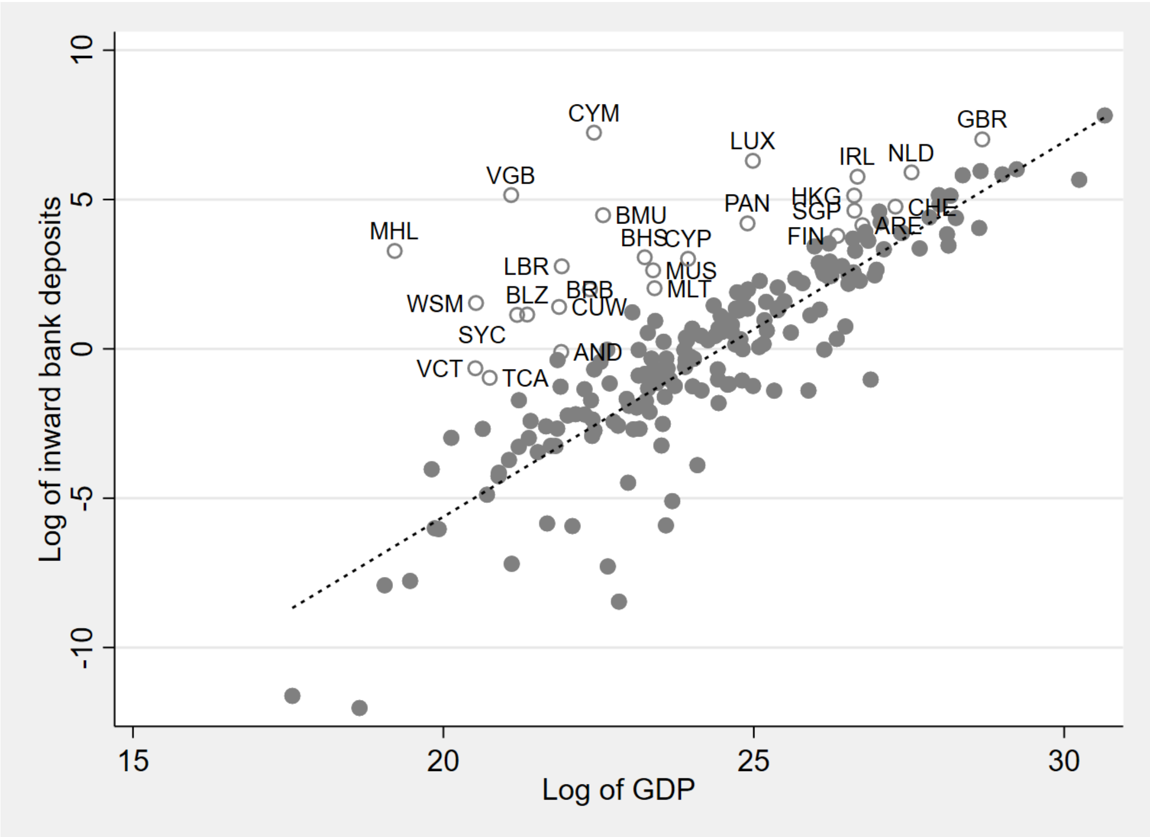
The list of these countries contains most of the important offshore financial centres. The full list is as follows: Andorra, Bahamas, Barbados, Belize, Bermuda, British Virgin Islands, Cayman Islands, Curacao, Cyprus, Finland, Gibraltar, Guernsey, Hong Kong, Ireland, Isle of Man, Jersey, Liberia, Luxembourg,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

Having excluded these jurisdiction, 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:

$$Inward\ bank\ deposits\ as\ share\ of\ GDP_i = \alpha * GDP_i + \epsilon$$

Figure 2.1 shows the resulting relationship between GDP and inward bank deposits. In total, the regression is carried out using a sample of 188 remaining countries which represent over 90% 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 0.79. Labelled individually and highlighted are those jurisdictions excluded from the regression (i.e. those with both a ratio of bank deposits to GDP of more than 15 per cent and a Banking Secrecy score of at least 20).

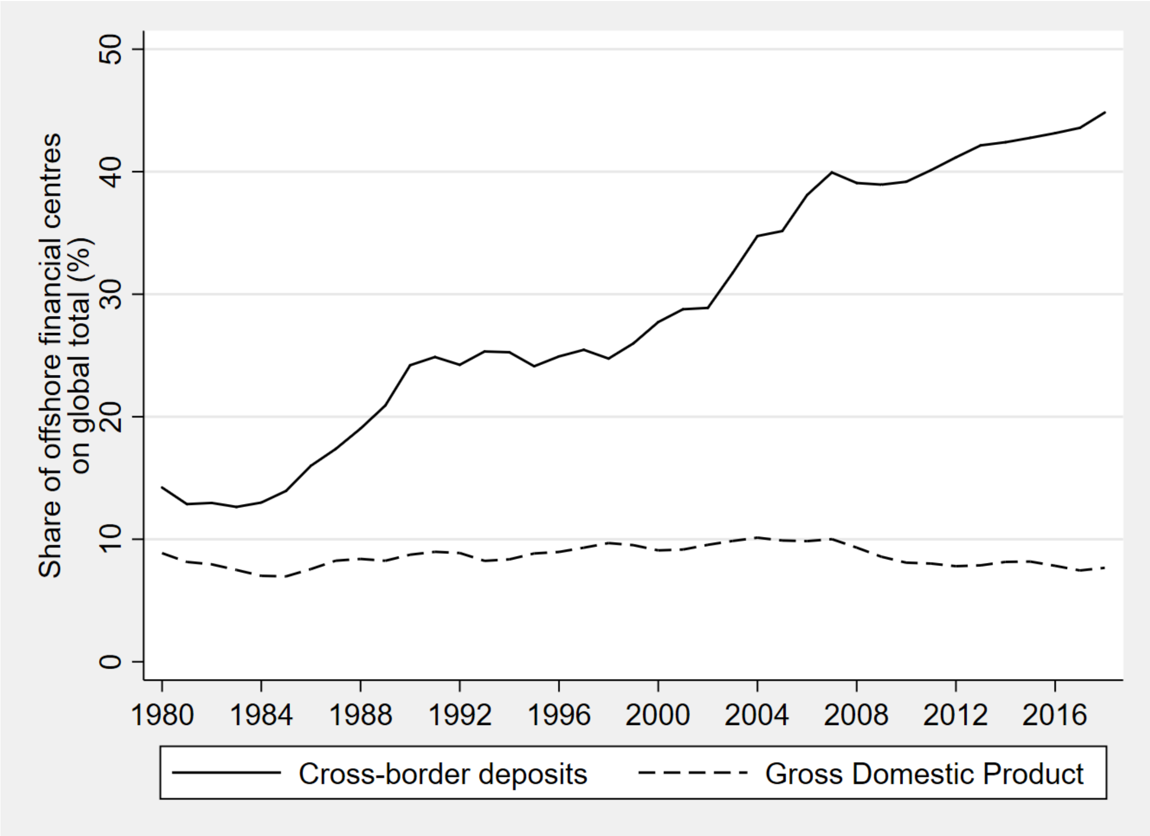
Figure 2.1: Bank deposits and GDP; 2018



Source: Authors.

The disproportionate amount of inward bank deposits (compared to GDP) in these 31 jurisdictions is further examined in Figure 2.2, where we present the development of the share of cross-border deposits in these jurisdictions in the global total. We observe that while they account for less than 10% of global GDP, a share which has remained relatively stable over time, they collectively hosted over 44% of global cross-border deposits in 2018, a share that has steadily risen from just around 13% in the year 1980.

Figure 2.2: 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 from Figure 2.1. 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 39.3% 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 31 pre-identified: that is, jurisdictions within the regression sample can also be identified as holding abnormal deposits, where the levels exceeds 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 2.1 provides an overview of each jurisdiction's value of abnormal deposits.

Table 2.1: Countries with abnormal deposits

Country	**Banking secrecy (FSI 2018; 100 = max.)**	**Total deposits (USD bn)**	**Abnormal deposits (USD bn)**	**Abnormal deposits (share of total)**	**BIS reporting**
Cayman Islands	40	1,391.8	**1,391.4**	99.97%	No
United Kingdom	43	1,110.9	**841.2**	75.72%	Yes
United States	20	2,477.4	**690.6**	27.87%	Yes
Luxembourg	60	541.5	**535.4**	98.86%	Yes
Netherlands	50	368.1	**285.7**	77.60%	Yes
Ireland	24	318.5	**285.2**	89.55%	Yes
British Virgin Islands	40	172.2	**172.1**	99.93%	No
Hong Kong	86	169.3	**137.8**	81.37%	Yes
France	54	385.0	**131.2**	34.08%	Yes
Italy	27	334.4	**125.8**	37.61%	Yes
Jersey	43	101.1	**100.7**	99.52%	Yes
Bermuda	67	87.7	**87.2**	99.37%	No
Singapore	40	102.2	**70.5**	69.00%	No
Panama	56	66.7	**61.0**	91.52%	No
Switzerland	73	116.9	**55.3**	47.25%	Yes
Belgium	7	99.2	**52.0**	52.41%	Yes
Guernsey	57	31.9	**31.6**	99.05%	Yes
Spain	7	171.6	**30.3**	17.65%	Yes
United Arab Emirates	47	62.8	**26.8**	42.65%	No
Marshall Islands	30	26.5	**26.5**	99.93%	No
Bahamas	70	21.4	**20.4**	94.96%	No
Finland	53	43.9	**19.2**	43.65%	Yes
Sweden	27	69.6	**18.7**	26.93%	Yes
Cyprus	50	20.4	**18.0**	88.12%	No
Liberia	53	15.8	**15.6**	98.20%	No
Qatar	N/A	30.9	**13.0**	41.93%	No
Mauritius	60	13.9	**12.6**	91.08%	No
Portugal	37	34.0	**11.2**	32.90%	No
Isle of Man	44	10.3	**9.6**	93.71%	Yes
Denmark	60	40.1	**9.2**	22.88%	Yes
Canada	14	168.7	**8.5**	5.02%	Yes
Barbados	53	7.3	**6.9**	93.88%	No
Malta	47	7.6	**6.4**	83.38%	No
Norway	20	50.2	**4.7**	9.34%	No
Samoa	63	4.6	**4.6**	98.44%	No
Curacao	60	4.1	**3.8**	93.25%	No
Belize	73	3.2	**3.0**	94.83%	No
Seychelles	73	3.1	**3.0**	95.57%	No
Oman	N/A	9.7	**2.7**	27.58%	No
New Caledonia	N/A	3.4	**2.5**	72.78%	No
Gibraltar	76	2.3	**2.1**	92.24%	No
Macao	60	6.6	**1.8**	27.45%	Yes
Ghana	53	7.3	**1.6**	22.12%	No
Germany	50	344.5	**1.1**	0.32%	No
Mozambique	N/A	2.5	**1.0**	39.52%	No
Bahrain	80	4.3	**1.0**	22.95%	No
Mongolia	N/A	1.7	**0.6**	33.51%	No
Andorra	87	0.9	**0.6**	61.28%	No
St. Vincent and the Grenadines	67	0.5	**0.5**	86.49%	No
Greenland	N/A	0.7	**0.4**	61.38%	No

Country	Banking secrecy (FSI 2018; 100 = max.)	Total deposits (USD bn)	Abnormal deposits (USD bn)	Abnormal deposits (share of total)	BIS reporting
Liechtenstein	73	1.0	**0.4**	39.14%	No
Turks and Caicos Islands	73	0.4	**0.3**	76.56%	No
Faroe Islands	N/A	0.5	**0.3**	53.51%	No
Croatia	37	6.2	**0.1**	1.44%	No
French Polynesia	N/A	0.6	**0.0**	4.46%	No
Montenegro	54	0.5	**0.0**	4.67%	No
Falkland Islands	N/A	0.0	**0.0**	35.84%	No
Aruba	57	0.3	**0.0**	1.21%	No
Dominica	70	0.1	**0.0**	1.47%	No

Source: Authors.

While some of the jurisdictions that appear in Table 2.1 are not routinely considered to be important destinations of offshore wealth (such as Italy or France) and their scores on the Banking secrecy indicator (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.

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 2.1, 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 – most notably the Cayman Islands, British Virgin Islands, Bermuda, Singapore and Panama. In total, 62.1 per cent of the global abnormal deposits are covered by the BIS data; if the five mentioned non-reporting jurisdictions published their data, this share would increase to 96.2 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.

In Table 2.2, the second column shows the share of global offshore wealth that is attributable 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 20.4% and 12.2%, 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 (1.5%) 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 might shed more 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 most widely cited estimate of global offshore financial wealth of 11.6 per cent of global GDP, or $10.9 trillion in 2018, as provided by Alstadsaeter, Johannesen, and Zucman (2018). 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 tax evasion. The third column of Table 2.2 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 wealth being stored in secrecy jurisdictions. Following Zucman (2015), we assume that investments made in secrecy jurisdictions yield an average of a 5 per cent return. We then multiply these returns by the top-bracket 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 not be likely to tax the returns at such high rates, perhaps because some of this income would be subject to the capital gains tax (CGT), which is generally set at a lower rate), 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 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 understate the total tax losses very substantially.

The fifth column of Table 2.2 shows the estimates of tax revenue loss for each country. Finally, in the sixth and seventh column of Table 2.2, 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 26 per cent of the global total, making it alone responsible for a tax revenue loss of $47.6 billion globally.

Table 2.2: Tax losses suffered and inflicted on others, by country

Country	Share of global offshore wealth	Offshore financial wealth (USD billion)	Offshore financial wealth (% of GDP)	Tax revenue loss (USD million)	Share of global tax loss inflicted by country	Tax loss inflicted (USD million)
United States	20.4%	2,168.3	10.6%	**40,113.0**	12.9%	23,635.9
United Kingdom	12.2%	1,302.8	42.0%	**29,314.1**	15.7%	28,793.3
Ireland	5.6%	594.3	155.4%	**14,263.5**	5.3%	9,762.1
China	4.7%	495.7	3.6%	**11,154.0**	0.0%	-
Luxembourg	4.4%	467.1	658.9%	**10,691.3**	10.0%	18,324.2
Germany	4.5%	474.2	12.0%	**10,669.1**	0.0%	38.2
Netherlands	3.5%	372.1	39.3%	**9,666.1**	5.3%	9,777.8
France	2.3%	240.2	8.2%	**5,884.2**	2.5%	4,491.2
Japan	1.9%	200.0	3.2%	**5,595.6**	0.0%	-
Switzerland	2.3%	240.0	33.8%	**4,799.8**	1.0%	1,891.3
Italy	1.6%	166.5	6.9%	**3,580.2**	2.4%	4,305.1
Taiwan	1.6%	169.3	14.3%	**3,386.0**	0.0%	-
Belgium	1.0%	108.5	20.0%	**2,712.6**	1.0%	1,779.3
Canada	1.4%	147.4	8.0%	**2,432.7**	0.2%	290.0
Singapore	1.7%	180.5	49.6%	**1,985.7**	1.3%	2,412.8
Australia	0.8%	81.4	5.2%	**1,832.0**	0.0%	-
Spain	0.7%	76.0	4.7%	**1,711.1**	0.6%	1,036.9
Jersey	1.5%	156.6	4683.7%	**1,566.3**	1.9%	3,445.2
Sweden	0.5%	54.3	9.3%	**1,557.4**	0.4%	641.5
Denmark	0.4%	40.3	11.3%	**1,125.8**	0.2%	314.0

Country	Share of global offshore wealth	Offshore financial wealth (USD billion)	Offshore financial wealth (% of GDP)	Tax revenue loss (USD million)	Share of global tax loss inflicted by country	Tax loss inflicted (USD million)
Hong Kong	1.4%	145.0	40.0%	**1,087.8**	2.6%	4,716.3
Cyprus	0.6%	60.9	218.6%	**1,065.4**	0.3%	614.7
Greece	0.4%	44.7	12.6%	**1,005.0**	0.0%	-
Israel	0.3%	35.1	9.5%	**877.7**	0.0%	-
Mexico	0.4%	46.7	3.5%	**816.7**	0.0%	-
Thailand	0.4%	42.3	8.4%	**740.2**	0.0%	-
South Africa	0.3%	30.4	7.3%	**683.1**	0.0%	-
Norway	0.3%	28.2	5.4%	**658.2**	0.1%	160.3
Austria	0.2%	23.8	5.2%	**653.7**	0.0%	-
Finland	0.2%	22.1	7.8%	**595.0**	0.4%	656.1
Panama	0.4%	47.3	72.8%	**591.6**	1.1%	2,089.3
Portugal	0.2%	23.0	8.8%	**552.0**	0.2%	382.9
South Korea	0.2%	22.4	1.4%	**469.4**	0.0%	-
Guernsey	0.4%	45.1	1836.9%	**450.8**	0.6%	1,080.2
Turkey	0.2%	25.4	2.7%	**444.9**	0.0%	-
Russia	0.6%	61.3	2.7%	**398.3**	0.0%	-
Curacao	0.2%	16.6	526.6%	**390.9**	0.1%	129.9
Malta	0.2%	21.8	150.0%	**382.0**	0.1%	217.4
Argentina	0.2%	19.6	3.1%	**343.1**	0.0%	-
Malaysia	0.2%	23.2	6.5%	**324.6**	0.0%	-
Brazil	0.2%	20.4	0.8%	**280.3**	0.0%	-
Isle of Man	0.3%	26.8	360.8%	**268.0**	0.2%	329.7
Venezuela	0.1%	15.2	3.2%	**258.4**	0.0%	-
Philippines	0.1%	14.7	4.4%	**257.7**	0.0%	-
Gibraltar	0.1%	12.6	614.1%	**251.0**	0.0%	72.4
Nigeria	0.2%	20.8	3.7%	**249.3**	0.0%	-
Angola	0.2%	23.8	16.4%	**202.5**	0.0%	-
India	0.1%	11.3	0.4%	**202.2**	0.0%	-
Egypt	0.2%	17.5	5.3%	**197.3**	0.0%	-
Liberia	0.1%	13.9	423.0%	**193.9**	0.3%	532.4
New Zealand	0.1%	10.6	5.2%	**175.3**	0.0%	-
Samoa	0.1%	12.0	1439.2%	**161.6**	0.1%	156.4
Poland	0.1%	10.1	1.7%	**161.5**	0.0%	-
Chile	0.1%	9.2	3.1%	**160.3**	0.0%	-
Lebanon	0.1%	14.5	25.6%	**145.1**	0.0%	-
Barbados	0.1%	6.9	134.6%	**138.5**	0.1%	234.8
Seychelles	0.1%	8.8	551.6%	**137.8**	0.1%	102.0
Colombia	0.1%	7.8	2.0%	**135.8**	0.0%	-
Peru	0.1%	8.3	3.7%	**124.3**	0.0%	-
Uruguay	0.1%	6.5	10.9%	**116.9**	0.0%	-
Slovenia	0.0%	4.7	8.4%	**116.8**	0.0%	-
Belize	0.1%	9.6	511.6%	**112.1**	0.1%	102.3
Mauritius	0.1%	14.4	101.0%	**107.7**	0.2%	432.0

Country	Share of global offshore wealth	Offshore financial wealth (USD billion)	Offshore financial wealth (% of GDP)	Tax revenue loss (USD million)	Share of global tax loss inflicted by country	Tax loss inflicted (USD million)
Marshall Islands	0.1%	13.7	6201.8%	**82.3**	0.5%	907.1
Indonesia	0.0%	5.3	0.5%	**78.8**	0.0%	-
Czechia	0.1%	6.9	2.8%	**75.8**	0.0%	-
Ghana	0.0%	4.2	6.4%	**72.9**	0.0%	55.4
Kazakhstan	0.1%	14.4	6.1%	**72.2**	0.0%	-
Morocco	0.0%	3.7	3.1%	**69.9**	0.0%	-
Kenya	0.0%	4.2	4.8%	**63.4**	0.0%	-
Liechtenstein	0.1%	5.5	81.0%	**61.6**	0.0%	13.0
Macao	0.1%	10.1	18.2%	**60.4**	0.0%	62.3
Hungary	0.1%	8.1	5.1%	**60.4**	0.0%	-
Jordan	0.1%	5.8	13.8%	**58.1**	0.0%	-
Algeria	0.0%	3.3	1.5%	**58.0**	0.0%	-
Slovakia	0.0%	4.6	4.3%	**57.1**	0.0%	-
Vietnam	0.0%	3.1	1.2%	**53.6**	0.0%	-
Libya	0.0%	4.5	5.2%	**53.0**	0.0%	-
Zimbabwe	0.0%	1.9	6.0%	**48.1**	0.0%	-
Ecuador	0.0%	2.7	2.5%	**47.1**	0.0%	-
Zambia	0.0%	2.3	8.3%	**43.5**	0.0%	-
Tunisia	0.0%	2.2	4.7%	**38.8**	0.0%	-
Pakistan	0.0%	3.8	1.2%	**37.6**	0.0%	-
Iceland	0.0%	1.6	6.2%	**37.3**	0.0%	-
Congo, Dem. Rep. of	0.0%	1.6	3.4%	**32.5**	0.0%	-
Bolivia	0.0%	2.2	5.5%	**32.5**	0.0%	-
Dominican Republic	0.0%	2.5	3.0%	**31.8**	0.0%	-
Bangladesh	0.0%	1.9	0.7%	**29.2**	0.0%	-
Ukraine	0.0%	3.2	1.7%	**28.7**	0.0%	-
St. Vincent and the Grenadines	0.0%	2.4	299.6%	**28.5**	0.0%	15.5
Latvia	0.0%	1.8	5.0%	**28.2**	0.0%	-
Senegal	0.0%	1.3	5.6%	**27.0**	0.0%	-
Cameroon	0.0%	1.8	4.5%	**25.8**	0.0%	-
Azerbaijan	0.0%	2.2	2.9%	**25.6**	0.0%	-
Mozambique	0.0%	1.6	8.8%	**25.1**	0.0%	34.5
Aruba	0.0%	0.8	26.1%	**24.7**	0.0%	0.1
Trinidad and Tobago	0.0%	2.0	7.0%	**24.5**	0.0%	-
Gabon	0.0%	1.9	10.5%	**22.3**	0.0%	-
Cote d'Ivoire	0.0%	1.4	3.3%	**20.8**	0.0%	-
Tanzania	0.0%	1.4	2.3%	**20.4**	0.0%	-
Croatia	0.0%	1.1	1.5%	**19.4**	0.0%	3.0
Uganda	0.0%	0.9	3.4%	**18.8**	0.0%	-
Ethiopia	0.0%	1.0	1.1%	**16.9**	0.0%	-
Cambodia	0.0%	1.7	6.8%	**16.8**	0.0%	-
Bulgaria	0.0%	3.2	5.0%	**16.2**	0.0%	-

Country	Share of global offshore wealth	Offshore financial wealth (USD billion)	Offshore financial wealth (% of GDP)	Tax revenue loss (USD million)	Share of global tax loss inflicted by country	Tax loss inflicted (USD million)
Turks and Caicos Islands	0.0%	1.0	98.1%	**15.8**	0.0%	9.9
Estonia	0.0%	1.5	4.8%	**14.7**	0.0%	-
Romania	0.0%	2.5	1.0%	**12.5**	0.0%	-
Congo, Rep. of	0.0%	0.8	5.6%	**12.2**	0.0%	-
Madagascar	0.0%	0.9	6.2%	**12.0**	0.0%	-
Costa Rica	0.0%	1.6	2.6%	**11.9**	0.0%	-
Suriname	0.0%	0.6	11.5%	**11.5**	0.0%	-
New Caledonia	0.0%	0.7	6.4%	**10.7**	0.0%	84.5
Botswana	0.0%	0.8	4.5%	**10.4**	0.0%	-
Honduras	0.0%	0.8	3.3%	**9.9**	0.0%	-
Iran	0.0%	0.8	0.1%	**9.6**	0.0%	-
Mali	0.0%	0.7	4.0%	**9.5**	0.0%	-
Nepal	0.0%	0.7	2.3%	**9.3**	0.0%	-
Lithuania	0.0%	1.2	2.3%	**9.1**	0.0%	-
Uzbekistan	0.0%	0.6	0.8%	**9.1**	0.0%	-
French Polynesia	0.0%	0.6	7.9%	**8.8**	0.0%	1.0
Andorra	0.0%	1.8	43.6%	**8.8**	0.0%	18.9
Jamaica	0.0%	0.6	3.6%	**8.5**	0.0%	-
El Salvador	0.0%	0.5	2.0%	**7.9**	0.0%	-
Sri Lanka	0.0%	0.6	0.7%	**7.5**	0.0%	-
Nicaragua	0.0%	0.5	3.4%	**7.0**	0.0%	-
Iraq	0.0%	0.8	0.4%	**6.4**	0.0%	-
Mauritania	0.0%	0.3	5.6%	**6.3**	0.0%	-
Vatican	0.0%	0.5		**6.2**	0.0%	-
Kyrgyz Republic	0.0%	0.4	5.0%	**5.9**	0.0%	-
St. Lucia	0.0%	0.5	25.9%	**5.8**	0.0%	-
Georgia	0.0%	0.5	3.1%	**5.5**	0.0%	-
Malawi	0.0%	0.4	4.5%	**5.4**	0.0%	-
Paraguay	0.0%	1.1	2.7%	**5.4**	0.0%	-
Vanuatu	0.0%	0.4	40.1%	**5.4**	0.0%	-
Chad	0.0%	0.4	2.8%	**5.3**	0.0%	-
Serbia	0.0%	1.1	2.0%	**5.3**	0.0%	-
San Marino	0.0%	0.3	12.3%	**5.3**	0.0%	-
Guatemala	0.0%	1.4	1.8%	**5.0**	0.0%	-
Sint Maarten	0.0%	0.2	19.4%	**5.0**	0.0%	-
Armenia	0.0%	0.3	2.2%	**4.8**	0.0%	-
Dominica	0.0%	0.4	71.2%	**4.8**	0.0%	0.0
Djibouti	0.0%	0.3	10.2%	**4.4**	0.0%	-
Namibia	0.0%	0.2	1.6%	**4.4**	0.0%	-
Syria	0.0%	0.4	0.6%	**4.1**	0.0%	-
Equatorial Guinea	0.0%	0.3	1.5%	**4.0**	0.0%	-
Yemen	0.0%	0.5	1.2%	**3.9**	0.0%	-
Haiti	0.0%	0.3	2.8%	**3.8**	0.0%	-

Country	Share of global offshore wealth	Offshore financial wealth (USD billion)	Offshore financial wealth (% of GDP)	Tax revenue loss (USD million)	Share of global tax loss inflicted by country	Tax loss inflicted (USD million)
Albania	0.0%	0.3	2.2%	**3.8**	0.0%	-
Guinea	0.0%	0.3	2.4%	**3.6**	0.0%	-
Mongolia	0.0%	0.7	5.4%	**3.6**	0.0%	19.6
Falkland Islands	0.0%	0.3	129.2%	**3.1**	0.0%	0.3
Grenada	0.0%	0.3	22.0%	**3.1**	0.0%	-
US Pacific Islands	0.0%	0.3		**3.0**	0.0%	-
Togo	0.0%	0.2	3.7%	**2.8**	0.0%	-
Burkina Faso	0.0%	0.2	1.3%	**2.6**	0.0%	-
Eswatini	0.0%	0.2	3.1%	**2.5**	0.0%	-
Bonaire, Sint Eustatius and Saba	0.0%	0.2		**2.5**	0.0%	-
Benin	0.0%	0.2	1.7%	**2.5**	0.0%	-
Gambia	0.0%	0.2	10.1%	**2.3**	0.0%	-
Afghanistan	0.0%	0.2	1.1%	**2.3**	0.0%	-
North Macedonia	0.0%	0.5	3.6%	**2.3**	0.0%	-
Laos	0.0%	0.2	0.8%	**2.2**	0.0%	-
Rwanda	0.0%	0.1	1.5%	**2.0**	0.0%	-
Burundi	0.0%	0.1	4.5%	**2.0**	0.0%	-
Solomon Islands	0.0%	0.1	9.2%	**1.9**	0.0%	-
Palestine	0.0%	0.2	1.0%	**1.8**	0.0%	-
Guiana	0.0%	0.2	4.0%	**1.8**	0.0%	-
Greenland	0.0%	0.1	3.7%	**1.8**	0.0%	14.4
Guinea-Bissau	0.0%	0.1	8.6%	**1.7**	0.0%	-
Bosnia and Herzegovina	0.0%	0.3	1.6%	**1.6**	0.0%	-
Eritrea	0.0%	0.1	1.5%	**1.4**	0.0%	-
Cuba	0.0%	0.1	0.1%	**1.4**	0.0%	-
Papua New Guinea	0.0%	0.1	0.3%	**1.4**	0.0%	-
Cape Verde	0.0%	0.1	4.3%	**1.2**	0.0%	-
Niger	0.0%	0.1	1.0%	**1.2**	0.0%	-
Sierra Leone	0.0%	0.2	3.2%	**1.2**	0.0%	-
Myanmar	0.0%	0.1	0.1%	**1.1**	0.0%	-
Faroe Islands	0.0%	0.1	2.4%	**1.1**	0.0%	9.8
Sudan	0.0%	0.1	0.1%	**1.0**	0.0%	-
Belarus	0.0%	0.1	0.2%	**1.0**	0.0%	-
Montenegro	0.0%	0.2	3.7%	**0.9**	0.0%	0.8
Moldova	0.0%	0.1	0.9%	**0.9**	0.0%	-
Lesotho	0.0%	0.0	1.7%	**0.7**	0.0%	-
Maldives	0.0%	0.1	1.7%	**0.7**	0.0%	-
Fiji	0.0%	0.1	1.1%	**0.6**	0.0%	-
Tajikistan	0.0%	0.0	0.4%	**0.5**	0.0%	-
Turkmenistan	0.0%	0.0	0.1%	**0.5**	0.0%	-
Central African Republic	0.0%	0.0	1.2%	**0.4**	0.0%	-

Country	Share of global offshore wealth	Offshore financial wealth (USD billion)	Offshore financial wealth (% of GDP)	Tax revenue loss (USD million)	Share of global tax loss inflicted by country	Tax loss inflicted (USD million)
Comoros	0.0%	0.0	1.9%	**0.3**	0.0%	-
Wallis and Futuna	0.0%	0.0		**0.3**	0.0%	-
Somalia	0.0%	0.0	0.4%	**0.3**	0.0%	-
Micronesia	0.0%	0.0	4.5%	**0.3**	0.0%	-
Kiribati	0.0%	0.0	7.0%	**0.2**	0.0%	-
Sao Tome and Principe	0.0%	0.0	2.5%	**0.2**	0.0%	-
Timor-Leste	0.0%	0.0	0.1%	**0.1**	0.0%	-
South Sudan	0.0%	0.0	0.0%	**0.1**	0.0%	-
Bhutan	0.0%	0.0	0.2%	**0.1**	0.0%	-
North Korea	0.0%	0.0	0.0%	**0.0**	0.0%	-
Tonga	0.0%	0.0	0.2%	**0.0**	0.0%	-
Nauru	0.0%	0.0	0.1%	**0.0**	0.0%	-
Palau	0.0%	0.0	0.0%	**0.0**	0.0%	-
Qatar	0.3%	30.2	14.6%	-	0.2%	443.3
British Virgin Islands	3.0%	318.6	22038.3%	-	3.2%	5,890.2
Oman	0.1%	10.5	12.9%	-	0.1%	91.9
Bermuda	0.9%	92.8	1461.4%	-	1.6%	2,983.0
Cayman Islands	8.3%	880.7	16055.0%	-	26.0%	47,621.8
Saudi Arabia	1.0%	101.4	12.9%	-	0.0%	-
Brunei	0.0%	2.2	11.8%	-	0.0%	-
Bahrain	0.1%	7.0	18.6%	-	0.0%	33.5
Bahamas	0.6%	61.0	491.0%	-	0.4%	696.8
Kuwait	0.6%	59.0	33.9%	-	0.0%	-
United Arab Emirates	0.8%	80.8	19.5%	-	0.5%	916.9

Source: Authors.

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