Global Evidence on Profit Shifting Within Firms and Across Time

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Delis, F., Delis, M., Laeven, L., Ongena, S.

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Contact information
Name: Fotis Delis
Address: Edificio EXPO, C/ Inca Garcilaso, 3, E-41092 Seville/Spain.
Email: fotios.ntelis@ec.europa.eu

EU Science Hub
https://joint-research-centre.ec.europa.eu

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Contents

Abstract

We provide estimates of profit shifting for over 2 million firm-year observations in 100 countries over the period 2009-2020. Employing nonparametric estimation techniques within a mainstay model of profit shifting, we examine how profits for both parent and subsidiary firms within a multinational group respond to marginal changes in the composite tax indicator. The key merit of this approach is that it yields firm-year estimates of profit shifting. We find that multinational firms engage in extensive profit shifting by maintaining affiliates in low-tax countries and zero-tax havens. Multinational groups with an ultimate owner in tax havens exhibit the largest responses of profits to the tax incentive. Our comprehensive estimates of global profit-shifting volumes exceed those obtained elsewhere in the literature using firm-level data and are in line with estimates obtained using macro-level data. Our new database opens important avenues to analyse the sources and effects of profit shifting.

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Authors

Delis Fotis

Delis Manthos

Laeven Luc

Ongena Steven

Executive summary

This study explores the extent to which multinational enterprises (MNEs) transfer their profits from high-tax countries to those with lower taxes to maximize their overall earnings. It employs a method using micro-level firm data to develop a new way of measuring profit shifting for each company over time. By examining numerous companies worldwide, the research offers a clear and detailed view of how profit-shifting practices vary across different industries, countries, and over time.

Policy Context

Motivated by the significant implications of tax-motivated profit shifting, this paper quantifies the extent of profit shifting for as many firms as possible globally. It addresses the urgency of this issue in light of international efforts to mitigate profit shifting, including the OECD's Base Erosion and Profit Shifting (BEPS) initiative and the G7's agreement on a global minimum corporate tax rate. This research aims to deepen the understanding of the magnitude of profit shifting, thereby informing policy decisions.

Main Analysis

This study adopts a distinctive methodological approach, integrating micro-level data to estimate profit shifting at a detailed firm-year level globally. The application of nonparametric local regression techniques, distinct from traditional OLS methods, allows for a more granular analysis of profit shifting, capturing intricate patterns across industries, firms, and countries over a period of time.

Main Findings

The findings highlight extensive profit shifting activities, particularly pronounced in sectors such as pharmaceuticals, petroleum, and information technology. The research uncovers trends such as the increase in profit shifting among fossil fuel firms following the Paris Agreement and identifies significant profit shifting routes between high-tax countries and tax havens. These comprehensive global estimates bridge the gap between previous studies, which used micro versus macro data, elucidating the substantial impact of profit shifting in the global economic context.

1 Introduction

Tax-motivated profit shifting refers to the tax planning strategies of multinational enterprises (MNEs), and their "shifting" of profits from a parent or subsidiaries located in high-tax jurisdictions to subsidiaries in low-tax jurisdictions with the aim of increasing their net income. The practice has attracted considerable interest in recent years from academics and policy makers. Alongside decreased tax fairness due to the consequent erosion of government revenue bases, profit shifting poses welfare and fiscal challenges. This has triggered efforts and policies from governments and international organizations to contain the practice. The most prominent of these efforts are the OECD's Base Erosion and Profit Shifting (BEPS) initiative and the June 2021 agreement among G7 finance ministers to seek a global minimum corporate tax rate of at least 15 percent (Rappeport, 2021).

According to OECD estimates, profit-shifting practices cost governments 100-240 billion US dollars in lost tax revenue annually.[1] Using macro-level data, Wier and Zucman (2022) suggest that, in recent years, the annual revenue losses even exceed the upper end of the OECD's estimates. When using micro-level (firm) data to estimate profit shifting, the most common practice in the literature is to estimate a model of the response of firm (parent and/or subsidiaries) profits to tax incentives (Hines and Rice; 1994; Huizinga and Laeven, 2008; Dharmapala and Riedel, 2013). Tax incentives are typically measured as the differential corporate tax rates between the countries where the multinational firm operates. It is assumed that an increase in tax rate differences incentivizes firms to send more profit to the lower-tax jurisdictions. However, these models produce global estimates (a single parameter from the regression reflecting profit-shifting intensity) and thus do not identify profit shifting at the firm-year level. Such estimates substantially underestimate profit shifting when compared to estimates obtained using macro-level data, as they omit information on numerous firms (Tørsløv et al., 2023; Clausing, 2016; Clausing 2020). Additionally, many studies in the literature focus exclusively on either the parent firms or their subsidiaries, thereby not capturing the total profit shifting by the multinational firm.

Our main contribution is to introduce and estimate a new measure of profit shifting at the *firm-year* level for as many firms globally as possible. Our sample includes both parent firms and their subsidiaries. Providing such a comprehensive firm-year level measure of profit shifting is important for two main reasons. First, it can inform both academics and policy makers about the profit shifting intensity of each firm in each year, therefore allowing the identification of tax arbitrage behavior at a much more granular level. It also allows to capture the origin and destination firms of profit shifting even within an MNE over time. The latter is particularly important when MNEs substitute profit shifting from one (subsidiary) firm to another.

Second, our measure of profit shifting can be exploited to enhance the identification of the key drivers or the key effects of profit shifting. The variation across both the time series and cross-sectional dimensions allows to employ contemporary identification techniques at the firm level, and to include both firm and time fixed effects to absorb firm and time invariant factors, thus reducing omitted variable biases. This especially holds if the outcome variable of interest is observed at the firm-year level for which existing methods do not provide much information. Such analyses can identify a causal effect via contemporary identification methods (e.g., natural or semi-natural experiments).

Moreover, our comprehensive estimates of global profit shifting have the added benefit that they can reconcile apparent differences in the literature between profit-shifting estimates obtained using micro-level and macro-level data. By using the most comprehensive firm-level dataset available and estimating profit-shifting for both parents and their subsidiaries we obtain global estimates of profit-shifting volumes that exceed those generally obtained using firm-level data and that are closer to estimates obtained using macro-level data.

To achieve our objectives, a critical factor is the use of the most comprehensive dataset of multinational firms globally. To this end, we build a historical dataset of the financials of MNEs (including their parents and subsidiaries) using "vintages" of Bureau Van Dijk's Orbis database, in conjunction with historical ownership links data. Additionally, we incorporate unweighted tax differentials and reconstruct ownership links. With these advancements, we can expand our analysis over a broader time span, provide valuable insights into firm ownership across different years, and offer more detailed information regarding firm locations including tax havens. We include global data on all firms (parents and subsidiaries) available in the Orbis vintages database. Our intensive data matching and cleansing process yields the largest firm-year sample in the literature, amounting to 2,277,435 firm-year observations from 100 countries and 565,814 firms for the period 2009-2020.

[1] https://www.oecd.org/tax/beps/

Our empirical approach involves estimating the established Huizinga and Laeven (2008) model using nonparametric techniques, specifically nonparametric local regression. This method differs from ordinary least squares (OLS) in that it does not assume a fixed slope for the entire dataset. Instead, it creates sliding windows of observations around each data point, allowing us to estimate profit-shifting effects by considering nearby observations. We repeat this analysis for each data point in our dataset, resulting in a profit-shifting estimate for each firm-year observation in our sample. An additional merit is that nonparametric approaches fully account for the nonlinearity in the relationship between earnings and tax differences and are not influenced by the functional forms of the data structure or the underlying model, unlike existing measures of profit shifting.

From a micro perspective, we find that firms in the pharmaceutical, petroleum, and information technology industries engage in the most profit shifting. We identify large well-known firms as the top-20 profit shifters. We provide evidence of the consistency of these findings against news, empirical facts, and specific cases (e.g., previous studies, governmental investigations, and OECD estimations). Such evidence serves as an important first step in the validation of our profit-shifting indices.

From a macro perspective, our results are in line with aggregate estimates using macro-level data, and thus can reconcile the gap in the estimates of profit shifting between studies using micro data (such as ours) and those using macro data. Specifically, we find that the mean semi-elasticity of firm profits to the differential taxation between the countries where the MNE's firms are located increases from 2.4 in 2009 to 3.2 in 2015 and 2016. It then experiences a decrease in 2018 and 2019, only to rebound in 2020. This magnitude for the annual semi-elasticities is consistent with recent estimates by Clausing (2020). When translated into US dollars, our results indicate profit shifting of approximately 311 billion in 2009 to more than 700 billion in 2017. These numbers closely align with the estimates provided by Tørsløv et al. (2023) and Wier and Zucman (2022).

An important advantage of the firm-year estimates is that they allow to delve deeper into the direction of profit shifting between an MNE's firms in different countries. We find that the top inbound connections, in terms of the average profit shifting ratio (shifted profits to firm observed profits before taxes), are between firms in Ireland and Global Ultimate Owners (GUOs) in either France or the United States. In general, Irish firms claim most of the top spots in this ranking. This is not surprising given that until 2020, Ireland was widely considered to offer one of the largest profit shifting schemes, allowing firms to avoid taxes on their income from intellectual property rights in a tax arrangement known as the double Irish (e.g., Tørsløv et al. 2023). This arrangement allowed subsidiaries located in Ireland to divert their intellectual property rights income to tax havens with zero income tax without incurring Irish taxes. Delving further into these connections, we find that a significant portion of the highest profit shifting ratios in the Ireland-France and Ireland-United States connections are associated with tax havens where the MNEs maintain subsidiaries. Consistent with this finding, outbound connections with Global Ultimate Owners (GUOs) in countries like Bahrain, Bermuda, the Cayman Islands, Liechtenstein, Andorra, Cyprus, San Marino, Gibraltar, Bahamas, and the British Virgin Islands occupy the top positions in terms of the average semi-elasticity of profit responses to tax incentives.

Notably, among the MNEs engaging in the most profit shifting, those with their GUOs located in the US and subsidiaries in low-tax jurisdictions such as Bermuda, the Cayman Islands, the UAE, the British Virgin Islands, and Ireland are by far the most prominent. Moreover, we uncover an interesting pattern for firms in the fossil fuel extraction business. In the period following the Paris Agreement on climate change, these firms substantially increased profit shifting, possibly to avoid the increased stringency of environmental regulation. In general, the firm-year estimates allow uncovering several industry and country patterns of profit shifting over time.

In a final important extension, our analysis includes firm-year observations with negative profits (loss-making firms), adding 1,103,920 observations to our sample. The results are broadly consistent with those that exclude loss-making firms in terms of rankings of industries and country pairs. However, they reveal even larger estimates of profit shifting, with global profit-shifting estimates that surpass the trillion US dollars mark from 2013 onward, amounting to up to 47 percent of the reported consolidated profits in 2017. This compares favorably to estimates obtained by Wier and Zucman (2022) using macro-level data: they obtain an estimate of global profit shifting in 2019 of 969 billion US dollars, or 37 percent of global multinational profits.

The paper continues as follows. Section 2 discusses the empirical model used to identify profit shifting and provides thorough information on the data collection and cleansing processes. It also discusses the details of nonparametric estimation of the model and the importance of these estimates for academics and policy makers. Section 3 presents the estimates of the global profit-shifting database across years, firms, industries, and countries. Section 4 concludes and provides directions for future research.

2 Modelling profit shifting

2.1 Empirical model and variables

We rely on the model of profit shifting used in most of the micro-level studies (Heckemeyer and Overesch, 2017; Johansson et al., 2017; Beer et al., 2020; De Simone et al., 2022; references therein). The original version was developed by Hines and Rice (1994). At the core of this model is that the observed pre-tax income of an MNE's firm represents the sum of "true" and of "shifted" income (where the latter can be either positive or negative). A firm's true income originates from production, which is approximated by a Cobb–Douglas production function including capital and labor as inputs.[2] Shifted income is driven by the tax incentive to move income in or out of the firm, in consideration of the differential tax rate between the parent and the subsidiary countries. Huizinga and Laeven (2008) extend this tax motive by allowing for tax-rate differentials across countries of all subsidiaries of the same MNE. Profit reported by a low-tax firm that cannot be attributed to the firm's production implies profit shifting.

The empirical model is the following:

$$log\, \pi_{it} = a_1 CT_{it} + a_2\, log\, A_{it} + \gamma C_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{1}$$

In equation (1), π_{it} is firms' observed profit before taxes in logs (*Profit before taxes*). We intentionally use the term "firm" without distinguishing between subsidiaries and parents, because we estimate equation (1) for all the firms in our dataset for which we have unconsolidated data (to obtain the maximum profit-shifting flows). The variable A_{it} represents the country-year productivity parameter, which is measured with GDP per capita in logs (*GDP per capita*). C_{it} is a vector of firm-year and country-year controls, including the log of fixed assets (*Fixed assets*) as our measure of capital, the log of number of employees (*Number of employees*) as our measure for labor, and country level controls such as *GDP growth* and *Inflation*.[3] The term μ_i represents country fixed effects, which control for time-invariant unobserved characteristics specific to the countries where firms reside, and δ_t represents year fixed effects, which control for time-varying unobserved common changes in firm profitability. Finally, ε_{it} is the error term.[4] We provide explicit definitions of all variables and data sources in Table 1.

Using natural logarithms excludes firms with negative profits. Excluding loss-making firms may obscure the profit shifting that occurs when real losses exceed the shifted income from affiliates (e.g., De Simone et al., 2017) and introduce bias because loss-making entities can be tax planners (e.g., Johannesen et al., 2020). The alternative, using a profitability ratio as a dependent variable, might alleviate this bias, but it might also capture real responses to the tax rate in the denominator (e.g., total assets), confounding profit-shifting responses with real ones (Beer et al., 2020). We mainly follow the preferred specification in the literature, which uses the logarithm of the observed pre-tax income as dependent variable (Huizinga and Laeven, 2008; Dharmapala and Riedel, 2013; Heckemeyer and Overesch, 2017; Beer et al., 2020), and examine the robustness of our findings to an additional specification that includes negative profits.

The *Tax differential* variable CT_{it} is defined as:

[2] The assumption of a Cobb-Douglas production function is not a constraint for our empirical analysis because we estimate the model with nonparametric econometrics, which produce fully flexible functional forms.

[3] The specification that uses fixed assets as capital encompasses intangible assets because these are part of fixed assets. We recognize that intangible assets can be strategically located for tax purposes, but they only represent a small share of fixed assets (about 10% on average in our sample). Our intention in adopting this specification is to validate our approach by capturing certain aspects of the model proposed by Tørsløv et al. (2023) using Orbis data. Their model incorporates net plant, property, and equipment, as well as research and development (R&D) expenses of affiliated entities in different countries. It is important to highlight that not all R&D expenditures necessarily result in the creation of intangible assets, and our specification serves as a rough approximation of their model rather than an exact replication.

[4] In line with Heckemeyer and Overesch (2017) and Beer et al. (2020), we do not to control for leverage, as internal financing decisions represent one channel through which profit shifting occurs. We also do not control for subsidiary fixed effects because they could reduce identified tax effects on profitability, since much of the cross-sectional tax rate variation would be absorbed (Clausing 2006; Clausing 2016; Heckemeyer and Overesch, 2017).

$$CT_{it} = \frac{1}{(1-\tau_i)} \frac{\sum_{k\neq i}^{n}(\frac{1}{1-\tau_k})(\tau_i-\tau_k)}{\sum_{k=1}^{n}(\frac{1}{1-\tau_k})} \tag{2}$$

where τ_i is the statutory tax rate of the firm's country and τ_k the statutory tax rates of all the affiliated firms' countries. We obtain these tax rates from Ernst &Young's Worldwide Corporate Tax Guides, PwC Worldwide Tax Summaries, IBFD Tax Research Platform, and the Tax Foundation. Whenever there is a discrepancy in the data, specifically when different tax rates are reported for a particular country-year, we prioritize the information provided by the Tax Foundation.

The coefficient of main interest in equation (1), a_1, reflects the extent to which the firm *i* sends or receives profits to/from affiliates in the same MNE due to a marginal change in tax rates, *ceteris paribus*. A negative a_1 in equation (1) implies that an increase (decrease) in τ_i leads to an increase (decrease) in CT_{it}, which leads firms to send more profit abroad (receive more profit from abroad) and thus reduces (increases) π_{it}.

Note that the coefficient a_1 is an aggregate point estimate and thus does not have cross-sectional (firm) and temporal (year) variation. This coefficient simply provides an average estimate of profit shifting for the whole sample of firms. If estimated each year in the cross-section, the model would give an average coefficient in each year across all firms.

2.2 Data collection and summary statistics

A key distinction in our empirical analysis is our intensive sample construction process. We sequentially discuss the full process and its advantages in the Appendix, and here we briefly mention the key innovations. We integrate different historical disks of Bureau van Dijk (BvD)'s Orbis database (Orbis "vintages") instead of the usual online access. We combine data from these Orbis vintages with the historical ownership links (2009-2019). This is important for three interrelated reasons (thoroughly analyzed in the Appendix). First, we need dynamic ownership data, given that we document significant ownership changes during our sample period (Grosskurth, 2019). By doing so, we alleviate misclassification and any downward bias in our estimates of profit shifting, as highlighted by Budd et al. (2005). Second, our coverage extends well beyond the conventional ten-year period offered in the online version of the Orbis database, mitigating the impact of reporting lags (Kalemli-Özcan et al., 2022). Third, we observe significantly more details about the locations of the firms and Global Ultimate Owners (GUOs) worldwide, even when financial data is not provided. This enables better calculations of *Tax differential* in equation (2), because we use taxation data for more countries (more on this below).

Table 2 reports the summary statistics of the variables used in our analysis. Our main specification uses 2,277,435 firm-year observations. This sample, to the best of our knowledge, represents the most extensive dataset assembled for studying global profit shifting using micro data. It encompasses 565,814 firms, spanning 100 countries, and covers the period from 2009 to 2020. The firms included in this dataset are under the control of 214,001 GUOs across 189 countries. Appendix Tables A1 and A2 provide a comprehensive overview of the firm-year observations and GUO-year observations by country, respectively. The average statutory tax rate in our sample, for both the countries of firms and GUOs, is 0.25. This figure closely aligns with the global average statutory corporate tax rate of 0.24 reported in Tørsløv et al. (2023). Moreover, it mirrors the 0.25 average statutory corporate tax rate when weighted by GDP (Tax Foundation, 2021).[5]

Following the analysis of Dowd et al. (2017), in part of our analysis we include a dummy variable (*Tax haven*) that takes the value 1 when a multinational group includes a tax haven firm (equals 0 otherwise). We assign the value 1 not only to firm-year observations located in tax havens, but also to those associated with a firm in a tax haven through the same multinational group because this information is included in the *Tax differential*. This is the case for 439,897 firm-year observations, representing 19.3% of our sample. Our list of tax havens is from Tørsløv et al. (2023).

Estimating profit shifting using firm-level unconsolidated data is not without limitations, with the primary constraint being the global availability of data, especially for firms located in tax havens. Importantly, even though Orbis (or other Bureau van Dijk's databases) provides information about the global consolidated profits of most of the world's MNEs (Cobham and Loretz, 2014), these companies are generally not required to publish their profits country-by-country (or firm by firm). Tørsløv et al. (2023) give the

[5] Corporate Tax Rates by Country | Corporate Tax Trends | Tax Foundation

example of Apple, which reports large profits (billions) at the MNE level but summing the unconsolidated profits of all its subsidiaries yields just few millions. Another limitation, pointed out by Blouin and Robinson (2020), is that the BvD documentation lacks clarity when it comes to identifying the sources of unconsolidated financial information. This lack of clarity has significant implications because handling unconsolidated company filings involves dealing with the activities of indirectly owned affiliates. If different countries have distinct reporting requirements for income derived from investments in affiliates, any analysis comparing profit shifting across countries could potentially be biased.

As mentioned in this section's introductory paragraphs, we have two remedies to counter the limitation of global data availability. First, we construct the most comprehensive sample of MNEs to date, and second, we include all firms (including GUOs) from a specific multinational group when calculating the unweighted tax differential for the firm-year observations in our sample (equation (2)). These firms are included even if their financial information is not present in Orbis. Thus, we forego the need for relying on weighted tax rate differentials that require complete financial data. Huizinga and Laeven (2008) use sales or total assets as weights, which results in a significant reduction in the number of observations. Our approach provides a more comprehensive perspective on tax differentials across all countries in which the multinational group operates (Johansson et al., 2017). This is because it creates a more pronounced tax differential for the firms in our sample. The pronounced effect is primarily because we include tax havens, which subsequently influences how firms' profits respond to their tax incentives. Further, to address the limitation highlighted by Blouin and Robinson (2020), we incorporate country fixed effects in all of our specifications. This helps mitigate the possibility that our results are influenced by country-specific accounting practices.

Our sample construction involves reconstructing ownership links, following the guidelines outlined in Kalemli-Özcan et al. (2022) and Grosskurth (2019). This process aims to identify firms, which were not previously considered to be part of a specific multinational group. Finally, we consider both firms and individuals as potential GUOs, acknowledging that in certain cases it may not be feasible to determine a firm as the GUO. In such situations, we assign an individual as the GUO and subsequently construct the *Tax differential* for the firms under their control. We show in our results that these remedies produce estimates of profit shifting that are very close to the most recent literature using country-wide estimates (e.g., Tørsløv et al., 2023).

In our analysis, we do not rely solely on unconsolidated data; instead, we incorporate consolidated profits before taxes at the MNE-year level. Using consolidated data offers two advantages. First, it provides a profit measure that is immune to internal transactions within the MNE group. Second, it offers a comprehensive view of the profits of all firms within the multinational group.

Specifically, we merge the 2,277,435 firm-year observations with the consolidated profits before taxes (C1, C2) of their MNEs. We successfully merge 1,000,079 of our firm-year observations, which correspond to 43,395 unique GUOs. We replicate the analysis presented in Figure 1 of Tørsløv et al. (2023) and Table A2.1 (Appendix 2) of Johansson et al. (2017). We aggregate the unconsolidated *Profit before taxes* of all firms within a multinational group and compare it to the consolidated profits before taxes reported by the related GUO for a specific year. These figures are not directly comparable due to factors such as the elimination of intercompany transactions in consolidated profits, including dividends, or unrealized profits after intercompany transactions. However, this comparison allows us to assess whether the firms we observe in our dataset, reporting unconsolidated profits before taxes, represent a significant portion of the total firms within the related multinational groups. Among the 1,000,079 firm-year observations, we find that 496,407 (50%) belong to multinational groups where the aggregate *Profit before taxes* of all firms is equal to or higher than the consolidated profits. For these multinational groups, we can reasonably assume that the firms we observe through Orbis vintages provide a reliable representation.

On the other hand, there are 503,672 (50%) firm-year observations that belong to multinational groups where the aggregate unconsolidated *Profit before taxes* of all firms is lower than the consolidated profits. For this subset, the aggregate *Profit before taxes* of all firms represents, on average, 51% of the consolidated profits. The weighted average (weighted by profit) for both subsets is 57%.[6] These figures might be inflated due to the inclusion of internal transactions within multinational groups when adding up unconsolidated *Profit before taxes* of all firms. However, they still hold significant value in terms of data representativeness, especially when complemented with the inclusion of all existing firms within a specific multinational group in the *Tax differential*, as described above.

[6] Tørsløv et al. (2023) report a weighted average of 17% for 2012.

2.3 *Estimation of profit shifting by firm-year*

Firm–year estimates of profit shifting imply estimating responses $a_{1,it}$ in equation (1) by firm and year. We do so with nonparametric models, also known as varying coefficient models, because they allow coefficients to vary by observation (for an introduction, see, e.g., Loader, 1999). The advantage of these models is that they do not require the specification of functional forms for estimation. Instead, the models derive information directly from the data, enabling us to account for any nonlinearity in the relation between the *Tax differential* CT_{it} (which reflects both a multinational's international structure and the international tax system) and *Profit before taxes*. For that reason, the assumption of a Cobb-Douglas functional form in equation (1) is not directly relevant in our empirical analysis. Unlike recent literature, which relies on specifying a nonlinear functional form (Dowd et al., 2017; Bratta et al., 2021; Garcia-Bernando and Jansky, 2022; Fuest et al., 2022), our approach offers a data-driven solution.[7]

To draw a comparison, ordinary least squares (OLS) estimate the unknown parameters in a regression equation between an outcome variable *y* and a predictor variable *x*. In graphical form, OLS estimation fits a regression line with a unique slope through the full sample. In equation (1), this naturally implies a single estimate for a_1. In contrast, the nonparametric equivalent of OLS, the local linear regression, does not assume that the slope is the same for the full sample, but rather that the slope has a locally specific value around each observation ($a_{1,it}$). Although nonparametric regression is a way of obtaining varying estimates that are robust to functional form misspecification, this robustness comes at a cost. We need many observations to compute the estimates; this is referred to as the curse of dimensionality. However, given the large number of available firm-year observations in our study, the curse of dimensionality does not apply.

Formally, the regression model of outcome *y* (*Profit before taxes* in equation (1)) is:

$$y_{it} = v_{it}\beta + g(x_{it}) + \varepsilon_{it} \tag{3}$$

The $v_{it}\beta$ part is the usual parametric regression for explanatory variables *v* (A_{it} and C_{it} in equation (1)), the function *g* is the nonparametric part and it is unknown (obtains its shape from the data), x_{it} is the *Tax differential* CT_{it} in equation (1), and ε is the error term. We estimate equation (3) using the local regression (Fan and Gijbels, 1996).

To clarify, let us provide an example with the help of a graph (Figure 1) that plots the observations for a small subset of our sample in the *y-x* (*Profit before taxes-Tax differential*) space. Now, consider estimating the mean of *y* given that *x* = A, when *x* is continuous and A is a value observed for *x*. Because *x* is continuous, the probability of any observed value being exactly equal to A is almost 0. Therefore, we cannot compute an average for the values of *y* for which *x* is equal to a given value A. We use the average of *y* for the observations in which *x* is close to A to estimate the mean of *y* given that *x* = A. Specifically, we use the observations for which $|x - A| < h$, where *h* is the bandwidth (more on this below). The circles in Figure 1 delimit the values of *x* around A for which we are computing the mean of *y*. The square is our estimate of the conditional mean using the observations inside the first circle. Then we move to the next observation. To avoid complicating the figure by taking the observation closest to A, we focus on another observation we label B. The estimation is carried out again for the observations in the window around B.

[Please insert Figure 1 about here]

Doing this estimation for each point in our data produces a nonparametric estimate of the mean for a given value of the covariate *x*. This process is repeated several times for each of the observations (fitting points) in our sample, each time solving the minimization problem for the nonparametric part, given by:

$$\sum_{i,t=1}^{n} W\left(\frac{x_{it} - x}{h}\right)\left(y_{it} - \left(a_0 + a_{1,it}(x_{it} - x)\right)\right)^2 \tag{4}$$

[7] An alternative is random coefficients models. However, at least two theoretical aspects of nonparametric (semi-parametric) regressions are more appealing. We discuss these issues in the appendix.

The constant a_0 in equation (4) is the conditional mean of *y* at a specified point *x*. The slope parameter $a_{1,i}$ is the derivative of the mean function with respect to *x* (*Tax differential*). The size of the bandwidth, *h*, determines the shape and smoothness of the estimated conditional mean function because the bandwidth defines how many observations around each point are used. A too-large bandwidth includes too many observations, so the estimate is biased but it has a low variance. A too-small bandwidth includes too few observations, so the estimate has little bias, but the variance is large. In other words, the optimal bandwidth trades off bias and variance. Many alternatives have been proposed for the derivation of the optimal bandwidth (e.g., Greene, 2018; Li and Racine, 2004), and we choose the one that minimizes the integrated mean squared error of the prediction (cross-validation method). We find that our results are not overly sensitive to the bandwidth that is employed. *W* is the kernel function that assigns weights to observations x_{it} based on how much they differ from *x* and based on the bandwidth, *h*. The smaller *h* is, the larger the weight assigned to points between x_{it} and *x*. We use either a Gaussian or a Quartic (biweight) kernel. Results are not sensitive to this choice.[8]

We employ several specifications of equation (3) to align with the rationale of different OLS specifications applicable to equation (1), following the paradigm of Clausing (2016, 2020) and Blouin and Robinson (2020). Aside from country fixed effects (which are included in all specifications), we resort to three specifications that include controls for (i) macro determinants of profits (*GDP per capita*, *GDP growth*, and *Inflation*), (ii) micro determinants of production (*Fixed assets* and *Number of employees*), and *GDP per capita* (the country-year productivity parameter), and (iii) *Fixed assets*, *Number of employees*, and *GDP per capita*, along with an interaction term between *Tax differential* and *Tax haven* (a binary variable equal to 1 if there is a firm in the MNE that is located in a tax haven). We choose these specifications because they capture the macro and micro determinants of profits, along with the potential effect of the MNE choosing to establish themselves in tax havens for tax-related reasons.

We estimate each of these three specifications 12 times, once for every year in our sample, resulting in 36 local regressions. We choose this approach instead of running three regressions for all years (one for each specification) because each regression is computationally demanding and cannot yield results even on a very powerful computer. We do find, however, that in smaller subsamples, the results are very similar when comparing the two approaches. Subsequently, we average the firm-year estimates from the three specifications, and we multiply these averages by -1, so that higher values reflect more profit shifting. The resulting firm-year estimates, denoted as $a_{1,it}$, serve as our profit-shifting index (*Semi-elasticity*).

Following Huizinga and Laeven (2008), we employ the estimated values of $a_{1,it}$ in the subsequent equation to derive a monetary estimate of profit shifting for each firm-year in our sample:

$$S_{it} = \pi_{it} - \frac{\pi_{it}}{1-a_{1,it}*CT_{it}} \tag{5}$$

where S_{it} represents the dollar amount of shifted profits for firm *i* in year *t* (*Profit shifting $*), CT_{it} is the *Tax differential* variable and π_{it} represents the observed profit before taxes in US dollars. A firm's observed pre-tax income can be expressed as the sum of two components: its "true" income and its "shifted" income. We estimate the "true" pre-tax income as follows:

$$T_{it} = \pi_{it} - S_{it} \tag{6}$$

where T_{it} represents the true pretax income for firm *i* in year *t.*

Based on the above, we construct two profit-shifting ratios. The first, referred to as the *Profit shifting ratio*, is obtained by dividing *Profit shifting $* by observed profits before taxes. This ratio is

[8] We examine several different indices—based on different assumptions when estimating the nonparametric regressions. Specifically, we use an Epanechnikov kernel, and we select the bandwidth using the Akaike information criterion (AIC). Using different methods to select the optimal bandwidth, or different kernel functions, provides very similar indices (very high correlations with our baseline indices). We also experiment with different splines and with different assumptions within the spline-based methods. Finally, we experiment with computationally more involved, fully nonparametric methods (all explanatory variables enter the regression nonparametrically); we do not favor a fully nonparametric model only because it adds considerable estimation time without a gain in our inferences. In general, all of the above robustness tests yield very similar inferences.

particularly relevant for inbound firms, where *Profit shifting $* is less than or equal to observed profits before taxes. The second ratio is the *Profit shifting ratio true*, which is calculated by dividing *Profit shifting $* by the estimated firm-year "true" profits before taxes. This ratio is more pertinent for outbound firms, where *Profit shifting $* is lower than or equal to "true" profits before taxes. These two ratios, in conjunction with the profit-shifting index (*Semi-elasticity*), collectively provide valuable tools for the extent of profit shifting by each firm-year in our sample.

As explained in Section 2.2, we merge our firm-year observations with the consolidated profits before taxes at the MNE-year level. We group the two profit shifting ratios by MNE-year and calculate the average profit shifting intensity at this level. Subsequently, we apply this average ratio to the consolidated profits before taxes for each corresponding MNE-year observation.[9] This process allows us to estimate profit shifting amounts at the MNE-year level (denoted as *Profit shifting $Bn.*) and a corresponding ratio *Profit shifting ratio (Cons.)*, which is *Profit shifting ($Bn.)* divided by MNE's consolidated profits before taxes in billions US dollars for a specific year.

It is worth noting that the profit-shifting ratios applied to consolidated profits may correspond to the entire group in some multinational groups, while in others, they may only capture a portion of the group's firms. In the latter case, our estimates could be considered a lower bound for profit shifting. However, as extensively discussed in section 2.2, our sample construction methodology goes to great lengths toward data representativeness. Furthermore, we incorporate all firms from a specific multinational group into the *Tax differential* variable, even if they do not report financial data. This inclusion has an impact on the estimated coefficients (*Semi-elasticity*) of the firm-year observations in our sample, which, in turn, affects the profit-shifting ratios.

2.4 Importance of the profit-shifting index

The key novelty of the paper is the measurement of profit shifting by firm-year, and this offers several advantages. Most importantly, we provide academics and policymakers with panel data on firms' profit shifting. This means that policymakers can observe in a timely manner which firms shift profits to specific other firms and take appropriate action. Policymakers can also examine if specific policies or institutions affect profit shifting and obtain monetary estimates of their impact. In turn, academics have at their disposal, for the first time, a firm-year variable of profit shifting to be used in empirical analyses, both as a dependent and explanatory variable.

More specifically, considering the determinants of profit shifting, the current practice is to infer the determinants of profit shifting by interacting the response of firm profits to tax incentives (*CT)* with the determinant of interest, say *Z* (e.g., worldwide vs. territorial taxation in Markle, 2016; the role of patents in Cheng et al., 2021; etc.). The coefficient on the interaction term suggests, on average, how much firm profits increase or decrease for every change in *CT* at every one of the infinite values of *Z*, thus indirectly inferring the effect of *Z* on profit shifting.

A key problem with such approaches is the endogeneity bias that comes in many forms and is not easy to overcome. Having one variable of interest interacted with the tax incentives variable in Huizinga and Laeven (2008) implies that many other control variables need to be included in interaction terms to limit omitted-variable bias. Moreover, standard solutions to omitted-variable bias such as difference-in-differences (DID) would require a triple interaction term, while instrumental variable (IV) regressions would require several exogenous instruments (for each of the variables used in the interaction terms and the interaction terms themselves), making estimation impractical.[10] A related issue is that the nonlinear relation between the tax incentives variable and firms' earnings (e.g., Dowd et al., 2017; Garcia-Bernando and Jansky, 2022; Fuest et al., 2022) is very difficult to capture with these models. Therefore, identifying causal effects using the existing approaches is very challenging.

Using instead an explicit variable to measure profit shifting as a dependent variable in a regression model implies that the only endogeneity issue arises because the variable may be measured with error. However, the size of the error can be easily identified in our dataset via bootstrapping techniques, while measurement error in the dependent variable is not much of a problem (Wooldridge, 2009). Another

[9] We do so only for the MNEs that report consolidated pre-tax profits and exclude those reporting losses, as our profit shifting ratios are computed for profitable companies.

[10] Other types of endogeneity bias, such as simultaneity or selection are equally difficult to overcome within existing models.

advantage is that our nonparametric approach fully accounts for a potential nonlinear relation between the tax incentives variable and firms' earnings. Moreover, using profit shifting as an explanatory variable is considerably easier when the variable has a firm-year dimension. This facilitates the identification of a causal effect using standard identification methods (e.g., DID, IV, regression discontinuity, etc.) applied to the profit-shifting variable.

Lastly, but equally important, our comprehensive sample and estimation method aim to reconcile the gap in estimating total profit shifting between studies that use macroeconomic data and those that use firm-level data. Currently, this gap is very significant, with estimates of global profit shifting based on macro data far exceeding those obtained using micro-level data (e.g. Beer et al., 2020; Tørsløv et al., 2023). We provide inferences on this important issue in the next section, where we present our baseline findings.

3 Global estimates of profit shifting

3.1 Our profit shifting estimates and comparison with aggregate estimates

We first compare averages of our firm-year profit shifting index with the results from equivalent OLS models, as our first validation exercise and to facilitate a comparison with existing literature. In the first row of Table 3, we report annual averages of $a_{1,it}$, i.e., the semi-elasticity of firm profits with respect to the tax differential *CT* obtained from the nonparametric estimation of equation (1) (or equivalently equation (3)).[11] Moreover, we report the equivalent parametric OLS results in Table 4. In these specifications, we use the logarithm of fixed assets (*Fixed assets*) to measure capital and maximize the number of observations included in the analysis. We replicate the same table in the Appendix, employing tangible fixed assets (*Tangible fixed assets*) as proxy for capital (see Appendix Table A3).

[Please insert Tables 3 & 4 about here]

In line with our expectations, we observe that the coefficient of *Tax differential* in Table 4 is negative and statistically significant at the 1 percent level across all specifications. When considering the three specifications that we also use to estimate the nonparametric model (specifications 2, 4, and 6), the average coefficient (marginal effect) of the tax differential is approximately 2.5 (3.4+2.1+1.81+0.19*1.04 divided by 3).[12] This value is only a bit smaller than the average obtained from the nonparametric estimation, which equals 2.76. Thus, our results from the nonparametric regressions follow very closely the usual parametric results. Following the literature (Huizinga and Laeven, 2008; Beer et al., 2020; Heckemeyer and Overesch, 2017), we interpret this average coefficient as the average semi-elasticity within our sample.

There are two representative consensus estimates from the literature, based on meta-regression studies by Heckemeyer and Overesch (2017) and Beer et al. (2020). Heckemeyer and Overesch (2017) report a semi-elasticity of reported income with respect to the tax rate differential across countries of 0.8. Beer et al. (2020) argue that a semi-elasticity of 1 is a more accurate reflection of the literature. However, studies using macro-aggregate data (e.g., Blouin and Robinson, 2020; Clausing, 2016; Clausing 2020), as well as studies employing nonlinear techniques to capture tax rate effects on profitability measures (e.g., Dowd et al., 2017; Bratta et al., 2021), argue for significantly higher values.

This gap in the findings between the micro and the macro studies, forms the basis for the criticism on the studies using micro data (usually from Orbis). Beer et al. (2020) particularly address the dichotomy between "large aggregate effects" and "small micro effects," positing an implied semi-elasticity of 2.29 in macro studies. Clausing (2016) using macro data reports an average semi-elasticity of 2.92; more recently, Clausing (2020a, 2020b) finds a semi-elasticity of approximately 3. Our average estimates of semi-elasticity (2.76) align very closely with the estimates based on macro data.

Overall, our study is among the first to estimate semi-elasticities of this magnitude using a micro dataset.[13] We attribute our finding to the intensive data-selection process and cleansing. Thus, we show that our analysis bridges the gap in the estimation of profit shifting between micro studies using firm-level data and macro studies using aggregate data. We consider this to be an important contribution of our empirical analysis and a key validation of our new index.

3.2 Firm, industry, and country variation of profit shifting

Estimating profit shifting by firm-year implies identifying specific firms as the top profit shifters and specific industries as the most involved, with important policy implications. For example, firms and sectors with more profit shifting lower their average cost of capital and are thus able to attract more investment, potentially

[11] We estimate a kernel regression significance test based on Racine (1997), which aggregates all the estimated coefficients (partial derivatives), and we get a statistically significant average of our coefficients (*Semi-elasticity*) at the 1 percent level.

[12] In specification 6 of Table 3, we examine the interaction between *Tax haven* and *Tax differential*. We find that the coefficient of *Tax differential* is 1.81 for firms not associated with a firm in a tax haven country through the same multinational group. However, for firms that are associated with a tax haven firm, the coefficient is notably higher at 2.85 (1.81 + 1.04). This finding aligns with previous studies, such as Dowd et al. (2017), which report a significantly higher semi-elasticity in low tax jurisdictions.

[13] The only exception is Dischinger and Riedel (2011), who report an average semi-elasticity of 3.20 in a much smaller micro-data sample, after decomposing for locations with high and low intangible assets.

overperforming compared to sectors less able to evade taxes. To the extent that multinationals compete over market share and input factors, this heterogeneity translates into profit shifting acting as a subsidy to specific industries.

In Table 5, we report average estimates for the MNE that we identify as the top profit shifter (Apple Inc.). We find a steady increase in profit shifting from 2009 to 2015, reaching 26.33 billion US dollars or 36% of the MNE's total reported consolidated profits. Tørsløv et al. (2023) estimate that, in 2015, 36% of multinational profits were shifted to tax havens globally. Obviously, these are very large profit-shifting volumes. Consistent with the emergence of the first BEPS action plan in the fall of 2015 (OECD, 2015), we find a reduction of profit shifting in 2016. This was an unprecedented effort to strengthen the global corporate tax system by limiting tax opportunities by multinationals, especially via synchronizing single tax rules across countries. However, implementation delays in the United States (Avi-Yonah, 2020) prolonged the presence of high volumes until 2018 (when the Tax Cuts and Jobs Act of 2017 started to be implemented), when we see a clear drop in the profit shifting ratio. Still, we find a reduced but significant 12% of *Profit shifting ($Bn.)* as a share of total consolidated profits by 2020.

Several other well-known MNEs appear in the top-20 list (Table 6). For each of these firms, there is abundant anecdotal evidence (media articles and legal cases) that they conduct profit shifting. There is also hard evidence in our data that all these firms own subsidiaries in tax havens. These anecdotal and hard evidence provide further validation of our estimates. A striking observation is that the majority of the top-20 companies operate in the IT and energy sectors.

[Please insert Tables 5 & 6 about here]

Tables 7 and 8 corroborate and enhance this observation, by reporting the average values of profit shifting by industry and subindustry of the GUOs. The results in Table 7 show that manufacturing is by far the industry with most *Profit shifting ($Bn.)* (left panel), with the top subindustry being pharmaceutical firms (right panel). In fact, according to Table 8, the manufacturing of pharmaceutical preparations is the top subindustry by *Profit shifting ($Bn.)*. Again, this finding is fully consistent with anecdotal evidence suggesting very aggressive profit shifting activities by pharmaceuticals and related companies.[14] In recent years, this has called for many governmental investigations and reports to delegalize and limit the activity.[15]

The information and communication industry comes second, with telecommunications being the most aggressive subindustry. This industry includes most well-known profit shifting MNEs, included in Table 6, and is the industry most often hitting the news. Moreover, according to Table 8, subindustries like software publishing and computer programming activities have among the highest estimated semi-elasticities on the tax differential. The key characteristic of this industry is the very large share of intangible assets, which is a key explanatory variable of profit shifting in the literature (e.g., Grubert, 2003; Grubert, 2012; Cheng et al., 2021, Karkinsky and Riedel, 2012; Beer and Loeprick, 2015; De Simone et al., 2022). Thus, its effect serves as validation in our framework. Intangible assets include goodwill, brand recognition, and intellectual property, such as patents, royalties and licenses, trademarks, and copyrights. Obviously, all these assets can be shifted to tax havens more easily.

The third industry is mining and quarrying, which has two specific characteristics that favor profit shifting. First, it has many foreign-owned companies because reserves (mostly fossil fuel) and refineries are usually in different locations than the parent. Second, in many major mining countries firms are not obliged to disclose the financial accounts of their subsidiaries. Evidence that mining and oil companies engage in profit-shifting activities is increasing. The petroleum industry exploits profit shifting strategies, such as intercompany loans that create transfer pricing opportunities (Guvenen et al., 2022). Anecdotal evidence is also abundant on the issue from major news agencies.[16] De Simone et al. (2022) estimate the most positive value of their profit shifting index for the textiles, petroleum and natural gas sectors. Their index is increasing with income-shifting aggressiveness. The IGF (Intergovernmental Forum on Mining) and OECD have released guidance for source countries on transfer pricing in the mining sector. We validate our methodology against court cases for companies in the mining sector.[17] Moreover, the results of Table 8 show that among the top-20 subindustries, the second and sixth places go to oil refineries (included in the manufacturing industry) and the extraction firms (included in the mining industry). Also, Table 8 shows that companies providing support

[14] E.g., https://www.businessinsider.com/big-pharma-companies-taxes-american-billion-dollar-profits-drugs-healthcare-2023-8.

[15] E.g., https://www.finance.senate.gov/imo/media/doc/Setser%20Senate%20Finance%20Testimony.pdf; https://www.finance.senate.gov/chairmans-news/wyden-releases-new-findings-in-ongoing-pharma-tax-investigation.

[16] https://www.reuters.com/article/global-oil-tax-havens-idUSKBN28J1IK.

[17] https://tpcases.com/transfer-pricing-in-the-mining-industry/.

activities for petroleum and gas extraction boast the largest estimate of the *Semi-elasticity* (the largest response of firm profits to changes in the tax differential).

[Please insert Tables 7 & 8 about here]

Table 9 reports the top-40 inbound profit shifting connections between the country where the firms are located (comprising firms that report their unconsolidated profits) and the GUO's country, based on the *Profit shifting ratio*. Except for the Slovakia-France connection (in third place), the remaining top-8 connections involve a subsidiary in Ireland with a GUO in France (32%), the United States, Japan, Spain, Australia, Belgium, and Germany. Another notable country in this ranking is Hungary, which has a current corporate tax rate of 9%, the lowest among OECD countries.

[Please insert Table 9 about here]

The connection between the subsidiary's country and the GUO's country might indicate the conduit countries used for profit shifting, potentially masking the true destination that typically involves a small country with a 0% corporate tax rate. This is especially true because we account for subsidiaries that report unconsolidated profits in this connection. Therefore, going beyond the analysis presented in Table 9, we identify the location of firms with the lowest corporate tax rate within the MNE (we include them in the *Tax differential*). We provide examples based on the first two rows of Table 9 (i.e., the Ireland-France and Ireland-U.S. connections). Specifically, in appendix Table A4, we rank the 560 firm-year observations of the Ireland-France connection based on the *Profit shifting ratio* and identify the country with the lowest tax rate where the MNE has a subsidiary. Vanuatu with just one observation but the highest profit-shifting ratio and semi-elasticity comes first, whereas Hungary with 35 observations is second. We identify the highest number of lowest-tax subsidiaries in the Ireland-France connection (240) to be in the United Arab Emirates (UAE) (0% corporate tax rate), with many connections remaining in Ireland (161 cases).

In appendix Table A5, we provide the equivalent results for the Ireland-U.S. connection. Bosnia and Herzegovina take the first place with a profit shifting ratio equal to 0.38 and Cyprus, Belize, and North Macedonia take the second place. For these countries, we have relatively few firm-year observations. The largest number of observations are firm-years with lowest-tax subsidiaries in Ireland, with the UAE in second place, followed by Bermuda and Cayman Islands. Overall, these results show that many firms choose to locate subsidiaries in zero percent tax heavens, but other firms also make choices based on other country characteristics, especially related to the quality of institutions and cultural proximity (as is possibly the case with Ireland). All other usual suspects, like Bahamas, Macao, Gibraltar, Bahrain, Bulgaria, British Virgin Islands, etc. appear in the table.

In Table 10, we rank GUO countries based on the average semi-elasticity of outbound profit-shifting firms within our sample. We anticipate that the GUOs of these firms are likely in countries with low corporate tax rates, such as Alphabet in Bermuda. Consequently, these firms tend to report a higher semi-elasticity, indicating a stronger incentive to shift profits towards these low-tax jurisdictions. The country with the highest semi-elasticity is Bahrain, and it is followed in the top-10 by Bermuda, Cayman Islands, Liechtenstein, Andorra, Cyprus, San Marino, Gibraltar, Bahamas, and the British Virgin Islands. All these locations are red flags for the OECD's BEPS framework, further validating our index.

In Table 11, we aggregate the total profit-shifting estimates attributed to MNEs in our sample, *Profit shifting ($Bn.),* according to the countries of their GUOs and the countries with the lowest tax rates within the MNE group. Among the MNEs engaging in the most profit shifting in our sample, we find that those with their GUO located in the US and a subsidiary in Bermuda stand out prominently. Out of the total profit shifting reported in these top 40 connections between GUO country and the lowest tax subsidiaries, which amounts to $4,022 billion, nearly half, specifically $1,908 billion, pertains to MNEs with a GUO based in the US and low-tax subsidiaries in Bermuda, the Cayman Islands, the UAE, the British Virgin Islands, and Ireland.

[Please insert Tables 10 & 11 about here]

Figure 2 compares our annual average semi-elasticities with the average semi-elasticities of firms that have their GUOs in Bermuda and the Cayman Islands, as well as those with GUOs in the "Support Activities for Petroleum and Natural Gas Extraction" sub-industry. We observe that the average semi-elasticities of firms with GUOs in Bermuda and the Cayman Islands consistently exceed the annual average semi-elasticities of the entire sample. We can obtain several similar patterns for firms in other tax havens.

For firms supporting fossil fuel extraction, we find a very interesting pattern. Until 2017, their average semi-elasticities are lower than the annual average semi-elasticities of the overall sample. At this point, there is a notable shift, with the semi-elasticity of the involved firms becoming higher than the annual average semi-elasticities. One potential explanation for this finding is that following the Paris Agreement in

2015, along with stricter environmental regulation implemented in many countries in the same period, fossil fuel firms increasingly aimed to relocate in tax havens that probably also have laxer environmental regulations. We leave this interesting observation for future research.

[Please insert Figure 2 about here]

3.3 Loss-making firms

In the bulk of our analysis, we exclude loss-making firms, in order to follow most of the profit-shifting literature, its findings, and validations (including those using macro data, such as Tørsløv et al., 2023). A recent literature highlights that loss-making firms are also shifting profit inward. Hopland et al. (2018) use detailed data for Norwegian firms and their foreign affiliates and a different model: they access tax return data on transactions and debt relationships and use the latter as the dependent variable in their analysis. De Simone et al. (2017) use the same model with our analysis, and discuss profit truncation because of the log transformation. Their solution is to use the log(return on assets + 1), which is a positive number. Their choice is driven by the fact that the transformation log(profit + absolute value of minimum profit in the sample + 1) leads to a large change in the distribution of the left hand-side variable that can yield vastly different estimation results (bias and inconsistency due to skewness).[18]

To avoid criticism related to sample truncation, we conduct additional analysis using the so-called neglog transformation (e.g., Whittaker et al., 2005).[19] This transformation transforms a variable y that can take negative values into -ln(-y+1) if y ≤ 0 and ln(y+1) if y>0, or sign(y)*ln(|y| +1). We favor this transformation because it behaves like ln(y) when y is positive and like -ln(-y) when y is negative, whereas it has very limited effect on data skewness. Moreover, we prefer this approach over using the log of a returns ratio because returns ratios capture not only profit shifting but also (potentially) asset-shifting (Beer et al., 2020).

In Table 12 we reproduce some of our main results after including loss-making firm-year observations (3,381,355 in total) into the sample. In terms of rankings by year (Panel A), firm (Panel B), industry (Panel C), and country connections (Panel D), our results closely resemble the ones obtained without loss-making firms. For example, profit shifting continues to show an upward trend over the years, especially up to 2017, and the rank correlations of profit shifting between firms, industries, and country pairs are very high.

However, as expected, estimates of profit shifting are now larger, because our estimates now include profit shifting by loss-making firms. For example, we now estimate profit shifting to be well into the trillion US dollars territory from 2013 onward, peaking in 2017. Similarly, the profit shifting ratio reaches 47% in 2017, showing a very large share of shifted profits to consolidated profits. These estimates top those in macro studies of profit shifting. For instance, Wier and Zucman (2022) using macro-level data obtain an estimate of global profit shifting in 2019 of 969 billion US dollars, or 37 percent of global multinational profits.

[Please insert Table 12 about here]

[18] In fact, the econometrics literature suggests that the y+1 transformation is almost never a good solution to this problem (e.g., Cohn et al., 2022).

[19] See also http://fmwww.bc.edu/repec/bocode/t/transint.html.

4 Conclusions and directions for future research

This paper constructs the first global database of firm-year estimates of profit shifting for 2,277,435 observations for the period 2009 to 2020. This new database shows that (i) the top-20 profit shifting MNEs are well-known firms that shift billions of US dollars annually and mainly belong to the information technology, pharmaceutical, and petroleum industries; (ii) the top inbound profit-shifting connections over this period are between high-tax countries (France and the United States in particular) and Ireland, with most of these MNEs also owning at least one firm in a tax heaven; (iii) the largest elasticities of firm profits in response to differential taxation between countries are associated with companies that have GUOs located in tax havens; and (iv) profit shifting reaches its peak in 2017, but remains very significant throughout our sample period.

Importantly, our findings reconcile differences in profit shifting estimates between studies using firm-level data and macroeconomic data, both in terms of the estimated semi-elasticities and total amounts of profit shifting. Specifically, we estimate an elasticity of approximately 2.8, which is very close to that obtained by Clausing (2020) using macro data. We estimate global profit shifting to range from 311 billion US dollars in 2009 to 770 billion US dollars in 2017. These figures closely align with those of Wier and Zucman (2022) using macro data, further validating our estimations. We attribute these findings to the intensive data collection and cleansing process. Last, when adding profit shifting from loss-making firms our annual estimates of global profit shifting increase intro trillion USD territory from 2013 onward and up to 47% of total consolidated profits in 2017.

Our new profit shifting index can be used both as an outcome and an explanatory variable in empirical analysis. Thus, our findings are only a first step to uncovering the potential of this database for analyzing profit shifting at the firm or aggregate level. The global profit shifting database and its updates, which we aim to provide, can be used by researchers to analyze either the factors that determine profit shifting or the causal effects of profit shifting.

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Table 1. Variable definitions and sources

Variable	Definition	Source
A. Profit-shifting indices		
Semi-elasticity	The firm-year estimates $a_{1,it}$ from the estimation of equation (1) using the local linear regression as described in section 2.3.	Own estimations
Profit shifting $	The dollar amount of shifted profits for firm *i* in year *t*, as determined by equation (5) and calculated using unconsolidated financial data.	Own estimations
Profit shifting ratio	*Profit shifting $* divided by observed profits before taxes.	Own estimations
Profit shifting ratio true	*Profit shifting $* divided by the estimated firm-year true profits, which are determined using Equation (6).	Own estimations
Profit shifting ($Bn.)	The dollar amount of shifted profits for MNE *i* in year *t,* in billions US dollars. It is estimated by applying the average profit shifting ratios of all firms within the MNE group for a specific year to the consolidated profits before taxes of each corresponding MNE-year observation.	Own estimations
Profit shifting ratio (Cons.)	*Profit Shifting ($Bn.)* divided by consolidated profits before taxes ($Bn.).	Own estimations
B. Dependent variables		
Profit before taxes	Firm observed profits before taxes (log).	Orbis
C. Firm characteristics		
Tax differential	Composite tax variable that summarizes all information about firms profit-shifting tax-incentives in year t.	EY, PwC, IBFD, Tax Foundation
Tangible fixed assets	Firm tangible fixed assets (log).	Orbis
Fixed assets	Firm fixed assets (log).	Orbis
Number of employees	Firm number of employees (log).	Orbis
Tax haven	Dummy variable equals to 1 if there is a tax haven firm in the multinational group.	EY, PwC, IBFD, Tax Foundation, Tørsløv et al. (2023)
Consolidated profits ($Bn.)	MNE observed consolidated profits before taxes.	Orbis
D. Country characteristics		
Statutory tax rate	Statutory tax rate of the firm's country.	EY, PwC, IBFD, Tax Foundation
	Statutory tax rates of all the firms' countries in the same multinational group.	EY, PwC, IBFD, Tax Foundation
GDP per capita	The natural logarithm of GDP per capita (current US$).	World Bank
GDP growth	GDP growth (annual %)	World Bank
Inflation	Inflation, consumer prices (annual %)	World Bank

Table 2. Summary statistics

The table reports the number of observations, the mean and standard deviation, minimum, maximum, and median of the main variables in the analysis. The variables are defined in Table 1 and the sample period is 2009-2020.

	(1) Observations	(2) Mean	(3) Standard deviation	(4) Min	(5) Median	(6) Max
Semi-elasticity	2,274,896	2.755	0.958	0.002	2.761	91.221
Profit before taxes (log)	2,277,435	13.152	2.474	0.000	13.251	27.439
Fixed assets	2,277,435	3.972	3.137	0.000	14.155	27.007
Tangible fixed assets	2,232,640	13.802	3.171	0.000	13.961	26.980
Number of employees	2,277,435	3.418	1.969	0.000	3.466	13.870
GDP per capita	2,277,435	10.202	0.710	6.128	10.465	12.098
GDP growth	2,277,416	0.970	3.568	-21.400	1.705	24.370
Inflation	2,277,416	2.267	3.449	-30.200	1.504	84.300
Tax differential	2,277,435	-0.015	0.078	-0.392	-0.002	0.654
Tax haven	2,277,435	0.193	0.395	0.000	0.000	1.000
Statutory tax rate	2,277,435	0.251	0.064	0.000	0.250	0.395

Table 3. Annual averages of profit-shifting estimates

The table provides annual averages of profit-shifting estimates. The first row displays the annual average semi-elasticities for all firms within a specific year. The second row reports the standard deviation of these semi-elasticities. The third row presents our annual profit-shifting estimates in billions of US dollars. The fourth line shows the total consolidated profits of the multinational enterprises (MNEs) in our dataset for each year. The fifth row presents a profit-shifting ratio, calculated by dividing profit-shifting (in billions of dollars) by consolidated profits (in billions of dollars). All variables are defined in Table 1.

Year	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Avg.
Semi-elasticity	2.36	2.93	3.02	2.74	2.71	2.75	3.16	3.15	3.02	2.53	2.14	2.66	2.76
Semi-elasticity (St. dev.)	0.78	0.74	0.85	0.86	0.9	0.69	0.82	0.7	0.92	1.02	1.02	1.23	0.88
Profit shifting $Bn.	311	475	583	579	560	631	623	581	770	478	384	341	526
Consolidated profits $Bn.	2,106	2,758	3,130	2,995	3,025	3,039	2,813	2,903	3,701	4,026	3,729	2,731	3,080
Profit shifting ratio (Cons.)	0.15	0.17	0.19	0.19	0.19	0.21	0.22	0.2	0.21	0.12	0.1	0.12	0.17

Table 4. OLS estimation of profit shifting

The table reports coefficient estimates and standard errors (in parentheses) from the OLS estimation of equation (1). Dependent variable is firm's *Profit before taxes* and all variables are defined in Table 1. The lower part of the table denotes the type of fixed effects. We report White's (1980) heteroscedasticity-consistent standard errors in parentheses for all specifications. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Fixed assets			0.356***	0.356***	0.361***	0.355***
			[0.001]	[0.001]	[0.001]	[0.001]
Number of employees			0.400***	0.399***	0.418***	0.393***
			[0.001]	[0.001]	[0.001]	[0.001]
GDP per capita		0.695***		0.349***	0.302***	0.338***
		[0.016]		[0.012]	[0.012]	[0.012]
GDP growth		0.002**				
		[0.001]				
Inflation		-0.005***				
		[0.001]				
Tax differential	-3.354***	-3.396***	-2.077***	-2.098***	-1.942***	-1.809***
	[0.024]	[0.024]	[0.019]	[0.019]	[0.018]	[0.021]
Tax haven						0.323***
						[0.003]
Tax differential # Tax haven						-1.040***
						[0.032]
Observations	2,277,435	2,277,416	2,277,435	2,277,435	2,243,338	2,277,435
Adjusted R-squared	0.175	0.176	0.552	0.552	0.565	0.555
Country	Y	Y	Y	Y	Y	Y
Year	Y	Y	Y	Y	Y	Y
Industry	N	N	N	N	Y	N
Standard errors	Robust	Robust	Robust	Robust	Robust	Robust

Table 5. Top profit shifting MNE

The table offers a comparison of annual profit shifting estimates, represented in billions of US dollars, for the leading multinational enterprise (MNE) in our dataset and their respective annual consolidated profits. We include a profit shifting ratio, which is derived by dividing Profit Shifting (in billions of dollars) by Consolidated Profits (in billions of dollars). Additionally, the table provides the annual average semi-elasticities for all firms within this MNE. All variables are defined in Table 1.

	Apple Inc.											
Year	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Profit shifting ($Bn.)	2.69	5.00	10.00	16.91	14.14	16.90	26.33	13.99	19.59	8.02	6.78	7.98
Consolidated profits ($Bn.)	12.07	18.54	34.21	55.76	50.16	53.48	72.52	61.37	64.09	72.9	65.74	67.09
Profit shifting ratio (Cons.)	0.22	0.27	0.29	0.30	0.28	0.32	0.36	0.23	0.31	0.11	0.10	0.12
Semi-elasticity	1.80	2.76	3.07	2.41	2.56	2.67	3.05	2.24	2.64	2.46	1.92	2.29

Table 6. Top 20 profit shifting MNEs

The table ranks the top 20 multinational enterprises (MNEs) in our sample based on their aggregate profit-shifting estimates in billions of US dollars, cumulated over the period 2009 to 2020. Additionally, it presents their aggregate consolidated profits in billions of US dollars, the corresponding profit shifting ratio (calculated as Profit shifting $Bn. divided by Consolidated profits $Bn.), and the average semi-elasticities of all the firms within these MNEs. All variables are defined in Table 1.

Company	Profit shifting ($Bn.)	Consolidated profits ($Bn.)	Profit shifting ratio (Cons.)	Semi-elasticity
Apple Inc.	148	628	0.24	2.49
Exxon Mobil Corp	117	449	0.26	2.78
Saudi Arabia Oil Company (Saudi Aramco)	107	628	0.17	2.52
Microsoft Corporation	95	357	0.27	2.53
Samsung Electronics Co. Ltd	80	347	0.23	2.25
Chevron Corporation	73	252	0.29	2.68
Shell Plc	70	311	0.22	3.03
Walmart Inc.	68	255	0.27	2.19
At&T Inc.	66	204	0.33	2.51
Verizon Communications Inc.	60	224	0.27	2.60
Intel Corp	59	203	0.29	2.67
Alphabet Inc.	56	273	0.21	2.46
Oracle Corp	45	141	0.32	2.19
General Motors Company	44	185	0.24	2.60
Johnson & Johnson	44	157	0.28	2.66
Nestle S.A.	44	205	0.21	2.76
Toyota Motor Corporation.	41	193	0.21	2.94
Petroliam Nasional Berhad	41	201	0.20	3.02
Roche Holding AG	40	166	0.24	2.70
Totalenergies Se	40	217	0.18	2.96

Table 7. Estimates of profit shifting by MNEs industry

This table provides a ranking of industries (NACE Rev.2) based on total profit-shifting estimates attributed to MNEs within these industries. These estimates are expressed in billions of US dollars and are cumulated over the period 2009 to 2020. Within each main industry section, we highlight the leading sub-industry along with its profit-shifting estimate. In the last column, we present a ratio that illustrates the extent to which profit shifting is concentrated within this particular sub-industry relative to the main section.

Industry	Profit shifting ($Bn.)	Top sub-Industry	Profit shifting ($Bn.)	Sub-industry Ratio
Manufacturing	3,502.1	Manufacture of pharmaceutical preparations	439.2	0.13
Information and communication	864.1	Telecommunications activities	353.6	0.41
Mining and quarrying	456.8	Extraction of crude petroleum	247.3	0.54
Wholesale and retail trade; repair of motor vehicles	339.7	Retail sale in non-specialised stores	79.8	0.23
Professional, scientific and technical activities	160.1	Activities of head offices	74.1	0.46
Transportation and storage	147.0	Postal and courier activities	28.3	0.19
Financial and insurance activities	146.0	Activities of holding companies	99.9	0.68
Electricity, gas, steam and air conditioning supply	136.9	Production of electricity	83.5	0.61
Accommodation and food service activities	65.4	Restaurants and mobile food service activities	40.6	0.62
Administrative and support service activities	58.6	Travel agency, tour operator reservation service & related	14.4	0.25
Real estate activities	53.1	Real estate agencies	42.7	0.80
Construction	50.9	Construction of buildings	24.2	0.48
Human health and social work activities	23.4	Human health activities	12.4	0.53
Other service activities	16.9	Activities of other membership organisations	14.7	0.87
Agriculture, forestry and fishing	11.3	Growing of fibre crops	3.1	0.27
Arts, entertainment and recreation	8.0	Amusement and recreation activities	5.1	0.64
Water supply; waste management and remediation	7.1	Water collection, treatment and supply	4.8	0.68
Public administration and defense; compulsory social security	1.7	Foreign affairs	1.4	0.82
Education	1.2	Other education	0.7	0.58

Table 8. Top 20 profit shifting sub-industries

This table provides a ranking of sub-industries (NACE Rev.4-digit classification) based on the total profit-shifting estimates attributed to MNEs within these sub-industries. These estimates are expressed in billions of US dollars and are cumulated over the period 2009 to 2020. Additionally, the table presents the aggregate consolidated profits of these sub-industries in billions of US dollars, along with the corresponding profit shifting ratio. The profit shifting ratio is calculated as the Profit Shifting ($Bn.) divided by Consolidated Profits ($Bn.) Furthermore, the table includes the average semi-elasticities of all the firms within these sub-industries. All variables are defined in Table 1.

Industry	Sub-Industry	Profit shifting ($Bn.)	Consolidated profits ($Bn.)	Profit shifting ratio (Cons.)	Semi-elasticity
Manufacturing	Manufacture of pharmaceutical preparations	439	1,965	0.22	2.54
Manufacturing	Manufacture of refined petroleum products	359	1,776	0.20	2.49
Information and communication	Telecommunications activities	354	1,821	0.19	2.66
Manufacturing	Manufacture of electronic components	278	1,357	0.21	2.39
Manufacturing	Manufacture of motor vehicles	261	1,206	0.22	2.54
Mining and quarrying	Extraction of crude petroleum	247	1,526	0.16	2.66
Manufacturing	Manufacture of computers and peripheral equipment	214	968	0.22	2.41
Information and communication	Software publishing	190	746	0.25	2.74
Information and communication	Information technology and computer service activities	145	813	0.18	2.58
Manufacturing	Manufacture of other organic basic chemicals	143	806	0.18	2.37
Manufacturing	Manufacture of air and spacecraft and related machinery	120	501	0.24	2.64
Manufacturing	Manufacture of other food products	114	595	0.19	2.41
Financial and insurance activities	Activities of holding companies	100	782	0.13	2.75
Manufacturing	Manufacture of tobacco products	87	439	0.20	2.50
Mining and quarrying	Support activities for petroleum and natural gas	84	711	0.12	2.85
Electricity, gas, steam and air conditioning supply	Production of electricity	84	785	0.11	2.65
Wholesale and retail trade; repair of vehicles	Retail sale in non-specialized stores	80	368	0.22	2.28
Manufacturing	Manufacture of communication equipment	76	362	0.21	2.54
Professional, scientific and technical activities	Activities of head offices	74	483	0.15	2.85
Information and communication	Computer programming activities	72	395	0.18	2.81

Table 9. Top 40 inbound profit shifting connections

The table ranks the top 40 inbound profit shifting connections, based on the average profit shifting ratio for firms residing in one country with a GUO in another country over the period 2009 to 2020. These connections involve at least 100 observations in each country-GUO pairing. Further, the table reports the average semi-elasticity (coefficients on the tax differential) of firms within these combinations. All variables are defined in Table 1.

Country	GUO country	Profit shifting ratio	Observations	Semi-elasticity
Ireland	France	0.32	560	2.49
Ireland	United States	0.31	3,931	2.52
Slovakia	France	0.31	1,630	3.42
Ireland	Japan	0.31	404	2.51
Ireland	Spain	0.31	221	2.73
Ireland	Australia	0.30	147	2.47
Ireland	Belgium	0.30	148	2.53
Ireland	Germany	0.30	677	2.45
Hungary	United States	0.30	2,655	2.45
Hungary	France	0.30	1,377	2.40
Czech Republic	France	0.29	2,663	2.74
Ireland	Denmark	0.29	139	2.68
Hungary	Japan	0.29	823	2.39
Ireland	Netherlands	0.28	337	2.70
Czech Republic	United States	0.28	4,635	2.72
Slovakia	Belgium	0.28	652	3.45
Ireland	Italy	0.28	187	2.31
Ireland	Switzerland	0.28	326	2.55
Czech Republic	Japan	0.28	1,319	2.82
Ireland	Canada	0.28	262	2.71
Slovakia	Japan	0.28	367	3.60
Ireland	Luxembourg	0.28	392	2.58
Ireland	Sweden	0.28	179	2.67
Slovakia	United States	0.28	2,120	3.40
Bulgaria	France	0.27	935	1.66
Finland	Japan	0.27	413	3.56
Finland	France	0.27	722	3.67
Hungary	Germany	0.27	4,779	2.64
Slovenia	France	0.27	457	2.50
Czech Republic	Belgium	0.27	775	2.87
Bulgaria	Japan	0.27	260	1.77
Hungary	Belgium	0.27	578	2.43
Hungary	Seychelles	0.27	235	2.60
Sweden	United States	0.27	6,851	3.89
Hungary	Italy	0.27	1,293	2.70
Bulgaria	United States	0.26	1,818	1.81
Hungary	Spain	0.26	355	2.68
Hungary	Ireland	0.26	222	2.59
Czech Republic	Italy	0.26	1,207	3.03
Romania	France	0.26	4,732	1.88

Table 10. Top 40 GUO countries ranking by average semi-elasticity

This table presents a ranking of GUO countries based on the average semi-elasticity of outbound profit-shifting firms over the period 2009 to 2020. The semi-elasticity reflects the extent to which these outbound profit-shifting firms are inclined to shift their profits to the corresponding GUO countries. We include only GUO countries with a minimum of 100 firm-year observations.

GUO country	Observations	Semi elasticity
Bahrain	106	3.03
Bermuda	7,361	2.97
Cayman Islands	11,027	2.90
Liechtenstein	4,327	2.89
Andorra	211	2.86
Cyprus	69,995	2.86
San Marino	342	2.84
Gibraltar	1751	2.82
Bahamas	1,349	2.82
British Virgin Islands	23,590	2.73
United Arab Emirates	3,149	2.71
Kuwait	583	2.70
Uruguay	198	2.67
Marshall Islands	328	2.67
Tunisia	848	2.60
Albania	197	2.57
Qatar	351	2.56
Algeria	859	2.55
Turkey	4,169	2.55
Iran	305	2.54
Lebanon	1,079	2.54
Malaysia	1,464	2.53
Vietnam	125	2.53
Belarus	1,693	2.51
Romania	5,967	2.50
Thailand	865	2.49
Indonesia	109	2.49
Singapore	5,748	2.47
Chile	518	2.45
Macao SAR, China	108	2.44
Portugal	31,740	2.43
Mauritius	862	2.36
Egypt	334	2.35
Moldova	690	2.31
Taiwan	5,734	2.24
Morocco	1,007	2.19
North Macedonia	1,010	2.16
Montenegro	740	2.15
Anguilla	345	2.14
Sri Lanka	248	2.14

Table 11. Top 40 profit-shifting connections by GUO country and low-tax MNE destination

The table ranks the top 40 connections between GUO countries and countries with the lowest tax rates in the MNE group based on the total profit-shifting estimates attributed to MNEs that engage in these connections, cumulated over the period 2009 to 2020. These connections involve at least 100 firm-year observations. Further, the table reports the average semi-elasticity (coefficients on the tax differential) of firms within these combinations. All variables are defined in Table 1.

GUO country	Lowest tax rate in the MNE group	Profit shifting Bn. $	Observations	Semi-elasticity
United States	Bermuda	578	17,121	2.74
United States	Cayman Islands	500	22,505	2.74
United States	United Arab Emirates	390	30,727	2.69
United States	British Virgin Islands	231	9,786	2.62
United States	Ireland	209	15,107	2.83
Japan	United Arab Emirates	164	26,410	2.44
Germany	United Arab Emirates	159	32,895	2.81
France	United Arab Emirates	126	47,169	2.80
United Kingdom	United Arab Emirates	120	17,231	2.90
United States	Bahamas	116	2,587	2.77
Saudi Arabia	United Arab Emirates	111	272	2.69
United States	Bulgaria	102	4,950	2.61
South Korea	United Arab Emirates	93	2,121	2.31
United Kingdom	British Virgin Islands	80	6,626	2.89
United Kingdom	Bermuda	79	3,138	2.93
Switzerland	United Arab Emirates	72	9,174	2.77
United States	Hungary	69	5,721	2.58
Japan	China, Hong Kong	58	21,257	2.10
Switzerland	Bermuda	56	2,575	2.92
United Kingdom	Cayman Islands	54	5,518	2.92
United States	United Kingdom	51	12,493	2.43
Taiwan	British Virgin Islands	41	2,690	2.30
China	British Virgin Islands	40	8,186	2.53
Japan	Singapore	40	20,215	1.97
United States	Bahrain	39	2,650	2.72
Japan	Ireland	39	4,985	2.60
United Kingdom	Ireland	38	19,502	3.00
United States	China, Hong Kong	38	5,637	2.68
United States	Singapore	35	4,841	2.64
Hong Kong	British Virgin Islands	34	2,679	2.14
Malaysia	Bermuda	32	191	2.84
Germany	Bulgaria	32	13,105	2.60
India	United Arab Emirates	31	2,081	2.60
France	Bermuda	31	2,559	3.05
United Kingdom	Bahrain	26	2,571	3.03
United States	Serbia	22	2,323	2.53
Germany	Cayman Islands	22	4,502	2.96
Mexico	Bahamas	22	186	2.98
South Korea	Cayman Islands	21	674	2.41
Germany	Bahrain	21	2,405	2.80

Table 12. Profit-shifting estimates including loss-making firms

Panel A. Profit-shifting estimates by year

Panel A provides annual averages of profit-shifting estimates. The first row displays the annual average semi-elasticities for all firms within a specific year. The second row presents our annual profit-shifting estimates in billions of US dollars. The third row presents a profit-shifting ratio, calculated by dividing profit-shifting (in billions of dollars) by consolidated profits (in billions of dollars). All variables are defined in Table 1.

Year	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Avg.
Semi-elasticity	1.52	3.34	3.49	3.82	3.76	4.63	5.31	5.80	6.00	6.09	5.91	6.89	4.71
Profit shifting $Bn.	252	660	902	982	1,252	1,229	1,231	1,220	1,746	1,487	1,435	1,087	1,124
Profit shifting ratio	0.12	0.24	0.29	0.33	0.41	0.40	0.44	0.42	0.47	0.37	0.38	0.40	0.36

Panel B. Top profit shifting MNEs

Panel B ranks the top multinational enterprises (MNEs) in our sample based on their aggregate profit-shifting estimates in billions of US dollars, cumulated over the period 2009 to 2020. Additionally, it presents their aggregate consolidated profits in billions of US dollars, the corresponding profit shifting ratio (calculated as Profit shifting ($Bn.) divided by Consolidated profits ($Bn.)), and the average semi-elasticities of all the firms within these MNEs. All variables are defined in Table 1.

Company	Profit shifting ($Bn.)	Consolidated profits ($Bn.)	Profit shifting ratio (Cons.)	Semi-elasticity
Apple Inc.	326	628	0.52	5.10
Saudi Arabia Oil Company (Saudi Aramco)	309	628	0.49	5.59
Microsoft Corporation	213	357	0.60	5.19
Exxon Mobil Corp	200	449	0.45	4.90
Samsung Electronics Co, Ltd	182	347	0.53	5.13
Walmart Inc.	153	255	0.60	5.27
Chevron Corporation	140	252	0.56	4.95
Verizon Communications Inc.	131	224	0.58	5.14
AT&T Inc.	130	204	0.64	5.04
Alphabet Inc.	127	273	0.47	4.86

Panel C. Top profit-shifting sub-industries

Panel C ranks sub-industries (NACE Rev.4-digit classification) based on the total profit-shifting estimates attributed to MNEs within these sub-industries. These estimates are expressed in billions of US dollars, cumulated over the period 2009 to 2020. Additionally, the table presents the aggregate consolidated profits of these sub-industries in billions of US dollars, along with the corresponding profit shifting ratio. The profit shifting ratio is calculated as Profit Shifting ($Bn.) divided by Consolidated Profits ($Bn). Furthermore, the table includes the average semi-elasticities of all the firms within these sub-industries. All variables are defined in Table 1.

Industry	Sub-Industry	Profit shifting ($Bn.)	Consolidated profits ($Bn.)	Profit shifting ratio (Cons.)	Semi-elasticity
Manufacturing	Manufacture of pharmaceutical preparations	891	1,965	0.45	4.76
Information and communication	Telecommunications activities	715	1,821	0.39	4.70
Manufacturing	Manufacture of refined petroleum products	645	1,776	0.36	4.64
Manufacturing	Manufacture of electronic components	620	1,357	0.46	4.82
Manufacturing	Manufacture of motor vehicles	505	1,206	0.42	5.01
Mining and quarrying	Extraction of crude petroleum	473	1,526	0.31	4.36
Manufacturing	Manufacture of computers and peripheral equipment	466	967	0.48	4.51
Information and communication	Software publishing	434	746	0.58	4.91
Manufacturing	Manufacture of other organic basic chemicals	376	806	0.47	5.02
Information and communication	IT and computer service	335	813	0.41	4.92

Panel D. Top profit-shifting connections by GUO country and low-tax MNE destination

Panel D ranks the top 10 connections between GUO countries and countries with the lowest tax rates in the MNE group based on the total profit-shifting estimates attributed to MNEs that engage in these connections, cumulated over the period 2009 to 2020. These connections involve at least 100 firm-year observations. Further, the table reports the average semi-elasticity (coefficients on the tax differential) of firms within these combinations. All variables are defined in Table 1.

GUO country	Lowest tax rate in the MNE group	Profit shifting (Bn. $)	Observations	Semi-elasticity
United States	Bermuda	1,222	22,630	5.12
United States	Cayman Islands	1,013	30,353	5.15
United States	United Arab Emirates	965	39,329	5.57
United States	British Virgin Islands	527	13,102	5.21
Japan	United Arab Emirates	399	32,113	5.32
United States	Ireland	387	20,416	4.88
Germany	United Arab Emirates	344	43,177	5.32
Saudi Arabia	United Arab Emirates	317	413	5.74
France	United Arab Emirates	287	66,913	5.12
United Kingdom	United Arab Emirates	262	23,764	5.42

Figure 1: Nonparametric estimates at two points

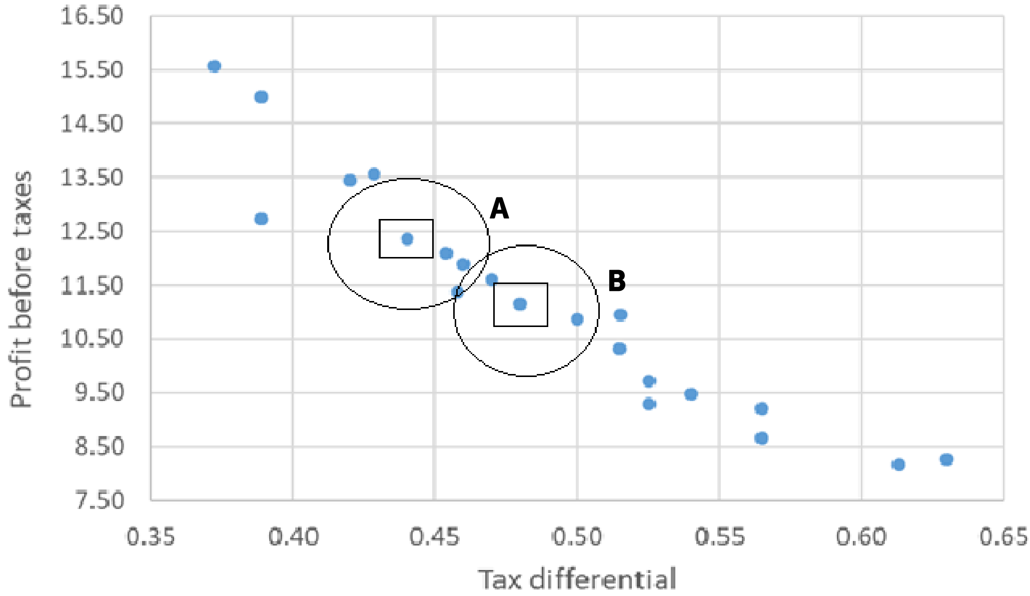
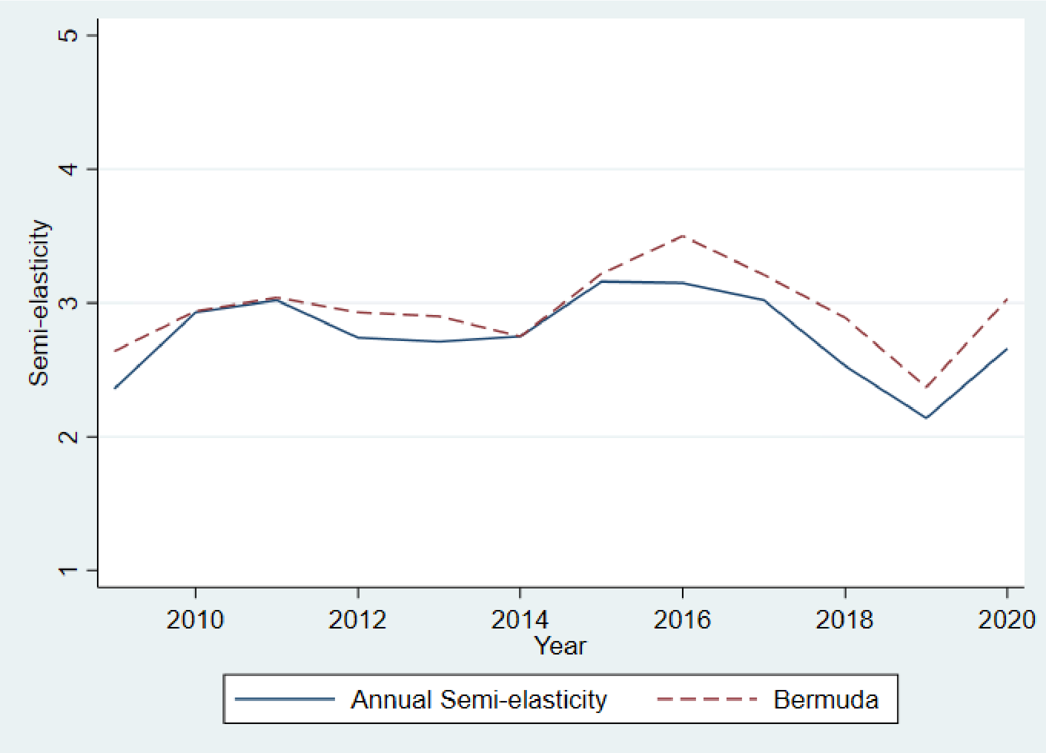
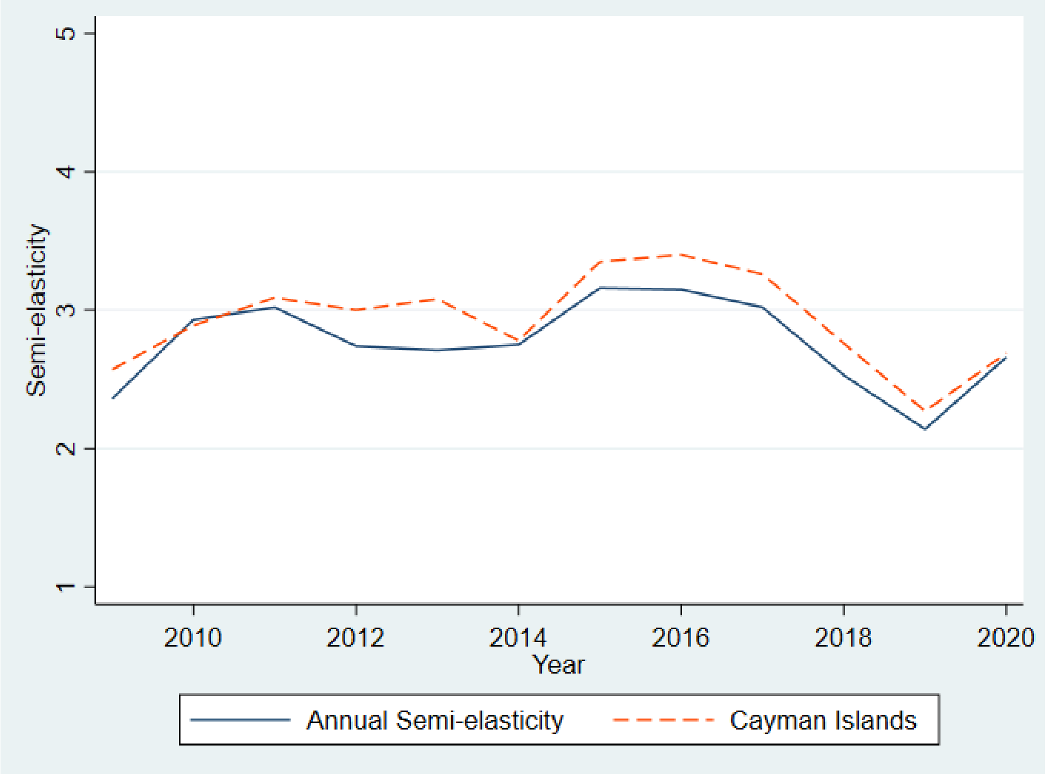
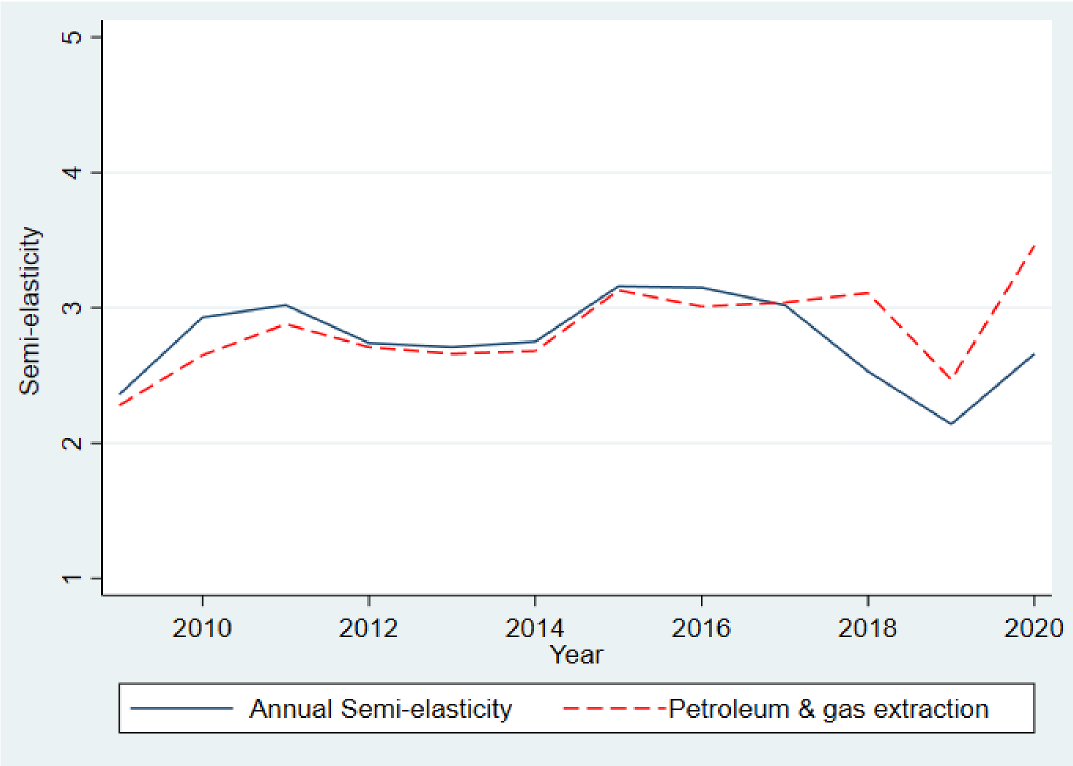


Figure 2: Annual profit shifting semi-elasticities






Semi-elasticity
1
2
3
4
5
2010
2012
2014
2016
2018
2020
Year
Annual Semi-elasticity
Petroleum & gas extraction

List of abbreviations and definitions

BEPS	Base Erosion and Profit Shifting
BvD	Bureau van Dijk
DID	Difference-in-Differences
GUO	Global Ultimate Owner
IBFD	International Bureau of Fiscal Documentation
IGF	Intergovernmental Forum on Mining
IV	Instrumental Variable
MNE	Multinational Enterprise
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
PwC	PricewaterhouseCoopers
US	United States

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Annexes

Annex 1. Sample construction

We use historical BvD Orbis disks, commonly referred to as "vintages," as a primary data source for extracting relevant information for our analysis. The use of these vintages offers distinct analytical advantages when compared to alternative data extraction methods such as BvD's proprietary web platform or the WRDS, as extensively discussed in Appendix A.2 of the work by Kalemli-Özcan et al. (2022). To the best of our knowledge, our sample represents the most extensive collection and analysis of data compiled for studying profit shifting using micro data from Orbis. This process of handling the data also aims to reconcile the discrepancy that exists between micro and macro profit shifting estimates.

We initially obtain data from Orbis vintage 2021. We extract the variables relevant to our research, including *bvd_id*, *Consolidation code*, *Filing type*, *Closing date*, *Accounting practice*, *Fixed assets*, *Total assets*, *Intangible fixed assets*, *Non-current liabilities*, *Current liabilities*, *Number of employees*, *Costs of employees*, *Sales*, *Profit before taxes*, *Taxation*, *Operating profit (EBIT)*, *EBITDA*, and *Cash flow*. We collect these data for all firms reporting unconsolidated financial accounts (U1, U2) during the period 2009 to 2020. The total number of observations obtained is 171,039,959.

Subsequently, we drop observations for firms with missing profit/loss before taxes (*Profit before taxes*) and total assets (*Total assets*), resulting in a significant reduction in the number of observations to 115,655,029. To facilitate the logarithmic transformation of the variable representing the number of employees (*Number of employees*), which serves as an approximation for the labor input of each firm, we replace the value 0 with 1 for all firms that report zero employees. This adjustment applies to 4,795,470 observations, which represents approximately 4% of our sample. We prioritize this variable as our labor input measure over the cost of employees' variable (*Costs of employees*) due to its superior coverage (71,015,869 observations compared to 57,456,683 observations for *Costs of employees*). It is worth noting that the coverage of *Number of employees* and *Costs of employees* in Orbis does not align with the coverage of *Total assets* and *Fixed assets*. *Fixed assets* are extensively used in the literature as a proxy for capital (Huizinga and Laeven 2008).

The variable *Closing date* is used to identify the fiscal year and fiscal quarters of the firms. Notably, we observe a decline in the number of observations per year starting from 2019 (12,369,055 in 2018, 10,664,167 in 2019, and 366,125 in 2020). This decline reflects the 2-3 years lag in Orbis data availability, as reported by Kalemli-Özcan et al. (2022). As a result, we exclude any observations recorded in the year 2020. For the period 2009 to 2019, we only consider data with closing dates that align with fiscal quarters, specifically quarters 3, 6, 9, and 12.

Our sample contains duplicates in terms of firm (*bvd_id*) and *Closing date* due to differences in filing types between firms (Annual reports and Local registry filings). To address this, we clean these duplicates by considering the filing type variable (*Filing type*), keeping only observations from Annual reports. Furthermore, we drop all observations with negative total assets.

We still face duplicates in terms of *bvd_id* and year (or firm-year) due to the presence of both quarterly and annual reports for certain firms. To address the issue of remaining duplicates, we employ a deduplication procedure based on the methodology described by Kalemli-Özcan et al. (2022). We use a variable with comprehensive coverage, such as *Total assets*, to identify quarterly reports. Consequently, we remove duplicates whose *Total assets* are less than the maximum per firm-year. Further, we remove a small number of remaining duplicates (0.01% of our sample).

At this stage, our sample includes 109,335,669 unique firm-year (*bvd_id*-year) observations. However, the number of observations continues to decline after 2018, from 11,805,003 in 2018 to 10,136,456 in 2019. We proceed with a remedy at a later stage. Finally, we calculate the tangible fixed assets (*Tangible fixed assets*) by taking the difference between fixed assets and intangible fixed assets.

To construct the *Tax differential*, CT_{it} in equations (1) and (2), it is necessary to identify the multinational group associated with each firm. To achieve this, we assign a Global Ultimate Owner (GUO) to each unique firm-year observation by reconstructing the corporate ownership links, following the suggestions provided by Kalemli-Özcan et al. (2022) and Grosskurth (2019). Our selection criterion for identifying a GUO is based on the presence of an entity that owns at least 50% + 1 of the firms in our sample. Initially, we merge our firm-year observations with the set of current ownership links. This merging process encompasses both the current corporate Global Ultimate Owner information (*GUO50c*), as well as the Global Ultimate Owner variable that combines data related to firms acting as Global Ultimate Owners or individuals (*GUO50*). The rationale behind this approach is to account for cases where we are unable to identify a company as the GUO, thereby enabling us to assign a person as the GUO and subsequently construct the tax rate differentials under this person. However, when a company is identified as the GUO, we prioritize it over individuals.

Subsequently, we merge the historical ownership links from previous years (2009 to 2019) with the firm-year observations to account for changes in the current ownership links. As anticipated, we observe a greater number of ownership link changes as we move further back in time. For instance, when comparing the ownership links from 2019 with the current situation, we find 394,131 changes, whereas merging the ownership links from 2013 yields a maximum of 1,454,145 changes. Following this, we drop observations for which we could not assign a GUO and ascertain that the remainder firms are of the corporate entity type. Consequently, this leads to a significantly reduced sample size of 64,880,507 firm-year observations.

Next, we establish the country code for each firm in our study sample. We perform a merge operation with BvD's country ISO code and cross-reference it with the country code derived from the first two letters of the *bvd_id*, as outlined in Kalemli-Özcan et al. (2022). In the rare occurrence of discrepancies between these two variables (accounting for only 0.1% of our sample), we prioritize the country ISO code (our results are robust to the exclusion of these cases). In terms of industry classification, we merge our firm-year level data with the NACE 4-digit level code and the NACE main section variable. However, we are unable to identify these two variables for 1,773,986 observations.

The current sample includes 64,880,507 firm-year observations. Among these, 52,346,485 observations have matching identifiers between the *bvd_id* and the GUO's *bvd_id* (referred to as *guobvd_id* for simplicity). It is important to note that these observations should not be discarded at this stage due to the presence of additional *bvd_ids* (firms) associated with the same GUOs in both the current sample and the corporate ownership links files. This is because we need to consider all available *bvd_ids* to construct the tax rate differentials.

Our current sample (from now on, our current sample will be referred to as the "main sample") includes firm-year observations that contain non-missing values for financial variables, namely *Profit before taxes* (pre-tax profits) and *Total assets*. However, historical corporate ownership link files reveal cases where other *bvd_ids*, associated with a particular GUO in our main sample, lack financial information. Following the approach outlined by Johansson et al. (2017), it is imperative to retain these firms *to construct unweighted tax rate differentials that account for tax rates across all countries where the multinational group operates*, including firms without available financial information. As a result, we create a separate sample called the "tax differential file" that exclusively contains unique *guobvd_id*-year observations from our main sample. We then merge this tax differential file with the ownership links files. In the tax differential file, we have 102,038,268 firm-year observations under the related GUOs. Here again, we observe that even for the ownership links of firms, ORBIS has a 2-3 year lag, resulting in a decrease in observations from 12,385,249 in 2018 to 11,437,434 in 2019.

Within the tax differential file, we refine the ownership links using the following procedure. Orbis defines the GUO as the top firm holding at least a 50% + 1 stake in the observed firm. However, there are cases where the GUO identified in Orbis vintage may be owned by a different company that, on its own, holds (indirectly) less than a 50% + 1 stake in the low-tier firm. In such scenarios, we systematically identify the top-tier firm or the individual within each multinational group. This identification process allows us to rectify the GUO not only in our tax differential file but also in our main sample.

Additionally, in the tax differential file, we exclude firms that lack a corporate legal entity type, and we follow a similar procedure to assign a country code as that in our main sample. We also remove all firms with a country ISO code equal to WW, YY, and ZZ, as these codes do not correspond to a country. Finally, we merge this tax differential file with the statutory tax rates of the country where each firm is located. We gather statutory tax rates from four different sources: Ernst & Young's Worldwide Corporate Tax Guides, PwC Worldwide Tax Summaries, IBFD Tax Research Platform, and the corporate tax rates of Tax Foundation. Whenever there is a disagreement in the data, specifically when different tax rates are reported for a particular country-year, we prioritize the information provided by Tax Foundation.

The literature distinguishes between the use of effective tax rates in one way or another (Clausing, 2020b; Guvenen et al., 2022; Tørsløv et al., 2023; Garcia-Bernando and Jansky, 2022) and statutory tax rates (Devereux, 2007; Bratta et al. 2021; Beer et al., 2020; Johansson et al. 2017). Several tax deductions offered by different national tax systems tend to differentiate effective tax rates (ETRs) from statutory ones. Given that effective tax rates relate to endogenous corporate choices (e.g., use of depreciation, amortization, debt, or other deductible expenses), we prefer statutory tax rates. Accounting for changes in ETRs and their impact on profits might overestimate profit shifting by adding tax deductions and depreciations on it. Absent special tax regimes and tax holidays, statutory corporate tax rates are precisely the rates applying to the marginal unit of profits and thus capture the true incentive for profit shifting. Moreover, MNEs shift profits among affiliates across countries in which they already operate. Thus, they exploit tax allowances, which depend on differences in the statutory (and not the effective) tax rate (Deveraux, 2007; Huizinga and Laeven, 2008).

Despite consulting four different sources of statutory tax rates, we were unable to identify the country-year statutory tax rates for 13,560 observations in our tax differential file. We exclude these observations from our analysis. To facilitate our analysis, we break down the data of the tax differential file into 11 separate files. Each file corresponds to a specific year, ranging from 2009 to 2019. This separation allows us to measure the tax rate differential for each firm under a GUO within a particular year.

To simplify our computationally intensive calculations within each annual file, we implement additional filters. We drop cases where multiple firms under a specific GUO reside in the same country or in different countries with identical statutory tax rates. In these situations, the numerator of the tax rate differential variable is zero, rendering the calculation unnecessary for our purposes.

We then merge back these annual files to our tax differential file and subsequently merge it with our main sample. From this process, we identify 5,048,651 observations in our main sample that have a non-zero tax rate differential. The presence of a zero tax differential indicates the absence of a tax incentive to shift profits, so our focus is on observations with a non-zero differential. These are the tax rate differentials for all the firm-year observations under a specific GUO. However, there are cases where the GUO has only one firm under it or some GUOs may not have their *bvd_id* included in the multinational group within the tax differential file, as we refine the ownership links in this file using the process described above. Nevertheless, we do possess information regarding the country where the GUO is located. Therefore, we incorporate this information into the tax rate differentials exclusively for corporate GUOs, excluding individual GUOs, as we are able to assign a tax rate to the former. To achieve this, we employ the same methodology used previously during the merging process by firm-year. We merge all GUO characteristics such as entity type, country ISO code, NACE 4-digit level code, NACE main section, and the statutory tax rates of the country where each GUO resides. Subsequently, we recalculate the tax rate differentials, resulting in 5,269,812 observations with a non-zero tax rate differential. Finally, we merge the names of all firms (*bvd_id*) and the names of all GUOs.

To employ the Huizinga and Laeven (2008) methodology and incorporate the various specifications proposed by Beer et al. (2020) and Heckemeyer and Overesch (2017), we proceed as follows. We merge GDP per capita, GDP growth, and Inflation from the World Bank Data in our main sample. Further, we apply the logarithmic transformation to most of the variables used in our specifications (*Fixed assets*, *Tangible fixed assets*, *Number of employees*, *Profit before taxes,* and *GDP per capita).* This results in a sample of 1,974,062 observations in our main specification. However, as mentioned earlier, when using Orbis vintage 2021, there is a time lag of 2-3 years in the available data. In our main specification, the table below presents the number of observations per year.

Year	Obs.	Percent
2009	141,215	7.15
2010	143,012	7.24
2011	153,820	7.79
2012	160,937	8.15
2013	166,447	8.43
2014	179,338	9.08
2015	197,695	10.01
2016	209,713	10.62
2017	226,902	11.49
2018	220,536	11.17
2019	174,448	8.84
Total	1,974,062	100

We notice a peak in observations in 2017, followed by a decline. To ensure comprehensive coverage for the years 2018, 2019, and even 2020 (which was initially excluded due to limited data), we conduct the same analysis described above using the Orbis vintage 2022 dataset. This provides more firm-year observations in our main specification (2,277,435). The table below presents the new number of observations per year, which are the ones used in the estimations of profit shifting:

Year	Obs.	Percent
2009	141,215	6.20
2010	143,012	6.28
2011	153,820	6.75
2012	160,937	7.07
2013	166,447	7.31
2014	179,338	7.87
2015	197,695	8.68
2016	209,713	9.21
2017	226,902	9.96
2018	246,665	10.83
2019	236,537	10.39
2020	215,154	9.45
Total	2,277,435	100

Our analysis reveals a peak in observations in 2018, which supports the findings of Kalemli-Özcan et al. (2022) regarding the improving data collection methods of BvD over time. However, this peak is followed by a subsequent decline, which also aligns with the argument regarding a reporting lag. Additionally, Kalemli-Özcan et al. (2022) highlight variations in the coverage of specific variables based on the release dates of BvD's product, and variations across countries. In our sample, it appears that the reporting is possibly around three years. This is supported by the discontinuation of the upward trend in observations from 2009 to 2018 after 2019. We attribute this to either a lag in the financial variables in the Orbis files or a lag in the historical corporate ownership files. Despite the potential presence of such a lag, we include all available years, and intend to further investigate this matter using upcoming editions of Orbis.

Annex 2. Relevance of the random coefficients model

The random coefficients model is a natural alternative to estimate observation-specific coefficients. However, there are two important theoretical advantages of the nonparametric approach in the current analysis:

1. Random coefficient models assume linearity in estimating varying coefficients, similar to linear regression. However, the relationship between *Tax differential* and *Profit before taxes* can be nonlinear due to diverse profit-shifting behaviors in multinational groups (Dowd et al., 2017; Garcia-Bernando and Jansky, 2022; Fuest et al., 2022). Nonparametric models offer an advantage in such cases, as they do not require specific functional assumptions; the data itself shapes the model. While there has been a proposal for nonparametric random coefficient models in recent literature, existing software tools have not yet incorporated this development. Even if they were to include it, we anticipate that the computational burden would be even higher.
2. Random coefficient models come in two main forms: stationary, which have constant means and variance-covariance, and nonstationary, which is of particular interest in our case. In nonstationary models, the varying coefficients are linked either to a nonstationary stochastic process or to exogenous variables (e.g., Hsiao and Pesaran, 2008). The assumptions in this context can lead to significantly different results, especially when using different exogenous variables, which is the prevalent approach. This reliance on exogenous variables makes it essential to carefully consider model specifications. However, the nonparametric model presents a promising solution by not requiring specific exogenous variables to form the varying coefficients.

Annex 3. Additional tables

Table A1. Summary Statistics by Country

This table lists the 100 countries included in our sample, providing information on the number of firm-year observations and average statutory tax rates for each country. The total number of observations is 2,277,435.

Country	Observations	Statutory tax rate (Avg.)
Albania	196	0.15
Argentina	81	0.35
Armenia	2	0.19
Australia	16,342	0.30
Austria	19,963	0.25
Bangladesh	6	0.25
Belarus	246	0.18
Belgium	106,581	0.32
Bermuda	5	0.00
Bolivia	22	0.25
Bosnia and Herzegovina	7,666	0.10
Botswana	6	0.22
Brazil	3,258	0.34
Bulgaria	28,635	0.10
Burkina Faso	4	0.28
Cabo Verde	6	0.25
Chile	73	0.19
China	75,940	0.25
Colombia	371	0.31
Croatia	25,619	0.19
Cyprus	1,166	0.12
Czech Republic	65,198	0.19
Denmark	64,543	0.23
Dominica	5	0.30
Ecuador	5	0.23
Egypt	115	0.23
Estonia	16,666	0.20
Ethiopia	5	0.30
Finland	34,712	0.22
France	183,184	0.35
Georgia	29	0.15
Germany	120,475	0.30
Greece	11,948	0.26
Hong Kong	30	0.17
Hungary	33,804	0.15
Iceland	1,626	0.20
India	1,288	0.33
Iran	61	0.25
Iraq	5	0.15

Ireland	15,306	0.13
Israel	43	0.24
Italy	230,229	0.30
Jamaica	2	0.33
Japan	92,368	0.33
Jordan	11	0.15
Kazakhstan	1,490	0.20
Kuwait	39	0.15
Latvia	18,900	0.16
Lebanon	6	0.16
Liechtenstein	21	0.13
Lithuania	13,647	0.15
Luxembourg	3,064	0.29
Malaysia	11	0.24
Malta	738	0.35
Mauritius	2	0.15
Mexico	1,500	0.30
Moldova	538	0.12
Monaco	6	0.33
Montenegro	1,412	0.09
Morocco	3	0.31
Namibia	2	0.32
Netherlands	34,829	0.25
New Zealand	10	0.28
North Macedonia	3,423	0.10
Norway	43,122	0.24
Oman	25	0.13
Pakistan	378	0.31
Panama	17	0.26
Peru	91	0.29
Philippines	390	0.30
Poland	54,654	0.19
Portugal	65,736	0.30
Qatar	6	0.10
Romania	70,127	0.16
Russia	155,751	0.20
Saudi Arabia	46	0.20
Serbia	23,856	0.14
Singapore	206	0.17
Slovak Republic	37,533	0.21
Slovenia	18,708	0.18
South Korea	25,527	0.25
Spain	179,238	0.27
Sri Lanka	225	0.27
St. Kitts and Nevis	3	0.34
St. Lucia	4	0.30

Sweden	142,332	0.23
Switzerland	305	0.21
Tanzania	10	0.30
Trinidad and Tobago	3	0.25
Turkey	90	0.20
Ukraine	47,447	0.20
United Arab Emirates	14	0.00
United Kingdom	174,031	0.22
United States	3	0.39
Uruguay	37	0.25
Uzbekistan	15	0.13
Vietnam	5	0.24
West Bank and Gaza	6	0.15
Zambia	5	0.35
Zimbabwe	2	0.26
Total / Average	2,277,435	0.25

Table A2. Summary Statistics by Country (GUO)

This table lists the 189 countries of GUOs included in our sample, providing information on the number of GUO-year observations and average statutory tax rates for each country. The total number of observations is 789,345.

Country (GUO)	Observations	Statutory tax rate (Avg.)
Afghanistan	11	0.20
Albania	156	0.14
Algeria	833	0.25
Andorra	130	0.09
Angola	210	0.32
Anguilla	333	0.00
Antigua and Barbuda	18	0.25
Argentina	151	0.34
Armenia	38	0.19
Aruba	9	0.28
Australia	6,558	0.30
Austria	18,794	0.25
Azerbaijan	86	0.20
Bahamas	820	0.00
Bahrain	65	0.00
Bangladesh	27	0.25
Barbados	61	0.22
Belarus	1,108	0.19
Belgium	29,024	0.32
Belize	2,016	0.24
Benin	16	0.30
Bermuda	2,243	0.00
Bhutan	1	0.30
Bolivia	7	0.25
Bosnia and Herzegovina	1,961	0.10
Botswana	10	0.22
Brazil	1,001	0.34
British Virgin Islands	14,676	0.00
Brunei Darussalam	31	0.20
Bulgaria	3,473	0.10
Burkina Faso	10	0.28
Burundi	1	0.30
Cabo Verde	44	0.24
Cambodia	62	0.20
Cameroon	78	0.35
Canada	4,271	0.27
Cayman Islands	3,451	0.00
Central African Republic	3	0.30
Chad	12	0.39
Chile	275	0.22
China	11,294	0.25
Colombia	211	0.31

Congo, Dem. Rep.	21	0.36
Congo, Rep.	16	0.32
Costa Rica	47	0.30
Cote d'Ivoire	58	0.25
Croatia	5,005	0.19
Cuba	10	0.35
Curacao	1,307	0.27
Cyprus	39,674	0.12
Czech Republic	13,917	0.19
Denmark	24,845	0.23
Djibouti	2	0.25
Dominica	276	0.28
Dominican Republic	40	0.27
Ecuador	36	0.24
Egypt	256	0.23
El Salvador	9	0.29
Eritrea	2	0.30
Estonia	4,749	0.20
Eswatini	2	0.28
Ethiopia	10	0.30
Fiji	5	0.29
Finland	10,297	0.22
France	37,045	0.35
Gabon	15	0.33
Georgia	74	0.15
Germany	65,349	0.30
Ghana	10	0.25
Gibraltar	1,092	0.13
Greece	3,499	0.26
Grenada	3	0.30
Guatemala	3	0.25
Guinea	6	0.35
Guinea-Bissau	28	0.25
Guyana	9	0.28
Haiti	28	0.30
Honduras	1	0.25
Hong Kong	8,632	0.17
Hungary	9,046	0.14
Iceland	915	0.20
India	3,135	0.33
Indonesia	94	0.25
Iran	224	0.25
Iraq	19	0.15
Ireland	4,636	0.13
Israel	2,545	0.25
Italy	72,385	0.30

Jamaica	30	0.28
Japan	29,927	0.33
Jordan	40	0.17
Kazakhstan	178	0.20
Kenya	8	0.30
Kiribati	4	0.35
Kuwait	193	0.15
Kyrgyz	25	0.10
Lao PDR	20	0.29
Latvia	2,642	0.16
Lebanon	614	0.15
Liberia	254	0.27
Libya	33	0.27
Liechtenstein	2,017	0.13
Lithuania	3,697	0.15
Luxembourg	19,507	0.28
Macao SAR, China	90	0.12
Madagascar	40	0.21
Malawi	5	0.30
Malaysia	715	0.25
Mali	11	0.30
Malta	2,488	0.35
Marshall Islands	170	
Mauritania	8	0.25
Mauritius	582	0.15
Mexico	706	0.30
Moldova	530	0.10
Monaco	283	0.33
Mongolia	15	0.25
Montenegro	552	0.09
Morocco	923	0.30
Mozambique	23	0.32
Namibia	4	0.33
Nepal	6	0.25
Netherlands	30,018	0.25
New Zealand	803	0.28
Nicaragua	2	0.30
Niger	3	0.30
Nigeria	51	0.30
North Macedonia	577	0.10
Norway	14,583	0.25
Oman	63	0.13
Pakistan	215	0.31
Panama	2,630	0.26
Papua New Guinea	4	0.30
Paraguay	10	0.10

Peru	75	0.29
Philippines	136	0.30
Poland	6,884	0.19
Portugal	13,229	0.30
Qatar	133	0.11
Romania	3,690	0.16
Russia	7,400	0.20
Rwanda	14	0.30
Samoa	267	0.00
San Marino	278	0.17
Sao Tome and Principe	23	0.25
Saudi Arabia	266	0.20
Senegal	72	0.28
Serbia	2,581	0.14
Seychelles	3,473	0.32
Sierra Leone	1	0.30
Singapore	2,650	0.17
Sint Maarten (Dutch part)	1	0.35
Slovak Republic	7,693	0.21
Slovenia	7,219	0.18
South Africa	699	0.30
South Korea	7,173	0.25
Spain	42,346	0.27
Sri Lanka	188	0.27
St. Kitts and Nevis	332	0.34
St. Lucia	12	0.30
St. Vincent and the Grenadines	283	0.32
Sudan	1	0.35
Suriname	106	0.36
Sweden	35,917	0.23
Switzerland	20,892	0.21
Syria	46	0.28
Taiwan	2,672	0.18
Tajikistan	4	0.23
Tanzania	15	0.30
Thailand	287	0.23
Timor-Leste	6	0.10
Togo	13	0.28
Trinidad and Tobago	12	0.25
Tunisia	803	0.27
Turkey	3,000	0.21
Turkmenistan	2	0.08
Uganda	5	0.30
Ukraine	1,424	0.19
United Arab Emirates	1,458	0.00
United Kingdom	39,428	0.22

United States	47,268	0.35
Uruguay	173	0.25
Uzbekistan	226	0.10
Vanuatu	17	0.00
Venezuela	72	0.34
Vietnam	108	0.22
West Bank and Gaza	7	0.15
Zambia	7	0.35
Zimbabwe	3	0.25
Total / Average	789,345	0.25

Table A3: OLS estimation of profit shifting

The table reports coefficient estimates and standard errors (in parentheses) from the estimation of equation (1). Dependent variable is firm's *Profit before taxes* and all variables are defined in Table 1. The lower part of the table denotes the type of fixed effects. We report White's (1980) heteroscedasticity-consistent standard errors in parentheses for all specifications. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)
Tangible fixed assets			0.340***	0.340***	0.345***
			[0.001]	[0.001]	[0.001]
Number of employees			0.421***	0.421***	0.444***
			[0.001]	[0.001]	[0.001]
GDP per capita		0.607***		0.394***	0.361***
		[0.018]		[0.013]	[0.013]
GDP growth		0.005***			
		[0.001]			
Inflation		-0.005***			
		[0.001]			
Tax differential	-3.363***	-3.402***	-2.071***	-2.095***	-1.933***
	[0.025]	[0.025]	[0.019]	[0.019]	[0.019]
Observations	2,232,640	2,232,621	2,232,640	2,232,640	2,199,896
Adjusted R-squared	0.173	0.174	0.548	0.548	0.562
Country	Y	Y	Y	Y	Y
Year	Y	Y	Y	Y	Y
Industry	N	N	N	N	Y
Standard errors	Robust	Robust	Robust	Robust	Robust

Table A4. Ireland-France connection (Case 1)

The table displays the top country-GUO connection from Table 9. It ranks the 560 firm-year observations of this connection based on their profit shifting ratio and identifies the country with the lowest tax rate within the MNE group associated with each firm-year observation. This lowest tax rate information is integrated into the tax differential for each specific firm-year observation. Further, the table provides the semi-elasticity values for these firm-year observations.

Lowest tax rate in the MNE group	Country	GUO country	Profit shifting ratio	Observations	Semi-elasticity
Vanuatu	Ireland	France	0.47	1	3.50
Hungary	Ireland	France	0.35	35	3.14
Maldives	Ireland	France	0.34	1	2.18
Serbia	Ireland	France	0.34	2	2.21
United Arab Emirates	Ireland	France	0.33	240	2.57
Ireland	Ireland	France	0.33	161	2.44
Cayman Islands	Ireland	France	0.32	12	2.12
Gibraltar	Ireland	France	0.31	3	2.88
Bahrain	Ireland	France	0.31	21	2.29
Bermuda	Ireland	France	0.31	23	2.29
Barbados	Ireland	France	0.30	2	2.95
British Virgin Islands	Ireland	France	0.28	17	2.45
Bulgaria	Ireland	France	0.28	34	1.95
Paraguay	Ireland	France	0.27	4	1.84
Uzbekistan	Ireland	France	0.25	3	1.59
Bahamas	Ireland	France	0.23	1	1.27

Table A5. Ireland-United States connection (Case 2)

The table displays the second-top country-GUO connection from Table 9. It ranks 3931 firm-year observations of this connection based on their profit-shifting ratios and identifies the country with the lowest tax rate within the MNE group associated with each firm-year observation. This lowest tax rate information is integrated into the tax differential for each specific firm-year observation. Further, the table provides the semi-elasticity values for these firm-year observations.

Lowest tax rate in the MNE group	Country	GUO country	Profit shifting ratio	Observations	Semi-elasticity
Bosnia and Herzegovina	Ireland	United States	0.38	2	2.48
Cyprus	Ireland	United States	0.34	32	2.44
Belize	Ireland	United States	0.34	3	3.48
North Macedonia	Ireland	United States	0.34	1	1.97
Bahamas	Ireland	United States	0.33	33	2.63
China, Macao	Ireland	United States	0.33	20	2.78
Gibraltar	Ireland	United States	0.32	11	2.45
Cayman Islands	Ireland	United States	0.32	540	2.49
Bermuda	Ireland	United States	0.32	580	2.52
Bahrain	Ireland	United States	0.32	51	2.60
United Arab Emirates	Ireland	United States	0.32	622	2.71
Bulgaria	Ireland	United States	0.31	69	2.30
Qatar	Ireland	United States	0.31	4	1.90
Ireland	Ireland	United States	0.31	1,586	2.44
British Virgin Islands	Ireland	United States	0.31	234	2.46
Serbia	Ireland	United States	0.31	17	2.12
Liechtenstein	Ireland	United States	0.30	2	3.01
Hungary	Ireland	United States	0.30	94	2.89
Paraguay	Ireland	United States	0.30	4	2.03
Barbados	Ireland	United States	0.30	11	3.09
Oman	Ireland	United States	0.29	1	1.55
Moldova	Ireland	United States	0.29	9	1.82
Anguilla	Ireland	United States	0.25	4	2.80
Montenegro	Ireland	United States	0.17	1	0.97

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