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Global evidence on profit shifting within firms and across time

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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 the profits of both parent and subsidiary firms within a multinational group respond to marginal changes in the composite tax indicator. The key advantage of this approach is that it yields firm-year estimates of profit shifting. Multinational firms engage in extensive profit shifting by maintaining affiliates in low-tax countries and zero-tax havens. Multinational groups with an ultimate tax-haven owner exhibit the largest profit response to tax incentives. Our new database opens important avenues for analyzing the sources and effects of profit shifting.

Keywords: Profit shifting; multinational enterprises; nonparametric estimation; tax arbitrage; global sample
JEL Classification: F23; H25; H26; H32; M41

Executive summary: Large global companies commonly engage in tax planning strategies to move their profits from high-tax countries to low-tax (or no-tax) countries to reduce the amount of taxes they pay. Such "shifting" of profits across borders within multinational enterprises is known as "profit shifting". Such profit-shifting practices cost governments billions of US dollars in lost tax revenues annually. This has triggered policy changes from governments to contain this practice. The most prominent policy change is the June 2021 agreement among G7 finance ministers to seek a minimum global corporate tax rate of at least 15 percent, which followed the OECD's Base Erosion and Profit Shifting (BEPS) initiative to limit profit shifting. In this paper, we provide global estimates of profit shifting using firm level data. Most existing studies either focus only on profit shifting within or across firms, and do not consider variation in profit shifting over time. We use the most complete sample of firms and their foreign subsidiaries to date to estimate profit shifting both within and across firms and measure shifts in such patters over time. In total, our dataset covers more than 2 million firm-year observations of around half a million firms from across 100 different countries over the period 2009–2020.

Our new estimates of profit shifting enable us to trace the origin of profit shifting and to better identify the underlying drivers of profit shifting. Moreover, our time-varying estimates of profit shifting, along with dynamic information on the corporate ownership links, allow us to identify the physical routes of profit shifting via intermediate countries. Specifically, we determine tax routes involving strings of multiple countries and identify the industries and ownership structures involved. Thus, we offer a more detailed view of how firms conduct profit shifting compared to simply specifying the origin and destination countries. This offers the information required to assess the effects of specific BEPS actions and bilateral agreements. Finally, with our richer dataset we obtain more comprehensive estimates of profit shifting that indicate that the amount of profits shifted globally exceeds the estimates obtained to date in the literature using firm level data.

To obtain firm-year estimates of profit shifting we estimates a standard model of profit shifting using local regression techniques. This technique differs from the more widely used method of ordinary least squares (OLS) because it does not assume that the relationship between company earnings and tax differences is constant over time. Instead, it creates sliding windows of observations around each data point, allowing us to estimate the response of firm profits to the tax incentive by considering nearby observations. Estimation of the local regression entails repeating this approach for each data point in our dataset, resulting in a profit-shifting estimate for each firm-year observation.

We find that profit shifting is heavily concentrated in several industries, such as the pharmaceutical, petroleum, and information technology industries engage in the greatest profit shifting. At a global level, we find that profit shifting increased over time from around 300 billion US dollars in 2009 to more than 700 billion US dollars in 2017. Delving deeper into the global routes of profit shifting, we find that a substantial amount of profit shifting flows through tax havens and low-tax jurisdictions, such as Bermuda, the British Virgin Islands, the Cayman Islands, the United Arab Emirates (UAE), and Ireland. Our more comprehensive estimates of profit-shifting obtained using firm-level data are broadly in line with those obtained based on aggregate data.

1. Introduction

Tax-motivated profit shifting refers to the tax planning strategies of multinational enterprises (MNEs) and their "shifting" of profits from parent companies or subsidiaries located in high-tax jurisdictions to subsidiaries in low-tax jurisdictions to reduce taxes. Recently, this practice has attracted considerable interest from academics and policymakers. The erosion of government revenue bases resulting from profit shifting poses fiscal risks and tax fairness issues. This has triggered efforts and policies from governments and international organizations to contain this practice. The most prominent of these efforts is the OECD's Base Erosion and Profit Shifting (BEPS) initiative and the June 2021 agreement among G7 finance ministers to seek a minimum global 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 revenues annually.[1] Using macro-level data, Wier and Zucman (2022) suggest that annual revenue losses have exceeded the upper end of these estimates in recent years. When using micro-level (firm) data to estimate profit shifting, the most common practice is to estimate a model of the response of firm (parent and/or subsidiaries) profit to tax incentives (Hines and Rice, 1994; Huizinga and Laeven, 2008; Klassen and Laplante, 2012; Dharmapala and Riedel, 2013; Dyreng et al., 2023). Tax incentives are typically measured as the differential corporate tax rates between the countries where the multinational firm has subsidiaries. It is assumed that an increase in tax rate differences incentivizes firms to allocate more profits to lower tax jurisdictions. 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. Estimates obtained using firm-level data are generally lower compared to estimates obtained using macro-level data (Clausing, 2016; Clausing, 2020; Tørsløv et al., 2023). Additionally, many studies focus exclusively on either parent firms or

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

their subsidiaries, thereby not capturing a significant part of the total profit shifting of the multinational firm.

Our study's contributions to the literature are threefold. First, we provide subsidiary-year, parent-year, and MNE-year estimates of profit shifting, and we do this for the largest global sample to date, if we consider both the country dimension and the number of firms. Most existing studies either focus only on one organizational dimension of profit shifting (subsidiary, parent, or MNE) or do not consider firm-year variation in profit shifting. Our new estimates enable us to better identify the patterns of profit shifting within and across firms and measure shifts in such patterns over time. Knowledge of such profit-shifting patterns allows researchers to examine the economic motivations (e.g., firm or country characteristics) driving profit shifting in more detail. Moreover, these estimates can be used to trace the origin of profit shifting (e.g., whether profit shifting to subsidiaries in a given country is the result of profit shifting out of the parent country or out of subsidiaries in another country).

Second, our firm-year estimates, along with dynamic information on the ownership links, allow us to identify the routes of profit shifting via intermediate countries. This directly relates to the analysis by Dyreng et al. (2015) who examine how U.S. MNEs strategically use and locate foreign subsidiaries and holding companies to shift profits. Specifically, we determine tax routes involving strings of multiple countries, including mediating countries, and identify the industries and ownership structures involved. Thus, we offer a more detailed view of how firms conduct profit shifting compared to simply specifying the origin and destination countries. This provides important information for policymakers and practitioners to analyze and inform specific BEPS actions and bilateral agreements.

Third, we add to the literatures on the estimation of profit shifting using micro and macro data, which tend to obtain a wide range of estimates (e.g., Blouin and Robinson, 2020; Dyreng et al., 2023; Tørsløv et al., 2023). Using more comprehensive micro-level data than those used to date, we obtain estimates of profit-shifting that are larger than those typically obtained in the literature using micro-level data and somewhat smaller than the macro estimates. We obtain these results in both the parametric and nonparametric models.

We build a dataset of the financials of MNEs (including their parents and subsidiaries) using the "vintages" of Bureau Van Dijk's Orbis database, in conjunction with historical ownership links data. We also incorporate unweighted tax differentials and reconstruct ownership links. With these advancements, we can expand our analysis over a broad timespan, provide valuable insights into firm ownership across different years, and offer detailed information on firm location, 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 2,277,435 firm-year observations from 100 countries and 565,814 firms for the period 2009–2020.

Our empirical approach involves estimating the model of Huizinga and Laeven (2008) using a nonparametric technique, specifically, the local regression, to obtain firm-year estimates of profit shifting. This method differs from ordinary least squares (OLS) because it does not assume a fixed slope for the entire sample. Instead, it creates sliding windows of observations around each data point, allowing us to estimate the response of firm profits to the tax incentive by considering nearby observations. Estimation of the local regression entails repeating this approach for each data point in our dataset, resulting in a profit-shifting estimate for each firm-year observation. An additional advantage of this nonparametric approach over OLS is that it fully accounts for the potential nonlinearity in the relationship between earnings and tax differences (e.g., Fuest et al., 2022).

From a micro perspective, we find that firms in the pharmaceutical, petroleum, and information technology industries engage in the greatest profit shifting. We identify well-known large firms as the top 20 profit shifters. We provide evidence of the consistency of these findings with anecdotal evidence, news reports, and empirical facts from specific case studies.

From a macro perspective, the mean semi-elasticity of firm profits to differential taxation between the countries where the MNE firms are located (our baseline measure of profit shifting) increases from 2.4 in 2009 to 3.2 in 2015 and 2016. It then decreases in 2018 and 2019 and only rebounds in 2020. These estimates tend to exceed those obtained in other studies using micro-level data but are slightly smaller than recent estimates based on macro data (Clausing, 2020). When translated into US dollars, our results indicate a profit shifting of approximately 311 billion USD in 2009 to more than 700 billion USD in 2017.

An important advantage of firm-year estimates is that they enable us to delve deeper into the direction of profit shifting between an MNE's firms in different countries. 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 France or the United States. Generally, Irish firms claim most of the top spots in this ranking. Delving deeper into these connections, we find that many of the highest profit-shifting ratios in the Ireland-France and Ireland-United States connections are associated with tax havens in which MNEs maintain subsidiaries. Consistent with this finding, outbound connections with Global Ultimate Owners (GUOs) in various tax havens occupy top positions in terms of profit shifting. Notably, among the MNEs engaging in the most profit shifting, those with GUOs in the US and subsidiaries in low-tax jurisdictions, such as Bermuda, the British Virgin Islands, the Cayman Islands, the United Arab Emirates (UAE), and Ireland, are by far the most prominent. Generally, firm-year estimates allow us to uncover profit-shifting patterns in several industries and countries over time.

Finally, we incorporate firm-year observations with negative profits (loss-making firms) into the analysis, adding 1,103,920 observations to our sample. The results obtained using this extended sample are broadly consistent with those excluding loss-making firms in terms of industry and country pair rankings. However, they reveal even larger estimates of profit shifting, with global profit-shifting estimates surpassing the trillion US dollar mark from 2013 onward, representing up to 38 percent of the reported consolidated profits in 2019. This aligns with the estimates obtained by Wier and Zucman (2022) using macro-level data, who estimate global profit shifting in 2019 of 969 billion US dollars or 37 percent of global multinational profits.

One validation of our approach is that the outbound estimates of profit shifting for each MNE-year should approximately equal the inbound estimates, which we find to be the case. In addition, we use Monte Carlo simulations to validate the robustness of our estimates. We simulate the data using the characteristics of our sample and execute four programs. The first program shows that the mean estimate from multiple replicates aligns with the baseline results. The second program shows that a shock that generates a higher incentive to shift profits decreases the semi-elasticity of firms' profits to the tax variable, implying increased profit shifting. The third program introduces a shock to only part of the sample and documents an increase in profit shifting solely among firms within that part. The last program introduces a placebo test that shocks only firm profits, holding taxes constant, and demonstrates that the semi-elasticity remains unchanged. All these tests support our main findings.

The remainder of this paper is organized as follows. Section 2 discusses the empirical model used to identify profit shifting and provides thorough information on the data collection and cleansing processes. We also discuss the details of the nonparametric estimation of the model and the importance of these estimates to academics and policymakers. Section 3 presents the estimates of the global profit-shifting database across years, firms, industries, and countries and validates our methodology. Finally, Section 4 concludes the paper and provides directions for future research.

2. Modelling profit shifting

2.1. Empirical model and variables

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

The empirical model is the following:

$$log\, \pi_{it} = gCT_{it} + a_2\, log\, A_{it} + \gamma X_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{1}$$

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, measured using GDP per capita in logs (*GDP per capita*). X_{it} is a vector of firm-year and country-year controls, including the log of noncurrent assets (*Noncurrent assets*) as our measure of capital,[2] the log of the number of employees

[2] The variable *Noncurrent assets* in our specification encompasses all noncurrent assets on a firm's balance sheet, both tangible and intangible. We acknowledge that while intangible assets can be strategically located for tax purposes, they represent only a small share of our noncurrent assets variable (about 10% on average in our sample).

(*Number of employees*) as our measure of labor,[3] and country-level controls such as *GDP growth* and *Inflation*. The term μ_i represents country fixed effects, which control for time-invariant unobserved characteristics specific to the countries where firms reside. These characteristics include, but are not limited to, regulatory quality, financial secrecy laws, and low transparency regimes. The term δ_t denotes year fixed effects, controlling for time-varying unobserved common changes affecting firm profitability. Finally, ε_{it} is the error term.[4] We provide explicit definitions of all the 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 to real ones (Beer et al., 2020). We mainly follow the preferred specification in the literature, which uses the logarithm of observed pre-tax income as a 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.

[3] Admittedly, using the number of employees instead of employee expenses is a deviation from a standard estimation of a profit function. We take comfort in the fact that *Number of employees* and *Cost of employees* are very highly correlated in our sample (88.4%), whereas the correlation coefficient between the tax variable and the two measures is lower than 6%. Using the number of employees allows us to maximize the number of observations in our sample. If we alternatively, use *Cost of employees* and a smaller sample, we find estimates of profit shifting that are a bit smaller. This decrease, however is entirely due to the smaller number of observations. We verify this by comparing estimates for the sample where *Cost of employees* is available.

[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 refrain from controlling for subsidiary fixed effects to avoid diminishing the identified tax effects on profitability, as substantial cross-sectional tax rate variation would be absorbed. Moreover, including GUO fixed effects would eliminate the variation stemming from established tax strategies, which are fundamental to our investigation, and would focus variation solely on changes in tax rate differentials within the multinational groups (Clausing 2006; Clausing 2016; Heckemeyer and Overesch, 2017).

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

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

where τ_i is the statutory tax rate of the firm's country and τ_k the statutory tax rates of all *N* affiliated firms' countries. We obtain these tax rates from Ernst and Young's Worldwide Corporate Tax Guides, PwC's Worldwide Tax Summaries, the 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. A higher value for the composite tax differential variable CT_{it} denotes steeper tax-incentives to shift profits outward for firm i, thereby lowering its reported profits (π_{it}). If $\tau_i > \tau_k$ for every country k, then CT_{it} is positive and there are strong incentives to shift profits away from firm i, while if $\tau_i < \tau_k$ for every country k, then CT_{it} is negative and there are strong incentives to shift profits to firm i.

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

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

2.2. Data collection and summary statistics

A key distinction of our empirical analysis is the intensive sample construction process. We discuss the full process 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 historical ownership links (2009-2019). This is important for three interrelated reasons (thoroughly analyzed in the Appendix). First, we need dynamic ownership data since we document significant ownership changes during our sample period (Grosskurth, 2019). Doing so alleviates misclassification and any downward bias in our profit-shifting estimates, as also highlighted by Budd et al. (2005). Second, our coverage extends 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 firms and GUOs worldwide, even when financial data are 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 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 controlled by 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 by Tørsløv et al. (2023). Moreover, it mirrors the 0.25 average statutory corporate tax rate when weighted by GDP (Tax Foundation, 2021).

Following Dowd et al. (2017), in part of our analysis, we include a dummy variable (*Tax haven*) that takes the value of 1 when a multinational group includes a tax haven firm (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. This approach is used because this information is included in the *Tax differential*, creating more pronounced tax rate differentials for the firm-year observations associated with these tax havens, which results in more incentive to shift profit. This is the case for the 439,897 firm-year observations, representing 19.3% of the sample. Our list of tax havens is from Tørsløv et al. (2023). When we assign a value of 1 only to those firm-years that are in tax havens, the results remain robust.

Estimating profit shifting using firm-level unconsolidated data has limitations, with the primary constraint being the global availability of data, especially for firms located in tax havens and in countries without mandatory public disclosure of unconsolidated financial statements for subsidiaries, such as the United States. Importantly, although Orbis 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). This is highlighted in Table A1 in the Appendix, where the US has only three observations because it does not mandate public disclosure of unconsolidated financial statements for subsidiaries. Tørsløv et al. (2023) give the example of Apple, which reports large profits (billions) at the MNE level. However, summing up the unconsolidated profits of all its subsidiaries yields just a few million. Another limitation, as pointed out by Blouin and Robinson (2020), is that BvD documentation lacks clarity when identifying 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 that compares profit shifting across countries could be biased.

As mentioned in the introductory paragraphs of this section, there are two ways to counter the limitations of global data availability. First, we construct the most comprehensive sample of MNEs to date. 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 unavailable in Orbis. This is highlighted in Appendix Table A2, which shows that 47,268 US GUO-year observations are incorporated into the analysis, even though we miss unconsolidated financial information for these firms. The same is true for many firms (and GUOs) located in tax havens. If instead we were to use weighted tax rate differentials, this would significantly reduce the sample because of missing financial data. For instance, Huizinga and Laeven (2008) lose many firm-year observations by using sales or total assets as weights, which are missing for many firms. Our approach provides a more comprehensive perspective on tax differentials across all countries where multinational groups operate (Johansson et al., 2017), and creates larger tax differentials for many firms, especially when part of their business is located in tax havens. To address the limitations of using accounting data from different countries, as highlighted by Blouin and Robinson (2020), we incorporate country fixed effects in all specifications. This helps mitigate the possibility that country-specific accounting practices influence our results.

Our sample construction involves reconstructing ownership links following the process outlined by Kalemli-Özcan et al. (2022) and Grosskurth (2019). This process aims to identify firms not previously considered part of a specific multinational group. Finally, we consider both firms and individuals as potential GUOs, given that it is not feasible to determine a firm as a GUO in all cases. In such situations, we assign an individual as the GUO of the multinational group and subsequently construct a *Tax differential* for the firms under their control using the corporate tax rates of the firms under the individual GUO.

Our analysis does not rely solely on unconsolidated data; instead, we incorporate consolidated profits before taxes at the MNE-year level. Consolidated data offers two advantages. First, it provides a profit measure immune to internal transactions within the MNE group. Second, it offers a comprehensive view of all firms' profits within a multinational group, which is particularly useful for U.S. MNEs that are not mandated to publicly disclose unconsolidated financial statements for their subsidiaries.

Specifically, we merge the 2,277,435 firm-year observations with consolidated profits before taxes of their MNEs. We successfully merge 1,000,079 firm-year observations, corresponding to 43,395 unique GUOs. The unconsolidated data covers a sizeable part of the consolidated data. By simply dividing the total unconsolidated profits of the firm-year observations ($22 trillion) in our sample by the total consolidated profits of the multinational groups ($36.7 trillion), we obtain a ratio of 60%. Further, we assess the representativeness of our data by replicating 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* for all firms within a multinational group and compare them with the consolidated profits before taxes reported by the related GUO for a specific year. These figures are not directly comparable because of factors such as eliminating intercompany transactions from 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 that report unconsolidated profits before taxes represent a significant portion of all firms within the related multinational groups.

Among the 1,000,079 firm-year observations, 496,407 (50%) belong to multinational groups in which all firms' aggregate *Profit before taxes* is equal to or higher than the consolidated profits. We can reasonably assume that the firms we observe in the Orbis vintages provide a reliable representation of these multinational groups. Conversely, 503,672 (50%) firm-year observations belong to multinational groups, where all firms' aggregate unconsolidated *Profit before taxes* is lower than consolidated profits. For this subset, the aggregate *Profit before taxes* of all firms represents, on average, 51% of consolidated profits. The weighted average (weighted by profit) for both subsets is 57%. These figures may be inflated owing to the inclusion of internal transactions within multinational groups when adding up unconsolidated *Profit before taxes* for all firms. However, they still hold significant value in data representativeness, particularly when complemented by including all existing firms within a specific multinational group in the *Tax differential*.

To further illustrate the representativeness of our sample, we report the data for GUO countries and GUO-year observations. This information is presented in Table A3 in the Appendix. The total number of GUO-year observations is 179,370, corresponding to 43,395 unique GUOs successfully merged with 1,000,079 firm-year observations. For these GUO-year observations, we have access to consolidated data on profits before taxes. The column labeled "Aggregate unconsolidated/consolidated" presents the total unconsolidated profits from the firm-year observations in our sample (*Profit before taxes*), aggregated by their GUO countries and divided by the total consolidated profits of the MNE groups, also aggregated by their GUO countries. Essentially, this works as follows. Consider the U.S. as an example of a GUO country with 10 GUO-year observations, each with its own value for consolidated profits. We aggregate all the unconsolidated profits of the affiliates/subsidiaries of these 10 GUO-years (regardless of the country in which they are located) and divide this by the total consolidated profits of these 10 GUO-years. A ratio of 1 indicates that the total unconsolidated profits of the affiliates are equal to or higher than the total consolidated profits of the groups, suggesting that the unconsolidated profits observed in our sample provide a reliable representation of consolidated profits. It is evident that for most GUO countries, the ratio of total unconsolidated profits to total consolidated profits is high. However, there are some notable exceptions, such as the United States.

2.3. Estimation of profit shifting by firm-year

Firm-year profit shifting estimates imply estimating coefficients g_{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 (Fan and Gijbels, 1996; Loader, 1999; Cattaneo and Jansson, 2018). 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, accommodating any nonlinearity in the relationship between the $Tax\ differential\ CT_{it}$ (which reflects a multinational's international structure and international tax system), and *Profit before taxes*. 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.[5]

For comparison, the graphical OLS estimation fits a regression line with a constant slope through the full sample, implying a single g estimate in equation (1). In contrast, its nonparametric counterpart, the local linear regression, assumes that the slope has a locally specific value around each observation (g_{it}). Although local linear regression provides varying estimates without fixed functional forms, it requires a significant number of observations to avoid the curse of dimensionality. The large number of firm-year observations in this study mitigates this issue.

We employ semiparametric and fully nonparametric methodologies to estimate Equation (1). Our semiparametric methodology incorporates linear components (non-varying

[5] An alternative would be to use random coefficients models. However, at least two theoretical aspects of nonparametric (semi-parametric) regressions are more appealing. We discuss these issues in the Appendix.

coefficients for *Noncurrent assets*, *Number of employees*, *GDP per capita, GDP growth*, and *Inflation*; the use of these variables varies depending on which specification we use) and the fixed effects of our model, as well as a nonlinear component (*Tax differential*). We use Stata's standard *npregress kernel* command and apply the Frisch-Waugh-Lovell (FWL) theorem.[6]

Specifically, our first step involves partialling out the nonparametric effect of the *Tax differential* from the dependent variable (*Profit before taxes)* and the independent variables. We achieve this by using kernel regression for each variable against the *Tax differential*, which allows us to remove the nonlinear influence of the tax differential. Subsequently, we conduct a fixed effects regression on the residuals obtained in the first step. This regression estimates the linear part of the model. Combining these two steps ensures that the residuals are purged, not only of the fixed effects and linear controls but also of the indirect, nonlinear influence of tax differentials. After regression, we predict the residual *Profit before taxes*. This "clean" residual is then regressed nonparametrically against the *Tax differential*. The last step is pivotal as it captures the firm-year specific effects of tax differentials (g_{it}).

Furthermore, we experiment with fully nonparametric models, wherein all variables are introduced nonparametrically. This approach allows greater flexibility for all variables in the model, thereby avoiding the potential for misspecification that could arise from forcing a part of the empirical specification to be linear, which might result in the *Tax differential* capturing more variation than expected. However, we do not favor this approach because of the considerable increase in estimation time it entails without yielding large differences in our inferences. The Appendix further clarifies how the nonparametric methods derive firm-year coefficient estimates.

We employ several semiparametric specifications of Equation (1) to align with the rationale of the different OLS specifications applicable to Equation (1), following the

[6] We use the suggestion in the Stata list forum, available here: Semiparametric coefficients - Statalist.

paradigms 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 (*Noncurrent assets* and *Number of employees*), and *GDP per capita* (the country-year productivity parameter), and (iii) *Noncurrent 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 and the potential effect of the MNE choosing to establish itself in tax havens for tax-related reasons.

In our sample, we estimate each of these three specifications 12 times, once for every year, 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. However, the results of the two approaches are very similar in smaller subsamples. Subsequently, we average the firm-year estimates from the three specifications and multiply these averages by -1, so that higher values reflect more profit shifting. The resulting firm-year estimates, denoted as g_{it}, serve as a profit-shifting index (*Semi-elasticity*).[7]Following Huizinga and Laeven (2008), we employ the estimated values of g_{it} (*Semi- elasticity*) in the following equation to derive a monetary estimate of profit shifting for each firm-year in our sample.

$$S_{it} = \pi_{it} - \frac{\pi_{it}}{1-g_{it}*CT_{it}} \qquad (3)$$

where S_{it} represents the dollar amount of shifted profits for firm *i* in year *t* (*Profit shifting unc.*), CT_{it} is the *Tax differential* variable, and π_{it} represents the observed profit before taxes

[7] De Simone et al. (2019) also develop a firm-year measure of profit shifting using a different approach.

in US dollars. A firm's observed pre-tax income can be expressed as the sum of its "true" income and its "shifted" income. We estimate the "true" pre-tax income as follows:

$$T_{it} = \pi_{it} - S_{it} \tag{4}$$

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

Based on this, we construct two profit-shifting ratios. The first, referred to as the *Profit shifting ratio*, is obtained by dividing the shifted profits (*Profit shifting unc.*) by the observed profits before taxes (π_{it}). This ratio is particularly relevant for inbound firms for which *Profit shifting unc.* (S_{it}) is less than or equal to observed profits before taxes (π_{it}). The second ratio is the *True profit shifting ratio*, calculated by dividing *Profit shifting unc.* (S_{it}) by the estimated firm-year "true" profits before taxes (T_{it}). This ratio is more pertinent for outbound firms where *Profit shifting unc.* (S_{it}) is lower than or equal to "true" profits before taxes (T_{it}). These two ratios, in conjunction with the profit-shifting index (*Semi-elasticity*), collectively provide a complete picture of the extent of profit shifting by firm-year in our sample.

As explained in Section 2.2, we merge our firm-year observations with consolidated profits before taxes at the MNE-year level. We group the *True profit shifting ratio* by MNE-year and compute the average profit-shifting ratio at this level. Subsequently, we apply this average ratio to consolidated profits before taxes for each corresponding MNE-year observation.[8] This yields *MNE Profit shifting ($Bn.)* and a corresponding ratio *MNE Profit shifting ratio*, which is *MNE Profit shifting ($Bn.)* divided by the MNE's consolidated profits before taxes in billions of US dollars for a specific year. This approach is particularly useful for U.S. MNEs, for which access is available only to the unconsolidated profits of some of their non-US affiliates (see Appendix Table A3). For instance, in the case of Apple Inc., we would capture only 7 percent of Apple's consolidated income if we were to limit the sample to Apple

[8] 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.

companies (and subsidiaries) that report unconsolidated data in Orbis, without relying on Apple's consolidated profits before taxes.

The profit-shifting ratios applied to consolidated profits may correspond to the entire group in some multinational groups, whereas in others they may capture only a portion of the group's firms. In the former case, our estimates should be more accurate; in the latter, they can be considered an approximation of profit shifting. This is especially relevant for US firms that shift their profits directly to tax havens. However, as extensively discussed in section 2.2, we go to great lengths to construct a large representative sample. 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 considerably impacts the estimated coefficients (*Semi-elasticity*) and the profit-shifting ratios.

2.4. Importance of the profit-shifting index

The key novelty of this study is the measurement of profit shifting by subsidiary-year, parent-year, and MNE-year, for the largest global sample to date. This granularity level offers several advantages. First, we provide academics and policymakers with panel data on firms' profit shifting. This means that policymakers can identify patterns of profit shifting within and across firms, observe in a timely manner which firms shift profits to others, trace origin and destination firms, identify routes of profit shifting via intermediate countries and specific industries, and take appropriate action. Additionally, policymakers can examine whether specific policies affect profit shifting and obtain monetary estimates of their impacts. For the first time, academics have a detailed firm-year variable of profit shifting to be used in empirical analyses, both as a dependent and explanatory variable, to examine the economic motivations behind these practices in more detail.

The current practice of inferring the determinants of profit shifting is to interact the response of firm profits to tax incentives (*CT)* with the determinant of interest, *Z*. Examples of such determinants include the role of worldwide vs. territorial taxation (Markle, 2016), the adoption of IFRS in De Simone (2016), and the role of patents in Cheng et al. (2021). The coefficient of the interaction term suggests the extent to which firm profits increase or decrease, on average, for every change in *CT* at every infinite value of *Z*, thus indirectly inferring the effect of *Z* on profit shifting.

A key problem with this approach is endogeneity bias, which occurs in many forms and is difficult to overcome. Having one variable of interest interacted with the tax incentive variable implies that many other control variables must be included in the 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 the estimation impractical.[9] A related issue is that the nonlinear relationship between the tax incentive variable and firms' earnings (e.g., Dowd et al., 2017; Garcia-Bernando and Jansky, 2022; Fuest et al., 2022) is difficult to capture using these models. Therefore, identifying causal effects using the existing approaches is challenging.

Instead, using 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 easily be identified in our dataset using bootstrapping techniques, whereas measurement error in the dependent variable tends to be more innocuous than measurement error in the explanatory variables (see Wooldridge, 2009; see also deHaan et al., 2019, and Millimet and Parmeter, 2022, for a discussion of some

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

exceptions). Another advantage is that our nonparametric approach fully accounts for the potential nonlinear relationship between the tax incentive variable and firms' earnings. Moreover, using profit shifting as an explanatory variable is considerably easier when it has a firm-year dimension. This facilitates the identification of causal effects using standard identification methods applied to the profit-shifting variable.

3. Global estimates of profit shifting

3.1. Our profit shifting estimates and comparison with aggregate estimates

We first compare the average estimates of our firm-year profit-shifting index with the results from equivalent OLS models as our first validation exercise to facilitate a comparison with the existing literature. The first row of Table 3 reports the annual averages of g_{it}, that is, the semi-elasticity of firm profits with respect to the tax differential *CT* obtained from the semi-parametric estimation of Equation (1).[10] The equivalent parametric OLS results are reported in Table 4. In these specifications, we use the logarithm of Noncurrent assets (*Noncurrent assets*) to measure capital and maximize the number of observations included in the analysis. We replicate the same table in the Appendix by employing tangible assets (*Tangible assets*) as a proxy for capital (see Appendix Table A4).

[Please insert Tables 3 and 4 here]

In line with our expectations, 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 semi-parametric model (specifications 2, 4, and 7), the average coefficient (marginal effect) of the tax differential is approximately 2.5

[10] 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.

(3.4+2.1+1.81+0.19*1.04 divided by 3).[11] This value is slightly smaller than the average obtained from the semi-parametric estimation, which equals 2.76 in Table 3. Thus, our results from the semiparametric regressions closely follow the parametric results. Following the literature (Huizinga and Laeven, 2008; Heckemeyer and Overesch, 2017; Beer et al., 2020), we interpret this average coefficient as the average semi-elasticity within our sample.

Two representative consensus estimates from the literature are 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 to the tax rate differential across countries of 0.8. Beer et al. (2020) argue that a semi-elasticity of 1 accurately reflects the literature. There are also several studies that use macro data to estimate total profit shifting across countries (e.g., Clausing, 2016, 2020; Tørsløv et al., 2023). These studies generally provide larger implied estimates of profit shifting than studies using firm-level data and might suffer from their own limitations, as pointed out by Dyreng et al. (2023).[12] Although reconciling the differences between the macro and micro estimates is beyond the scope of this paper, we contribute to the literature by using a larger firm-year sample and information on GUOs, which allows being more comprehensive when aggregating the firm-year estimates (across countries receiving profits, countries sending profits, as well as relevant country pairs).

Our aggregate estimates are generally larger than most firm-level studies but smaller than those from macro studies. Moreover, we note that our aggregate estimates become larger when we expand the sample of firms by including information on GUOs and other non-reporting affiliates, include firms with negative profits, and include annual changes in ownership. This suggests that using a comprehensive sample of firms can lead to larger

[11] In specification 7 of Table 4, 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.

[12] Moreover, studies employing nonlinear techniques to capture tax rate effects on profitability measures (e.g., Dowd et al., 2017; Bratta et al., 2021), have also argued for significantly higher values.

estimates of profit shifting.

To demonstrate the impact of our sample construction steps on both the sample size and the coefficient of *Tax differential*, we introduce Table A5 in the Appendix. The first specification, which is also specification 4 in Table 4, serves as the benchmark. The second specification is based on a sample that excludes annual ownership changes and relies on the current ownership structure available on the Orbis website. It also excludes firms lacking financial data on Orbis from constructing *Tax differential*. This adjustment decreases the number of firm-year observations from 2.3 million to 1.5 million and significantly lowers the coefficient of the *Tax differential*. The third specification significantly increases the dataset by 400,000 observations through an annual update of ownership information. This approach allows us to include firms that change their GUO over time and those that might be overlooked when considering only current ownership structures. It is particularly valuable to identify firms that, although not currently active, were established to exploit tax rate differentials or those that existed before certain mergers and acquisitions.

The fourth specification, which does not include annual ownership changes, enhances the construction of tax rate differentials by including all firms within a multinational group, expanding the sample from 1.5 million to over 2 million firm-year observations. Unlike previous approaches, this method incorporates tax haven and U.S. firms and any firms within Orbis ownership groups that do not report financial data. This approach significantly broadens the sample size and diversifies the tax rate differentials. For instance, consider a multinational group with two firms in France and one in a tax haven country. If only the two French firms report their financials, a tax rate differential for these firms would not be constructed because of their similar tax rates. However, we retain the two French firms in the sample by including tax-haven firms in their tax differential calculations. Essentially, this method aids in retaining firms that report unconsolidated data for which we could not identify tax rate differences with affiliated firms if we were looking solely at a sample of firms that report financial data.

This methodology significantly changes *Tax differential*, affecting the estimated coefficients (*Semi-elasticity*) and profit-shifting estimates. In Specification 4, the tax differential coefficient increases significantly. To illustrate the impact of this approach, Apple Inc. has 242 firm-year observations with reported financial data. When constructing tax rate differentials for the multinational group, irrespective of whether financial data is reported or not, we obtain a considerably increased sample of 8,383 firm-year observations. When limiting the sample to firms with financial data, the lowest tax rates for Apple are identified in Bulgaria and Hungary, which would incorrectly identify these two countries as primary profit-shifting destinations. However, once we include data from Apple-affiliated firms without financial reports to construct tax differentials, we find that the lowest tax rates are in the Cayman Islands and the United Arab Emirates, offering a more complete picture.

3.2. Firm, industry, and country variation of profit shifting

Estimating profit shifting by firm-year implies identifying specific firms as 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 can thus attract more investment, potentially overperforming sectors less able to evade taxes. To the extent that multinationals compete for market share and input factors, this heterogeneity translates into profit shifting acting as a subsidy for specific industries.

Table 5 reports the average estimates for the MNE identified 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. These are large profit-shifting volumes. Consistent with the emergence of the first BEPS Action

Plan in the fall of 2015 (OECD, 2015), we find a profit-shifting reduction in 2016. This unprecedented effort was to strengthen the global corporate tax system by limiting tax opportunities for multinationals, especially by 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 was implemented), at which point a clear drop in the profit-shifting ratio is observed. Still, we find a reduced but significant 12% of *MNE Profit shifting ($Bn.)* as a share of the total consolidated profits by 2020.

Several well-known MNEs appear in the top 20 list (Table 6). These firms have abundant anecdotal evidence (media articles and legal cases) that they conduct profit shifting. Table A6 provides additional validation of our methodology by comparing our profit-shifting estimates with those reported in the anecdotal evidence. These estimates align closely with each other. There is also strong evidence in our data that all these firms own subsidiaries in tax havens. A striking observation is that most of the top 20 companies operate in the IT and energy sectors.

[Please insert Tables 5 and 6 here]

Tables 7 and 8 corroborate and enhance this observation by reporting the average values of profit shifting by industry and subindustry of GUOs. The results in Table 7 show that manufacturing is the industry with the highest *MNE Profit shifting ($Bn.)* (left panel), with the top subindustry being pharmaceutical firms (right panel). In fact, according to Table 8, the manufacturing of pharmaceutical preparations is the top subindustry by *MNE Profit shifting ($Bn.)*. Again, this finding is consistent with the literature (Dyreng et al., 2023) and anecdotal evidence suggesting aggressive profit-shifting activities by pharmaceutical companies and related companies.[13] In recent years, this has called for many government investigations and

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

reports to delegalize and limit the activity.[14]

The information and communications industry is second, with telecommunications being the most aggressive subindustry. This industry includes the most well-known profit-shifting MNEs, included in Table 6, and is the industry that hits the news most often. Moreover, according to Table 8, subindustries such as software publishing and computer programming activities have among the highest estimated semi-elasticities on the tax differential. The key characteristic of this industry is its large share of intangible assets, which is a key explanatory variable for profit shifting in the literature (e.g., Grubert, 2003; Grubert, 2012; Karkinsky and Riedel, 2012; Beer and Loeprick, 2015; Cheng et al., 2021; De Simone et al., 2022). Intangible assets include goodwill, brand recognition, and intellectual property such as patents, royalties and licenses, trademarks, and copyrights. All of 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 fuels) and refineries are usually in locations different from the parent. Second, firms in many major mining countries are not obliged to disclose the financial accounts of their subsidiaries. Increasing evidence suggests that mining and oil companies engage in profit-shifting activities. The petroleum industry exploits profit-shifting strategies such as intercompany loans, creating transfer pricing opportunities (Guvenen et al., 2022). Anecdotal evidence from major news agencies is also abundant on the issue.[15] De Simone et al. (2022) estimates the most positive value of their profit-shifting index for the textile, petroleum, and natural gas sectors. Their index is increasing with income-shifting aggressiveness. The Intergovernmental Forum on Mining (IGF) and OECD have released guidance for source

[14] 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.
[15] https://www.reuters.com/article/global-oil-tax-havens-idUSKBN28J1IK.

countries on transfer pricing in the mining sector. We validate our methodology against court cases involving companies in the mining sector.[16] Moreover, the results in Table 8 show that among the top 20 subindustries, the second and sixth places are oil refineries (included in the manufacturing industry) and extraction firms (included in the mining industry). Table 8 also shows that companies supporting petroleum and gas extraction boast the largest estimate of *Semi-elasticity* (the largest response of firm profits to changes in the tax differential).

[Please insert Tables 7 and 8 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 here]

The connection between the subsidiary and GUO countries might indicate the conduit countries used for profit shifting, potentially masking the true destination, which typically involves a small country with a 0% corporate tax rate. This is particularly true because we consider subsidiaries that report unconsolidated profits. Therefore, going beyond the analysis presented in Table 9, we identify the locations of firms with the lowest corporate tax rates 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-US connections). Specifically, in Appendix Table A7, 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

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

subsidiary. Vanuatu has only one observation, but has the highest profit-shifting ratio and semi-elasticity, followed by Hungary with 35 observations. 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).

Appendix Table A8 provides equivalent results for the Ireland–United States connection. Bosnia and Herzegovina take first place with a *Profit shifting ratio* equal to 0.38, and Cyprus, Belize, and North Macedonia second place. We have relatively few firm-year observations for these countries. The largest number of observations are firm-years with lowest-tax subsidiaries in Ireland, with the UAE in second place, followed by Bermuda and the Cayman Islands. These results show that many firms locate subsidiaries in zero-percent tax havens. Still, other firms make choices based on other country characteristics, especially those related to the quality of institutions and cultural proximity (as is possibly the case with Ireland). All usual suspects, such as the Bahamas, Macao, Gibraltar, Bahrain, Bulgaria, and the British Virgin Islands, appear in the table.

Table 10 ranks the GUO countries based on the average semi-elasticity of outbound profit-shifting firms within our sample. We posit that the GUOs of outbound profit-shifting firms are likely to be domiciled in countries with low corporate tax rates. Consequently, these firms report higher semi-elasticity, indicating a stronger incentive to shift profits to these low-tax jurisdictions. Bahrain has the highest semi-elasticity, 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 in the OECD's BEPS framework.

In Table 11, we aggregate the total profit-shifting estimates attributed to the MNEs in our sample, reflecting the total amount of profits shifted by these MNEs across all countries they operate, 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, those with a GUO in the US and a subsidiary in Bermuda stand out prominently. Of the total profit shifting reported in the top 40 connections between the 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 and 11 here]

Figure 1 compares our annual average semi-elasticities with the average semi-elasticities of firms with GUOs in Bermuda and the Cayman Islands and 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-elasticity for the entire sample. We obtain several similar patterns for firms in other tax havens.

[Please insert Figure 1 here]

3.3. Loss-making firms

In our baseline analysis, we exclude loss-making firms to follow most studies in the literature relying on micro data. Recent literature highlights that loss-making firms also shift their profits 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 as our analysis and discuss profit truncation due to log transformation. Their solution is to use log (return on assets + 1), 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, which can yield vastly different estimation results (bias and inconsistency due to skewness).[17]

To avoid criticisms of sample truncation, we conduct an additional analysis using the so-called neglog transformation (e.g., Whittaker et al., 2005).[18] 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 a very limited effect on data skewness. Moreover, we prefer this approach to using the log of a return ratio because return ratios capture profit shifting and (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) in the sample. In terms of the rankings by year (Panel A), firm (Panel B), industry (Panel C), and country connections (Panel D), our results closely resemble those obtained without loss-making firms. For example, profit shifting continues to show an upward trend over the years, especially until 2017, and the rank correlations of profit shifting between firms, industries, and country pairs are very high.

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

[Please insert Table 12 here]

[17] 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).
[18] See also http://fmwww.bc.edu/repec/bocode/t/transint.html.

3.4. Validation of methodology

A validation of our method is that within an MNE-year, the sum of the outbound and inbound profit shifting must theoretically be zero. We can only test this condition with error, because we do not have data on all subsidiaries. Given that our coverage of firms is arguably sufficiently large, the difference between the dollar value of outbound and inbound profit shifting by MNE-year must be close to zero. We provide the results of this exercise in the histogram of Figure 2a. Aside from some extreme outliers with negligible population density, the histogram shows an obvious concentration (more than 90%) around the value zero, indicating that the zero-sum condition is met for most MNE-year pairs in the sample.

We also estimate equation 1 without the *CT* variable and collect the residuals $\widehat{\varepsilon_{it}}$. It should hold that $\widehat{\varepsilon_{it}} < 0$ for high *CT* and $\widehat{\varepsilon_{it}} > 0$ for low *CT*. Using the median value of *CT*, we indeed find that $\widehat{\varepsilon_{it}}$ = -0.86 for the sample of above-median firm-year observations and $\widehat{\varepsilon_{it}}$ = 0.86 for below-median firm-year observations. Moreover, similar to the difference between the outbound and inbound profit shifting by MNE-year, the sum of the residuals within each MNE-year is approximately equal to 0 (results in Figure 2b).

[Please insert Figures 2a and 2b here]

We also conduct Monte Carlo simulations to validate that the coefficient estimates of the *Tax differential* capture profit shifting. Our approach is like that of Dechow et al. (1995), who shock discretionary accruals in part of their sample to test for earnings management. We strictly base our Monte Carlo on Equation 1 and for the data generation process (DGP), we use information from our sample (mean, standard deviation, skewness, and kurtosis) to generate simulated data with 1,000 observations. Based on this information, we use the normal distribution for *Noncurrent assets*, *Number of employees*, and *Tax differential* (means and standard deviations, as in Table 2). We use the beta distribution with shape parameters 6 and 2 for GDP per capita to generate the negative skewness observed in the real data and multiply the result by 15 to approximate the real sample's mean value. Finally, we generate the stochastic term from the normal distribution (with a mean of 0 and a standard deviation of 1). We set the seed to produce the same observations for all the programs.

We estimate Equation 1 using these simulated data and nonparametric regression. We execute the program using 1,000 replications, a sufficiently large number to obtain inferences in our setting. The mean coefficient estimate of the *Tax differential* across these 1,000 samples is -2.107, fully in line with our baseline estimates in Specification 4 of Table 4 (as expected). This is our first (benchmark) Monte Carlo.

Subsequently, we modify the first program to introduce a shock to the semi-elasticity of firm profits to the tax variable *CT* by one standard deviation of the actual data. We aim to verify that running the shocked program on 1,000 simulated samples decreases the profits' semi-elasticity to the tax differential and thus increases profit shifting precisely because of the MNEs' higher tax incentive. We find that this is the case, with the mean semi-elasticity decreasing to -3.008 (implying more profit shifting).

In the third program, we shock only part of the 1,000 observations. Specifically, we introduce a higher profit-shifting incentive by decreasing the semi-elasticity of firm profits to the tax variable *CT* (by one standard deviation) in the first 250 observations of our simulated samples. In Equation 1, we include an interaction term of the *Tax differential* with a dummy equal to one for shocked observations and zero for the rest. We run this third program 1,000 times and find a mean difference of -0.81 between the treated and control observations. This finding is consistent with the idea that firms' profit shifting increases because of higher tax incentives.

Finally, we modify the program to introduce a placebo test. Specifically, in this fourth program, we shock *Profits before taxes* (the outcome variable) without introducing a shock to the semi-elasticity. This implies that firm profits increase for reasons unrelated to the tax incentive. Thus, the coefficient on the *Tax differential* should be statistically equal to that identified in the first program (the one without any shock). We find a mean coefficient on the *Tax differential* equal to -2.097, which is statistically equal to that of the first program (again using a standard t-test).[19]

This framework could also be used to examine a minimum global corporate tax rate (e.g., 15%), by replacing the tax rate for any low-tax affiliate with that minimum tax rate. As a result, the CT variable of equation 2 in our model would be smaller for firms in high-tax countries with affiliates in low-tax countries (i.e., in countries with corporate tax rates below the global minimum), and outbound profit shifting would be reduced. Our Monte Carlo simulation can then be used to estimate how much profit shifting would be reduced by comparing the current model to a model where tax rates of low-tax affiliates are fixed at a specific rate.

4. Conclusions and directions for future research

This study constructs the first global database of firm-year profit-shifting estimates for 2,277,435 observations from 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

[19] An alternative setup for the Monte Carlo would be to estimate equation 1 without the *CT* variable and introduce two separate shocks to the stochastic term: the first would be a positive shock to income for low-tax subsidiaries (to be previously setup as such in the DGP) and a negative shock to income for high-tax subsidiaries. We run this variant and, as expected, the results show that income increases in the low-tax subsidiary.

period.

We contribute to the literature by using the largest (to our knowledge) firm-year sample, which enables a comprehensive aggregation of firm-year estimates across countries receiving and sending profits, as well as relevant country pairs. Our aggregate estimates are generally larger than those from most firm-level studies but smaller than those from macro studies. Notably, these estimates increase when we expand the sample by including GUOs, non-reporting affiliates, firms with negative profits, and accounting for annual ownership changes, indicating that a more comprehensive sample leads to larger profit-shifting estimates. Specifically, we estimate a semi-elasticity of profits to the tax incentive that is approximately 2.8 and find that global profits shifted increased from 311 billion USD in 2009 to 770 billion USD in 2017.

Our new profit-shifting index, validated inter alia by Monte Carlo simulations, can be used as both an outcome and explanatory variable in future empirical analyses. Thus, our findings are only the first step in uncovering the potential of this database to analyze 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 the factors determining profit shifting or its causal effects.

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Table 1. Variable definitions and sources

Variable	Definition	Source
A. Profit-shifting indices		
Semi-elasticity	The firm-year estimates g_{it} from the estimation of Equation (1) using the local linear regression as described in section 2.3.	Own estimations
Profit shifting unc.	The dollar amount of shifted profits for firm *i* in year *t*, as determined by Equation (3) and calculated using unconsolidated financial data.	Own estimations
Profit shifting ratio	*Profit shifting unc.* divided by observed profits before taxes.	Own estimations
True Profit shifting ratio	*Profit shifting unc.* divided by the estimated firm-year true profits, which are determined using Equation (4).	Own estimations
MNE Profit shifting ($Bn.)	The dollar amount of shifted profits for MNE *i* in year *t,* in billions US dollars. It is estimated by applying the average *True profit shifting ratios* of all firms within the MNE group for a specific year to the consolidated profits before taxes of each corresponding MNE-year observation.	Own estimations
MNE Profit shifting ratio	*MNE Profit shifting ($Bn.)* divided by consolidated profits before taxes ($Bn.).	Own estimations
B. Dependent variables		
Profit before taxes	Firm observed profits before taxes (log). It is named as “P/L before tax” in the Orbis website version. It contains only unconsolidated profits and losses before tax (U1, U2).	Orbis
C. Firm characteristics		
Tax differential	Composite tax variable that summarizes all information about firms profit-shifting tax-incentives in year t.	EY, PwC, IBFD, Tax Foundation
Tangible assets	Firm tangible assets (log). Encompasses only firm’s tangible noncurrent assets. It is named as “Fixed assets (property, plant and equipment)” in the Orbis website version.	Orbis
Noncurrent assets	Firm noncurrent assets (log). Encompasses all noncurrent assets on a firm's balance sheet, both tangible and intangible assets. It exists only in the flat files version (vintages) of Orbis.	Orbis
Number of employees	Firm number of employees (log). It is named as “Number of employees” in the Orbis website version.	Orbis
Tax haven	Dummy variable equals to 1 if there is a tax haven firm in the multinational group.	EY, IBFD, Tax Foundation, Tørsløv et al. (2023)
Consolidated profits ($Bn.)	MNE observed consolidated profits before taxes. It is named as “P/L before tax” in the Orbis website version. It contains only consolidated profits and losses before tax (C1, C2).	Orbis
D. Country characteristics		
Statutory tax rate	Statutory tax rate of all the firms’ countries.	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
Noncurrent assets	2,277,435	13.972	3.137	0.000	14.155	27.007
Tangible 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 *MNE Profit shifting ratio*, calculated by dividing *MNE 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
MNE 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
MNE Profit shifting ratio	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)	(7)
Noncurrent assets			0.356***	0.356***	0.361***	0.372***	0.355***
			[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Number of employees			0.400***	0.399***	0.418***	0.431***	0.393***
			[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
GDP per capita		0.695***		0.349***	0.302***	0.525***	0.338***
		[0.016]		[0.012]	[0.012]	[0.002]	[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***	-1.818***	-1.809***
	[0.024]	[0.024]	[0.019]	[0.019]	[0.018]	[0.015]	[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	2,277,435
Adjusted R-squared	0.175	0.176	0.552	0.552	0.565	0.535	0.555
Country	Y	Y	Y	Y	Y	N	Y
Year	Y	Y	Y	Y	Y	N	Y
Industry	N	N	N	N	Y	N	N
Standard errors	Robust	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 *MNE Profit shifting ratio*, which is derived by dividing *MNE 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
MNE 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
MNE Profit shifting ratio	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 *MNE Profit shifting ratio* (calculated as *MNE 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	MNE Profit shifting ($Bn.)	Consolidated profits ($Bn.)	MNE Profit shifting ratio	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	MNE Profit shifting ($Bn.)	Top sub-Industry	MNE Profit shifting ($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-specialized 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 organizations	14.7	0.87
Agriculture, forestry and fishing	11.3	Growing of fiber crops	3.1	0.27
Arts, entertainment and recreation	8.0	Amusement and recreation activities	5.1	0.64
Water supply; sewerage, 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 (*MNE Profit shifting ratio*). The profit shifting ratio is calculated as the *MNE 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	MNE Profit shifting ($Bn	Consolidated profits ($Bn.)	MNE Profit shifting ratio	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 extractior	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 motor vehicle	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 (Global Ultimate Owner) 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 these MNEs, reflecting the total amount of profits shifted by these MNEs across all countries they operate, 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	MNE 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 *MNE Profit shifting ratio*, calculated by dividing *MNE Profit shifting ($Bn.)* 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
MNE Profit shifting	252	660	902	982	1,252	1,229	1,231	1,220	1,746	1,487	1,435	1,087	1,124
MNE 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 *MNE Profit shifting ratio* (calculated as *MNE 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	MNE Profit shifting ($Bn.)	Consolidated profits ($Bn.)	MNE Profit shifting ratio	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 *MNE Profit shifting ratio*. This is calculated as *MNE 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.

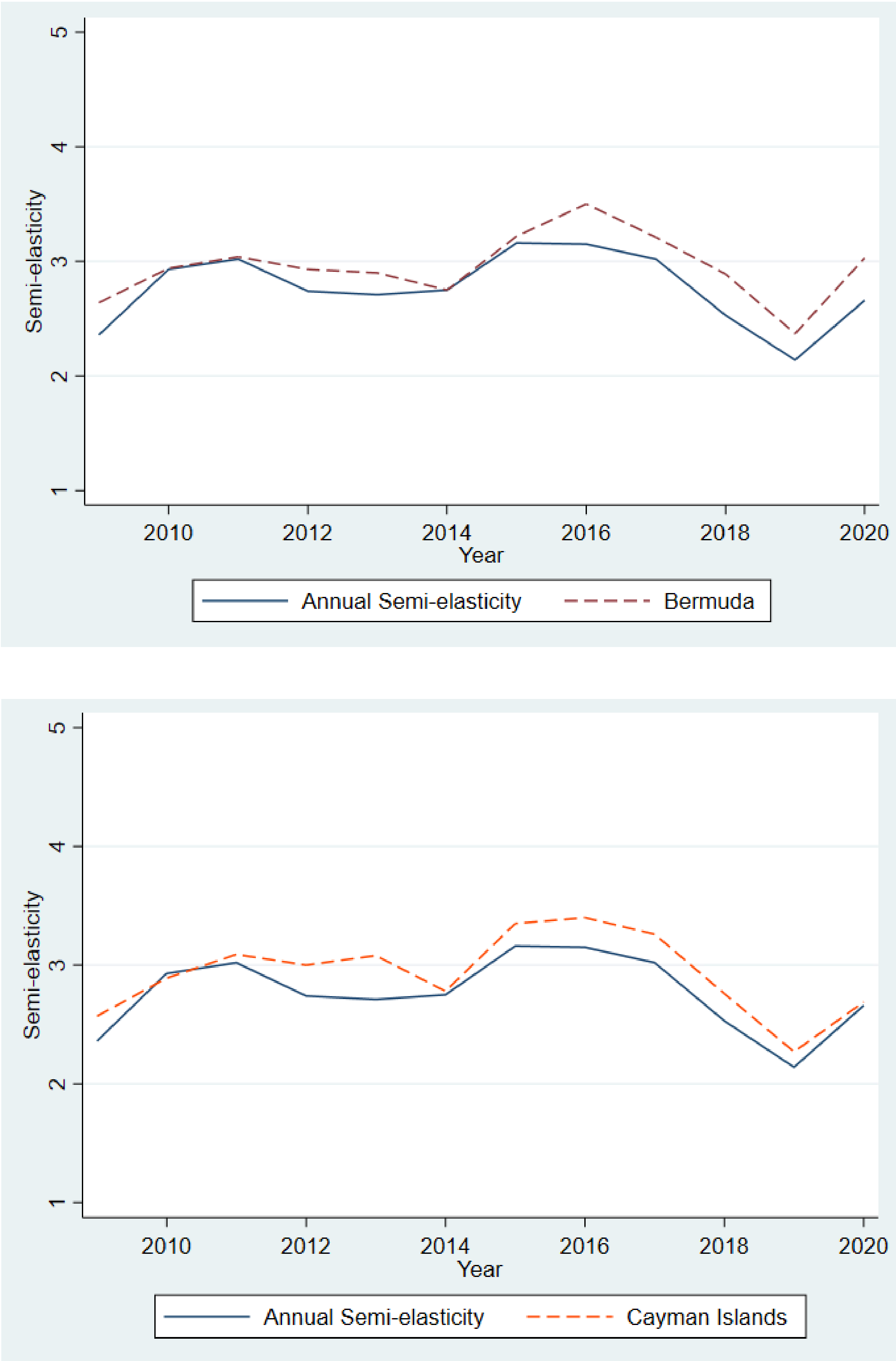
Industry	Sub-Industry	MNE Profit shifting ($Bn.)	Consolidated profits ($Bn.)	MNE Profit shifting ratio	Semi-elasticity
Manufacturing	Manufacture of pharmaceutical preparations	891	1,965	0.45	4.76
Information and communication	Telecommunications activities	715	1,821	0.39	4.70
Manufacturing	Manufacture 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	Information technology and computer service activities	335	813	0.41	4.92

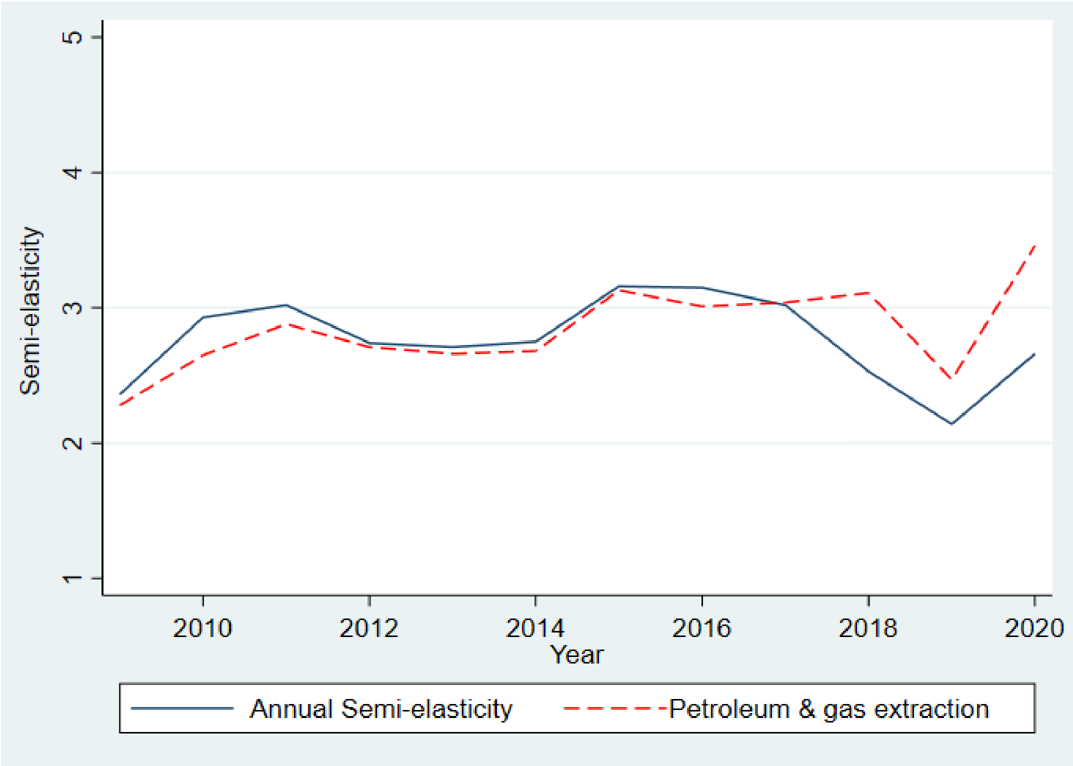
Panel D. Top profit-shifting connections by GUO country and low-tax MNE destination

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 these MNEs, reflecting the total amount of profits shifted by these MNEs across all countries they operate, 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	MNE 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: 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

Figure 2a: Sum of outbound-inbound profit shifting within MNE-years

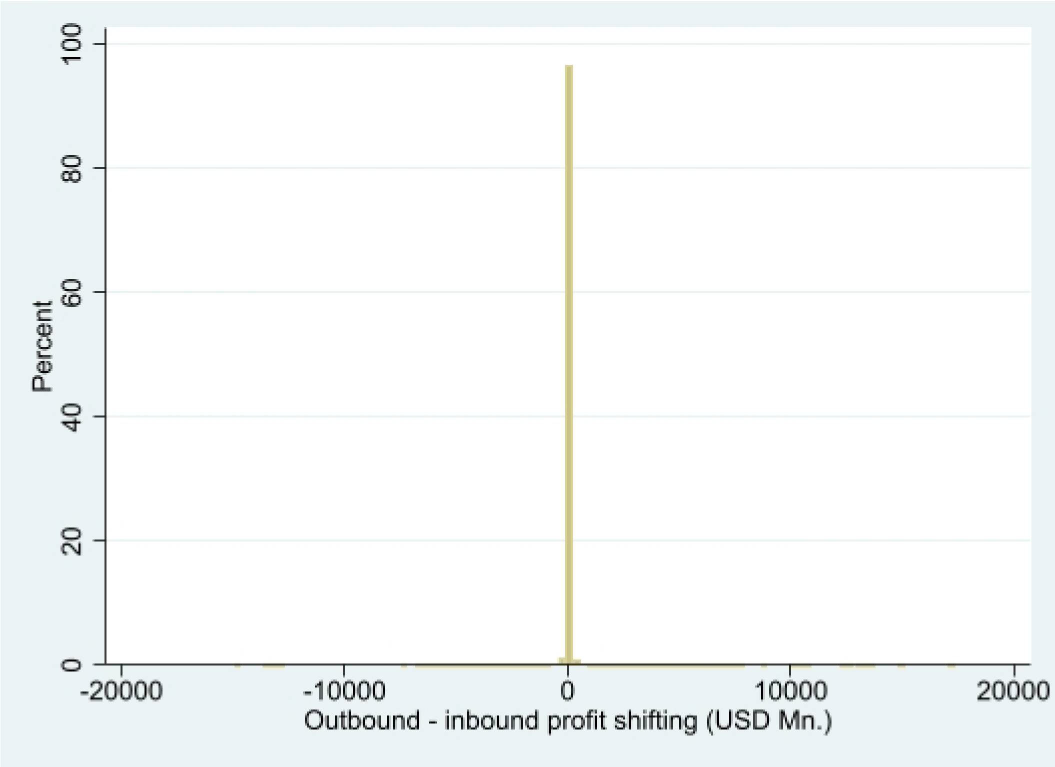
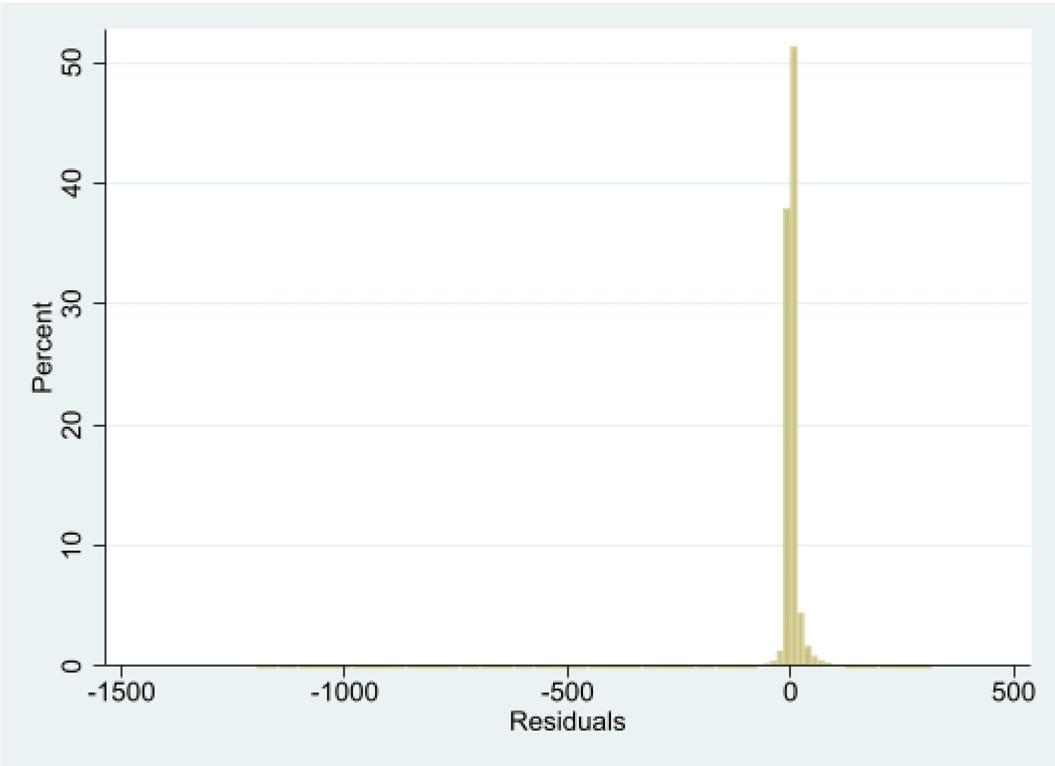


Figure 2b: Sum of residuals within MNE-years



Appendix
Global Evidence on Profit Shifting Within Firms and Across Time

This online-only appendix provides additional details on our sample construction and our non-parametric methodology, along with the relevance of the random coefficients model to our non-parametric approach. It includes summary statistics for both the countries of firms and the countries of Global Ultimate Owners (GUOs) used in our analysis. Additionally, it features a table comparing the unconsolidated and consolidated profits in our sample by GUO country, and another table that replicates the analysis in our Table 4, using tangible assets as capital. It also presents a table analyzing the impact of our sample construction steps and another one that validates our profit-shifting estimates against reported anecdotal evidence. Last, it offers two examples based on the first two rows of Table 9, analyzing the top inbound profit-shifting connections in our sample, specifically the connections between Ireland and France, and Ireland and the U.S.

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.

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*, *Noncurrent assets*, *Total assets*, *Intangible 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 *Noncurrent assets*. *Noncurrent 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 assets ($Tangible\ \ assets$) by taking the difference between Noncurrent assets and intangible 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 for the firms under the control of 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 (*Noncurrent assets*, *Tangible assets*, *Number of employees*, *Profit before taxes,* and *GDP per capita).* This results in a sample of 1,974,062 observations. However, as mentioned earlier, when using Orbis vintage 2021, there is a time lag of 2-3 years in the available data. 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.

Non parametric / Semi parametric estimation

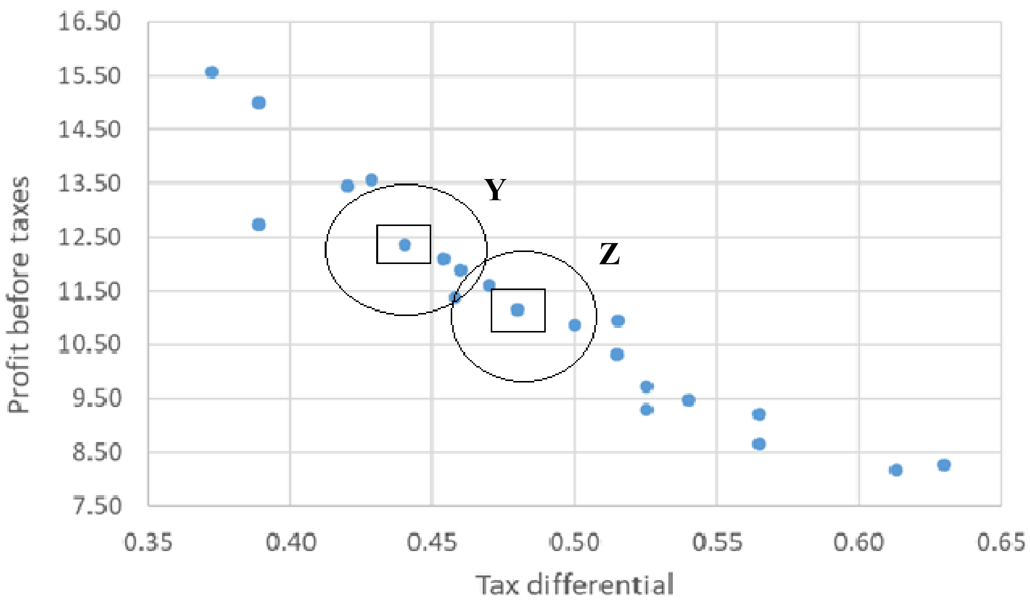
In this section, we clarify our methodology for the estimation of non/semi-parametric models. We provide a graphical illustration (Figure 2) that plots observations for a small subset of our sample in the *Profit before taxes-Tax differential* space. This graph demonstrates the mechanics of nonparametric kernel models in estimating the conditional mean value of *Profit before taxes* at a specified *Tax differential* point (point Y) by focusing on observations near this point. This process is crucial for estimating the derivative of this conditional mean with respect to the *Tax differential*, which indicates a unique profit-shifting estimate for this firm-year observation (g_{it}). The circles on the graph indicate the range of values considered close to certain *Tax differential* points, and the square marks the estimated conditional mean for *Profit before taxes* at these points. Bandwidths determine which observations fall within the circles, with a too-large bandwidth leading to a biased estimate with low variance and a too-small bandwidth resulting in an estimate with little bias but high variance. Observations are weighted by their proximity to the point of interest, ensuring estimates are not overly influenced by distant data points. We use either a Gaussian or a Quartic (biweight) kernel, with results showing no sensitivity to this choice. This methodology is carried out again for all the firm-year observations in our sample (point Z and others).

The logic behind our semi-parametric methodology is outlined in the main text. Specifically, we use the "*npregress kernel*" command in Stata and apply the Frisch-Waugh-Lovell (FWL) theorem. We opt for this approach because, although Stata offers various semi-parametric packages (such as semipar), none provide the coefficients (derivatives) for each observation in the sample. In contrast, the "*npregress kernel*" command in Stata reports varying coefficients but does not accommodate linear components. This necessitates our adjustment using the FWL theorem.

We examine several indices, based on different assumptions, when estimating the nonparametric regressions. This involves experimenting with various kernels (e.g., Gaussian, biweight, Parzen) and selecting the bandwidth using the Akaike Information Criterion (AIC). Employing different methods to determine the optimal bandwidth or using different kernel functions yields very similar indices, which highly correlate with our baseline indices. Additionally, we explore the use of different splines and assumptions within spline-based methods.

It is essential to implement the recommended semi-parametric methodology only after verifying that the sample size for analysis is sufficiently large, surpassing 1 million observations, to avoid the curse of dimensionality.

Figure 2: Nonparametric estimates at two points



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.

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. Unconsolidated vs. Consolidated Profits by GUO Country

This table presents GUO countries and GUO-year observations. The total number of GUO-year observations is 179,370, corresponding to 43,395 unique GUOs, which are successfully merged with 1,000,079 of our firm-year observations. These specific GUO-year observations have consolidated data on pre-tax profits. The last column aggregates unconsolidated profits (*Profit before taxes*) of firm-year observations, grouped by their GUO's country, and then divides this by total consolidated profits of MNE groups, also grouped by their GUO countries.

GUO country	GUO-year Observations	Aggregate unconsolidated/consolidated profits before taxes
Bosnia and Herzegovina	83	1.00
Croatia	267	1.00
Cyprus	1,157	1.00
Czech Republic	130	1.00
Denmark	8,885	1.00
Estonia	127	1.00
Finland	5,039	1.00
France	8,038	1.00
Hungary	484	1.00
Latvia	441	1.00
Lithuania	549	1.00
Malta	145	1.00
Montenegro	24	1.00
North Macedonia	80	1.00
Poland	1,879	1.00
Portugal	1,714	1.00
Romania	90	1.00
Russia	726	1.00
Serbia	134	1.00
Slovakia	269	1.00
Spain	8,769	1.00
Sweden	12,547	1.00
Ukraine	57	1.00
Kazakhstan	77	1.00
British Virgin Islands	309	0.98
Australia	1,566	0.96
Germany	15,822	0.95
Belgium	4,231	0.95
Egypt	84	0.95
Italy	16,223	0.94
Austria	2,953	0.91
Kuwait	92	0.90
South Korea	4,411	0.86
Bulgaria	139	0.82
Japan	16,526	0.80
Bahamas	30	0.72
Lebanon	25	0.72
China	6,182	0.69
Luxembourg	1,963	0.68

United Kingdom	13,175	0.65
Pakistan	104	0.65
Greece	950	0.62
Rest of the world	460	0.61
Ireland	1,441	0.61
Slovenia	159	0.58
Panama	47	0.58
United Arab Emirates	105	0.56
Norway	4,791	0.54
Netherlands	10,602	0.46
Iceland	290	0.44
Belize	22	0.41
Canada	852	0.41
Iran	42	0.39
Cayman Islands	785	0.36
Mexico	326	0.35
Bermuda	802	0.32
Liechtenstein	91	0.31
Marshall Islands	45	0.30
Switzerland	1,968	0.30
Brazil	385	0.28
India	2,105	0.26
Gibraltar	30	0.26
United States	10,236	0.26
Sri Lanka	107	0.25
Hong Kong	1,300	0.25
Mauritius	65	0.23
Curacao	133	0.20
Singapore	949	0.19
Israel	587	0.18
Indonesia	30	0.16
New Zealand	255	0.15
Taiwan	2,061	0.14
South Africa	375	0.13
Jamaica	25	0.10
Turkey	282	0.08
Morocco	27	0.07
Colombia	39	0.06
Thailand	192	0.06
Saudi Arabia	122	0.06
Philippines	72	0.06
Chile	136	0.05
Qatar	32	0.04
Malaysia	446	0.03
Vietnam	31	0.03
Argentina	24	0.03

Table A4: 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 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 A5. Impact of sample construction steps

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. Specification (1), which is also specification 4 in Table 4, serves as our benchmark. Specification (2) excludes annual ownership changes and firms lacking financial data in Orbis from the construction of the *Tax differential*. Specification (3) includes only annual ownership changes. Specification (4) enhances the construction of the *Tax differential* by including all firms within a multinational group, even if they do not report financials. 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)
Noncurrent assets	0.356***	0.358***	0.355***	0.359***
	[0.001]	[0.001]	[0.001]	[0.001]
Number of employees	0.399***	0.393***	0.405***	0.393***
	[0.001]	[0.001]	[0.001]	[0.001]
GDP per capita	0.349***	0.394***	0.330***	0.395***
	[0.012]	[0.015]	[0.013]	[0.013]
Tax differential	-2.098***	-0.662***	-0.813***	-1.953***
	[0.019]	[0.022]	[0.019]	[0.019]
Observations	2,277,435	1,533,244	1,927,293	2,019,475
Adjusted R-squared	0.552	0.566	0.558	0.556
Country	Y	Y	Y	Y
Year	Y	Y	Y	Y
Standard errors	Robust	Robust	Robust	Robust

Table A6. Validation against reported cases

This table compares our profit-shifting estimates (in the last column) with those reported in the sources below (5th column presents estimates from the reported sources).

Source	Title	Firm	Year	Estimate bn. USD	Our estimate bn. USD
Reuters	Google to end "Double Irish, Dutch sandwich" tax scheme	Alphabet Inc. (Google)	2018	24.5	16.8
Reuters	Google shifted $23 billion to tax haven Bermuda in 2017 - filing	Alphabet Inc. (Google)	2017	22.5	24.6
Reuters	Google shifted $23 billion to tax haven Bermuda in 2017 - filing	Alphabet Inc. (Google)	2016	18.5	18.6
Forbes	How Google Saved $3.6 Billion Taxes From Paper 'Dutch Sandwich'	Alphabet Inc. (Google)	2015	15.5	14.8
Financial Times	‘Dutch sandwich’ grows as Google shifts €8.8bn to Bermuda	Alphabet Inc. (Google)	2013	11.75	11.3
NL Times	Netherlands earned €25 mil. from Google's tax avoidance	Alphabet Inc. (Google)	2012-2019	153.6	124.0
Seattle Times	How Microsoft moves profits offshore to cut its tax bill	Microsoft Corporation	<=2015	108	141.0
Reuters	Microsoft, HP skirted taxes via offshore units: U.S. Senate panel	Microsoft Corporation	2009-2011	21	24.7
ICIJ	Leaked Documents Expose Secret Tale of Apple’s Offshore Island Hop	Apple Inc.	<=2017	252	290.0

Table A7. 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 A8. 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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