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## Profit shifting and industrial heterogeneity

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## JRC TECHNICAL REPORTS

# Profit shifting and industrial heterogeneity

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Barrios, Salvador and d'Andria, Diego

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## **Abstract**

Base erosion and profit shifting (BEPS) undermines tax revenues collection and raises public discontent in times when the tax burden has increased significantly for households in most developed economies. In addition, new forms of profit shifting related to intangible investment have emerged rapidly along the traditional use of transfer pricing and debt shifting by multinational companies.

In this paper, using worldwide company level data for the period 2004-2013, we demonstrate that the sectoral differences in profit shifting are a serious concern from a welfare and policy perspectives. Sectors performing more profit shifting lower their average cost of capital and are thus able to attract more investment to the detriment of sectors less able to dodge taxes.

We develop a multilevel model and provide indirect evidence of the welfare costs caused by profit shifting by estimating the cross-sectoral variance of semi-elasticity of declared profit. We also demonstrate that having a larger share of intangible assets is not per se related to more profit shifting and that it may point instead to cross-sectoral differences. Finally, we detect almost no financial shifting and find that the largest part of profit shifting is done by means of transfer pricing.

# 1 Introduction

In recent years a large number of policy initiatives have been discussed worldwide to curb profit shifting activities. For instance, the OECD (2013) presented its Base Erosion and Profit Shifting (BEPS) plan which comprises a number of actions aimed at closing tax loopholes, eliminate mismatches between jurisdictions, improve the monitoring and measurement of BEPS and provide best-practice guidelines for anti-avoidance policies. The European Commission (2015) re-launched a proposal for a Common Consolidated Corporate Tax Base (CCCTB) across the EU territory to remove opportunities for transfer pricing within the EU by harmonizing tax base definitions and allocate revenues through an apportionment formula. More recently the US Presidency proposed a major reform of corporate taxation which would introduce a destination-based tax, with the double aim to provide incentives to corporations to repatriate production into the US territory and to impede transfer pricing (the theoretical underpinning of such a reform can be found in: Auerbach 2010, Devereux and de la Feria 2014). All these proposals were preceded by reforms enacted individually in several countries and which already feature all sorts of restrictions to profit shifting such as thin-cap rules, earning-stripping rules, arm's length pricing rules, controlled foreign companies rules, and more.

From a theoretical viewpoint, though, the desire to recover lost tax revenues is not enough to accept anti-BEPS policies on the grounds of welfare maximization. Allocative efficiency (and disregarding fairness concerns) requires undistorted investment choices by multinational firms and none of the corporate taxation schemes currently in existence grants complete neutrality (see Cnossen 2017 for a review). Thus, as multinational enterprises are by definition mobile cross-border and thus sensitive to tax differentials, letting them avoid corporate taxation and recovering lost revenues by raising taxes on less mobile factors (i.e. labour income, consumption, real estate income) might even be welfare-improving. Sørensen (2007) discussed how a differentiated tax rate that favours internationally mobile investments can be superior welfare-wise to an undifferentiated tax, the reason being similar to the well-known inverse elasticity rules in a second-best optimal policy context (Ramsey 1927). It is not straightforward then to disregard the latter argument without proper empirical evidence about both the benefits and the losses caused by profit shifting, not least because estimating the size of tax avoidance is a challenging task as an obvious incentive exists for firms to conceal such activities.

This paper provides several contributions. First and foremost, we provide indirect evidence of welfare costs associated with profit shifting. We propose a multilevel estimation strategy as an alternative to existing empirical methodologies to properly account for and quantify industrial heterogeneity. To the extent that multinationals compete over market shares and input factors, this heterogeneity translates into profit

shifting acting as a subsidy to some industries only, who are capable to engage more intensively in tax dodging. When talking about the subsidization of an industry, we do not refer to an advantage that firms in that industry would gain in terms of sales or revenues, as most products are not substitutes across different industrial sectors. Rather, what we mean is that those firms operating in industries where profit shifting is easier or less costly to perform enjoy lower effective tax rates and thus, their investments face a lower cost of capital. As worldwide investors try to diversify their portfolios and are able to shop both across borders and sectors, such lower cost of capital for high-avoidance sectors translates into an economic distortion (compared to the ideal first-best benchmark of a world without corporate taxation) that drives funds toward high-avoidance sectors and away from low-avoidance sectors.

Our argument is that while tax avoidance may indeed reduce some types of tax-induced distortions in the geographical allocation of investment (thus being welfare-improving), it can cause other kinds of distortions if not all industrial sectors have access to the same avoidance technologies. If the latter is the case, then profit shifting could act as an implicit subsidy to some industries to the detriment of others, thus being welfare-deteriorating. While the distortions caused by tax differentials in the geographical allocation of investments have been documented, this second type of cross-sector distortion has never been demonstrated before nor quantified. We employ our multilevel model to estimate semi-elasticities of pre-tax profit to the tax rate, and also estimate separately semi-elasticities of earnings before interests and taxes, or "EBIT" (the latter to measure transfer pricing separately from financial shifting), and of financial costs and revenues (to capture financial shifting). We can then assess the variance of profit shifting elasticities across industries, which could not be obtained by means of traditional econometric techniques. Our estimates obtained using either a fixed-effects panel model or our multilevel model, point to an overall semi-elasticity of about -0.45, meaning that for a rise in CIT rate of 10 percentage points we expect pre-tax profit to decrease by about 4.5%. The standard deviation of cross-industry variations in semi-elasticities, though, is found to be at least ten times this mean semi-elasticity value even after controlling for firm-level and company group-level characteristics. This finding points to large welfare costs caused by profit shifting. When comparing transfer pricing activities with financial shifting we find the former to be much more sensitive to the tax rate than the latter.

As a second contribution, we disentangle the role of intangible assets from sector-specific characteristics. We find, contrary to previous findings, that the share of intangibles at firm level does not seem to play any statistically significant role in predicting profit shifting. We could not replicate previous findings from the literature,

regardless of the fact that they also employed Orbis data as we did. However we detect a very large variance at industry level of an interaction term between intangibles and our measure of tax differentials. The latter result better qualifies previous literature: intangible assets may indeed allow firms to more easily circumvent anti-avoidance rules (most notably, arm's length pricing rules), but the estimated effects at firm level might be inflated by the fact that measures of intangible-intensity proxy for other characteristics of industries, which we believe to be related to monopolistic competition.

The rest of the paper is organised as follows. Section 2 presents the relevant literature and provides reasons for the idea that firms belonging to different sectors may face different costs (and therefore incentives) to engage in profit shifting. Section 3 describes our data set, and exploits it to address the questions posed here. Building on the premise that profit shifting elasticities across industries is large, we develop accordingly a multilevel model. After validating it, the multilevel model is also used in section 4 to provide estimates separately for transfer pricing and for financial shifting activities, and to estimate the specific transfer pricing channel that exploits intangible assets. Section 5 summarizes the main results and concludes.

## **2 Previous literature**

At least since the seminal work of Hines and Rice (1994) numerous studies (we count at least 28 of such papers at the time of writing, see Dharmapala 2014 for a review) have attempted to estimate profit shifting through least-square regressions using firm-level data. The methodology, which all said studies share in common, estimates a production function at the level of the subsidiary companies using before-tax profit as dependent variable and, as main independent variable, a regressor representing either the corporate income tax (CIT) rate in the country where the subsidiary is located, or alternatively a measure of differences in CIT rates between countries, in order to capture how much before-tax profit decrease as the tax rate differential increases. The coefficient estimated for the CIT rate (or CIT rate differential) variable, is a measure of the semi-elasticity of reported profit with respect to CIT rates, which is interpreted as indirect evidence of profit shifting behaviour. This approach has an advantage in that it allows to compare many countries, years, sectors and company groups simultaneously, thus obtaining estimates that are general and thought as reflective of average tax avoidance practices.<sup>1</sup>

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<sup>1</sup> Other approaches may offer more robust identification of the impact of taxation on profit shifting. Methodologies based on diff-in-diff estimations or quasi-experiments are able to eliminate several confound



Most of the older studies rely on cross-sectional data. Huizinga and Laeven (2008) found a semi-elasticity of 1.3 (using the EBIT as their measure of tax base)<sup>2</sup> based on cross-section firm-level data (using the Amadeus database from the Bureau van Dijk). Similarly, most of the studies published before 2010 do not exploit longitudinal or panel data.<sup>3</sup> By contrast Dischinger (2010) uses panel data (also from Amadeus) and finds a semi-elasticity of .7, i.e. a 10 percentage point increase in the tax rate differential between an affiliate and its parent is associated with a 7% increase in profit reported by that affiliate. Another study by Lohse and Riedel (2013) uses a more recent vintage of panel data from the same database (over 1999-2009) and finds an even lower semi-elasticity of about .4.

The panel data studies usually employ a fixed effects regression strategy, which means that any "between" effects due to unobserved differences in firms or company groups are not accounted for time-constant unobserved differences across countries. Riedel (2014) suggest in particular that the use of panel data allows one to look at the impact of change in corporate tax policies while controlling for time-constant unobserved differences across countries. Using a "within" estimator, like fixed-effects models, means that the cross-sectional information included in the data is discarded. Thus, the two sets of estimates, from cross-sectional data and from longitudinal data (or, from the longitudinal part of panel data), are therefore hardly comparable. Another potential source of difficulty in comparing estimates from different studies concerns the treatment of industry-specific effects. The meta-regression study by Heckemeyer and Overesch (2013) reports a large and significant effect on semi-elasticity estimates when industry fixed effects are controlled for. In studies employing industry-level regressors, these are found to have important and statistically significant effects. This is the case for instance in Loretz and Mokkas (2015) using as control the median leverage ratio at the industry level, or in Beer and Loeprick (2015) who include an industry-specific measure of the complexity of the supply chain. Because none of the previous studies employed multilevel modelling techniques, none of them provides estimates of the cross-industry variance of semi-elasticities, as classical panel models allow intercepts but not coefficients to vary by industry.

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factors and to address endogeneity issues, but produce estimates that are limited to individual markets, countries, times or industries, see for instance Egger et al. (2010), Finke (2013) and Cristea and Nguyen (2016). Combining micro and macro data, more recent studies have come to a better set of estimates of profit shifting that exploit tax havens, see e.g. Tørsløv et al. (2018) and the literature cited therein. But, these studies too face data limitations and, currently, do not provide estimates broken down by sectors.

<sup>2</sup> The value 1.31 comes from the "best guess" model in Huizinga and Laeven (2008). However the same paper provides 24 distinct regressions using EBIT as dependent variable, and the median of the semi-elasticities produced is 0.92. See also Heckemeyer and Overesch (2013): Table 4 in the Appendix.

<sup>3</sup> Out of the 25 studies listed in Heckemeyer and Overesch (2013), only five exploit panel data.

The literature reviewed so far, based on estimating a production function stemming from Hines and Rice (1994), suffers from some important issues due to data limitations. As the firm-level data are never complete and missing observations are not randomly distributed, the estimated betas can be biased and may assign more weight to countries, industries or types of companies just because they are better represented in the data. For instance, the Orbis dataset is known to be biased against smaller firms and to better cover larger countries. Moreover, financial figures for affiliates in tax havens are not always disclosed, as one of the reasons tax havens are used for the purpose of tax avoidance is because they provide secrecy over company data: Tørsløv et al. (2018) estimated that only about 17% of profit held in tax havens is visible in Orbis. This means that elasticities estimated using the Hines and Rice (1994) methodology are likely underestimating the full extent of profit shifting. Our methodology and data share these limitations. However, our aim is to disaggregate variance in order to show that the sector dimension matters. Therefore, although our betas also likely underestimate global profit shifting, there is no reason to believe that tax havens' affiliates are more visible for some industrial sectors and less so for others, as such visibility is exclusively due to the regulatory environment in place in the different countries.

In this paper we propose to employ multilevel hierarchical modelling in order to account for industry-specific effects. This comes natural as firms belong to industrial sectors, and each sector (as discussed further in the text) is characterized by different capabilities with respect to transfer pricing and financial shifting opportunities. These capabilities may depend on the nature of their activities. The use of tax avoidance schemes such as debt shifting, transfer pricing or through intangibles assets location will depend on the nature of economic activity. Different schemes will be used depending on a number of characteristics such as the traceability of corporate revenues, i.e., the possibility to associate these revenues to the markets (and countries) where they are generated, the assets structures and their modes of financing, or the global division of labour between affiliates belonging to a same multinational groups, to name a few. Another reason why the extent of profit shifting can vary between sectors is that some produce goods or services characterized by low substitutability which, as such, are harder to peg to some arm's length price (obtained from comparable products sold on the markets).<sup>4</sup> More generally, sectors of activity can face different incentives (different regulations, economic conditions, competition regimes) which can in turn affect the propensity to engage in profit shifting. All these elements have strong sector-specific features which also impinge of their tax avoidance *modus operandi*.

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<sup>4</sup> Also, sectors differ w.r.t. the level of riskiness and the collaterals firms may offer to lenders, thus the financial leverage and the possibility to exploit debt as a channel for profit shifting may differ too. The latter aspect will be discussed in the next sections.

One general problem with hierarchical data is that classical estimation strategies, even including sector-specific indicators, may fail to properly account for group-specific effects, as classical models assume that the residual variance is the same within each group. Moreover classical models do not allow slopes to vary across groups. On the contrary multilevel (also called "hierarchical mixed-effects") models take into account the relative size (in terms of observations) of each group and employ a probabilistic weighting. The group-specific intercepts are assumed to follow a Gaussian probability distribution, where the parameters of the distribution are estimated from the data. In this way, proper estimation is possible of the cross-industry heterogeneity both for reference levels and for the intensity of the effects (coefficients) of corporate taxation: see Gelman and Hill (2006) and Hox and Roberts (2011).

Although in our case we cannot exclude a very small degree of omitted variable bias in using multilevel models due to unobserved differences between individual firms (though we properly account for possible omitted variable bias, as detailed in Section 3), this shortcoming is traded-off against some benefits which are not available in classical fixed-effects panel models. These benefits refer to the explicit estimation of industrial heterogeneity in profit shifting sensitivity; the possibility to include time-invariant controls; the improved predictive power for individual predictors (which can be useful for applied policy modellers); better estimation for small industrial groups thanks to information sharing among distinct groups; better correction for strongly unbalanced panel (where the number of times the same subject is observed varies considerably). Given this trade-off, we propose the use of multilevel models as an additional tool together with classical fixed-effects models to better shed light on profit shifting activities. In particular we exploit multilevel modelling to obtain an estimate of the variance of profit shifting elasticities across industries, which could not be assessed at all using classical estimation techniques.

### **3 Data and methodology**

We use firm-level data from the Orbis database (published by Bureau van Dijk) for the years from 2004 to 2013. Orbis provides information on companies' ownership structure, activity, accounts, financial items and legal status for companies globally. The usual and well-known limitations of the Orbis data apply here: they are biased toward larger firms, not all countries are equally well covered, and the data requires some polishing before being ready for use (the latter is detailed below). Orbis (and its related product Amadeus) is however the most widely used database for profit shifting estimation, and as such, gives us a very high degree of comparability with previous studies.

From Orbis we extracted entries for firms that have "reasonable" values for selected items, that is, we choose to keep only observations having non-negative figures for the number of employees, cost of labour, turnover, and fixed assets (as negative values in these fields likely signal errors in the records). We only kept entries for which a global ultimate owner (GUO) defined based on a 50% shareholding rule was available owning at least one other company, as our interest is solely about company groups. The sample is restricted to multinationals only, defined as company groups with members in at least two distinct countries. In order to track changes in company ownership over time and thus identify the correct GUO in each year, we matched the Orbis data set with another Orbis product from Bureau van Dijk that provides detailed data, separately for each year, about the shareholding links between companies. The use of this more precise information about GUOs comes at the cost of panel length as we could only use yearly files from 2004 to 2013.

We thus obtain more than 700,000 firm-level observations across 55 different countries. The data set is very rich and provides figures for several accounting items (e.g. pre-tax profit, EBIT, turnover, fixed assets, intangible assets, cost of labour, number of employees, financial costs, financial revenues), historical ownership data (which we exploit to identify groups of companies) and Nace 4-digit industry classification.

We complemented Orbis data with country-level data in order to estimate a standard equation of profit shifting using variables which are typically used in existing studies. These include CIT rates, GDP (in levels and per capita) and an indicator measuring the strictness of regulation. CIT rates were obtained from multiple sources: KPMG, Ernst&Young, IBTS (Institute for Business Taxation studies), Deloitte. Where applicable, linearly interpolated data have been added for CIT rates in some years. GDP and GDP per capita are expressed in current USD and were obtained from the World Bank's World Development Indicators. The Freedom index is from the Fraser Institute and proxies for different countries' institutional characteristics (e.g. the quality of regulation) for the three areas related to: 2. Legal system and property rights, 4. Freedom to trade internationally, and 5. Regulation (we computed a simple average of these three sub-indexes). Table 1 summarizes the variables.

### **3.1 Replication of previous findings**

The first use of our data is to perform classical fixed-effects panel regressions to assess the size of profit shifting and compare our semi-elasticities with those from the literature, in order to validate our data against data sets used in previous studies. At this stage we just aim at providing a replication of existing studies. We will use these first-

stage results as benchmark estimation to compare against those produced by multilevel models presented in the next sections.

Our main reference for measuring the impact of international taxation is the work of Huizinga and Laeven (2008). Following their methodology we compute a "c-index" which captures the incentives for a subsidiary to under- or over-report before-tax profit. The c-index jointly takes into account the tax rates in all countries where a company group has affiliates, and also the opportunities for profit shifting a group has as a function of the size of economic activity in each country (proxied using turnover). The c-index thus better capture global incentives to engage in profit shifting, compared to simpler CIT rate differentials (between parent and host countries). A rationale for using c-indexes is also provided by the meta-regression analysis in Heckemeyer and Overesch (2013) where it is found that the use of worldwide tax incentives (such as those proxied by the c-index) can affect the estimates in a significant way. Moreover a large body of anecdotal evidence points to company groups being able to shift taxable bases across several jurisdictions, thus by considering statutory rates in the affiliate location only, one would misrepresent the overall set of incentives faced by multinational groups (on topic see Markle 2015). Finally, affiliates of a group may enter into transactions that do not directly involve their direct parent companies, thus using differences in rates between direct parent and owned companies would capture just one (out of many) of the possible ways profit can move between affiliates.

A set of tests was performed on the following firm-level fixed-effects panel regression model, for each firm  $j$  in year  $t$  as described in equation (1) below.

$$\pi_{jt} \sim \beta_0 + \beta_1 GPD_{jt} + \beta_2 CAPITAL_{jt} + \beta_3 LABOR_{jt} + \beta_4 C-INDEX_{jt} + \beta_x X_{jt} \quad (1)$$

As in previous literature, the dependent variable  $\pi_{jt}$  is EBIT (earnings before interests and taxes) or pre-tax profit. Fixed assets is used to proxy for capital inputs, labour costs are used for labour inputs, GDP per capita is meant to capture country-specific time-variant effects on productivity. We tested a "minimal model" that excludes controls  $X$  and is closer to the base model in Huizinga and Laeven (2008), and a "full model" using several controls in  $X$ . Vector  $X$  includes a set of group-level controls: the number of affiliates in the corresponding company group<sup>5</sup>, the number of countries the group is active in, consolidated EBIT, consolidated net financial costs, share of intangible over total assets at the level of the group, and country-level time-variant controls mentioned above (GDP, Freedom Index). Group controls are meant to capture both the size and

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<sup>5</sup> In line with the literature (see previous Section 2) we include multiple affiliates of a same company group that reside in the same country. This might over-represent groups with many affiliates, thus we also control for the number of affiliates of a group in vector  $X$ .

complexity characteristics of the group, as larger and more complex groups have been found to have both different productivity and different capabilities with respect to profit shifting activities (see for instance Gumpert et al. 2016 and the literature review therein). An additional model is tested which includes Nace 2-digit industry-year dummies to control for industry-year shocks. All mentioned variables except *c*-indexes are then transformed into logarithms. Accounting data is from unconsolidated accounts at the affiliate level, and at the company group level we use either consolidated accounts or data obtained by summing up unconsolidated accounts from companies belonging to the same group. Year dummies and a pseudo-continuous year variable are included to account for time-related effects. Standard errors are robust with respect to heteroskedasticity and autocorrelation. The share of intangible over total assets was found to be relevant for transfer pricing in several studies, starting at least from Desai et al. (2006). The role of intangibles will be further analysed in Section 4.

The full model with industry-year and year dummies is the preferred one based on comparisons of adjusted  $R^2$ , AIC and BIC statistics, and it generates a semi-elasticity of  $-.451$ , see the right-most column in Table 2. Reduced models (omitting some or all control variables) lower the estimated semi-elasticity up to  $-.23$ . All estimations for the semi-elasticity are significant at the 1% level and the adjusted  $R^2$  is always between  $.04$  and  $.06$ , the only exception being full models that include country-year dummies, the reason being collinearity with other covariates (particularly with non-standardized GDP per capita and *c*-indexes, see for example column 3 in Table 2). As one can see, the obtained coefficients are small and in line with estimations from some recent studies using panel data (e.g. see: Blouin et al. 2012, Becker and Riedel 2012, Lohse and Riedel 2013, Dischinger et al. 2014, Beer and Loeprick 2015) which obtain estimates in the range of  $-.4/-0.5$ . Our results would suggest a semi-elasticity estimate between  $-.25$  and  $-.55$ , therefore very close to, and slightly lower than, the previous studies.

### **3.2 Multilevel hierarchical model: preliminary discussion and motivation**

As a preliminary step in order to better motivate our modelling choices and usefulness of a multilevel approach, we first separate our data into 85 distinct industry sub-samples corresponding to 2-digit Nace industry code. We then run regressions using the same fixed-effects models as the ones in Table 2 (i.e. the minimal model, and the full model but omitting industry-year dummies), for each of the 85 sub-samples. The aim is to see how elasticity estimates (the "slopes" estimated for *c*-indexes) change across sectors.

Table 3 reports the average coefficient found across those tests, only keeping results where the *p*-value for *c-index* was equal or lower than 10%, or equal or lower than 5%.

The maximum and minimum coefficient values are also reported. The selection of the results at  $p\text{-value} < 10\%$  leaves between 26 (minimal model) and 30 (full model) estimated coefficients. At  $p\text{-value} < 5\%$  the number of estimated coefficients reduces to 18 (minimal model) and 22 (full model). In the lower part of Table 3 the same averages were computed weighting the coefficients by the number of observations in each industry sub-sample, in order to downplay the effects of smaller sub-samples (which are likely to produce less reliable estimates).

Several points are worth highlighting from Table 3. First, the variance across industries of the estimated coefficients is really large, suggesting that it might be worth using a multilevel model with different slopes at the industry level. Second, on average the coefficients are larger than the ones obtained pooling together all industries (compare with Table 2). The latter observation points to possible bias in estimations made pooling data together and disregarding their hierarchical structure. It is just the case to stress again that the tests summarized in Table 3 were performed using a fixed-effects model (as such, robust to omitted variable bias) and run separately for each industry sub-sample.

There are multiple reasons why the sensitivity of profit shifting to tax differentials can differ across industries. One prominent reason rests on the idea that firms who benefit from monopolistic positions can more easily circumvent arm's length pricing rules and thus more easily engage in transfer pricing. Monopolistic rents come to a relevant extent from innovations and product differentiation, that is, on average the larger is the value-added produced by a product, the more such product is different from what competing firms produce. If a product is more unique, then it is also harder for tax authorities to find (and justify) proper comparisons for the sake of applying arm's length pricing rules.

To support this idea we employed data on sectoral mark-up prices published in Christopoulou and Vermeulen (2012). We matched the industry classification in Christopoulou and Vermeulen (2012) with the NACE codes we use in this study. Then, we compared the c-indexes obtained from industry sub-samples (the same reported in Table 3) with the corresponding mark-ups. As an example, Figure 1 scatter-plots c-index coefficients (the same used in Table 3) against markups, for the 19 industry sub-groups for which we obtained coefficients at  $p\text{-value} \leq 10\%$ . The correlation coefficient between the two series is  $-.48$  and this negative correlation is quite visible, particularly for the largest mark-ups. When using coefficients with  $p\text{-value} \leq 5\%$  (not shown in the Figure for space reasons), the correlation is  $-.46$ .

The apparent variance in estimated elasticities across industries and the suggestive correlation with mark-up prices leads us to further inquire, in the following sections, the role of sectoral heterogeneity in shaping profit shifting behaviour. One additional

hypothesis we also study is that past studies reporting a significant relation between the intensity in intangible assets and profit shifting elasticities might be capturing sectoral characteristics that may correlate with intangibles, but not being due (or, not solely due) to the exploitation of intellectual property rights for the purposes of tax avoidance. This will be done in Section 4.

### 3.3 Multilevel hierarchical model estimation

We run a complete 3-level multilevel model of the form:

$$\begin{aligned} \Pi_{tfi} \sim & (\beta_0^{(t)} + \beta_0^{(f)} + \beta_0^{(i)}) + (\beta_1^{(t)} + \beta_1^{(i)}) GPD_{tfi} + (\beta_2^{(t)} + \beta_2^{(i)}) CAPITAL_{tfi} + \\ & + (\beta_3^{(t)} + \beta_3^{(i)}) LABOR_{tfi} + (\beta_4^{(t)} + \beta_4^{(i)}) C-INDEX_{tfi} + (\beta_5^{(t)} + \beta_5^{(i)}) INTANGIBLES_{tfi} + \beta_x^{(t)} X_{tfi} \end{aligned} \quad (2)$$

where the superscripts  $t$ ,  $f$  and  $i$  indicate the level, respectively, of: time, firm, and industry. The hierarchical structure of the data is nested: different observations in time  $t$  belong only to a single firm  $f$ , and each firm  $f$  belongs to one industry  $i$ .

The lowest level (level 1) groups the observations at different points in time related to the same firm. Here the choice of the independent variables is made as per the full model in (1), plus we add country dummies<sup>6</sup>. We also controlled for country-specific characteristics, in addition to the time-invariant country dummies and time-variant GDP per capita. We included the logarithm of GDP to capture the market size of host countries, a dummy equal to one if the host country is an EU member (to account for the effects of the common market on profitability), and the Fraser Institute's Freedom Index. Level-1 equation includes a time (year) variable as a pseudo-continuous variable to capture linear trends, and also year dummies to account for possible year-specific shocks to profitability due to the business cycle.

The middle level (level 2) computes firm-specific intercepts (that is, it captures time-invariant characteristics of the firms), and the highest level (level 3) computes sector-specific intercepts and sector-specific slopes for the c-index and for the affiliate-level variables labour, capital, GDP per capita, and intangibles share. Thus the production function plus the c-index is evaluated at the level of the firm (across time), but using slopes that differ between industries. A way to interpret the model, which is perhaps more intuitive, is to consider levels 1 and 2 jointly as a fixed-effects panel estimator (the firm dummy in level 2 indeed captures time-invariant firm-specific effects), which is then further decomposed and nested into the level-3 industrial decomposition.

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<sup>6</sup> An added advantage of using "random effects" lies in the possibility to include time-invariant controls such as country dummies, which we could not use in the fixed effects models discussed previously; country effects are meant to capture institutional conditions specific to countries that are fixed across the years we consider.



The model is solved by means of maximum likelihood estimation and using robust standard errors to deal with possible heteroskedasticity. Table 4 reports coefficients for our main specifications, separately for the two dependent variables (pre-tax profit and EBIT) and models (minimal and full). The minimal model produces a coefficient that is close to Heckemeyer and Overesch (2013) "consensus" estimate of -.82. The full model produces much smaller coefficients (-.475 in our best-performing model, chosen by comparing AIC and BIC criteria). Lacking any control for the company groups, however, the minimal model might be capturing "between" effects related to company groups. In terms of explanatory power the multilevel models performs well, for example looking at the Snijders-Bosker R-squared statistics for level 1 (firm), calculated for a reduced model without the middle level for firm-specific effects, the value ranges between .58 and .60, while for level 2 (industry) the R-squared ranges between .78 and .81. Comparing the multilevel models with the corresponding fixed-effects models, the predicting power (expressed as R-squared) is always larger for the multilevel models. Note that the obtained coefficients for the c-index are rather close to each other when using the full multilevel model (-.475) and the preferred full fixed-effects model (-.451).

The multilevel design obtains estimates of the standard deviation of the slopes at the level of the industries, which would not be available using classical models. A reading of the random effects in Table 4 is per se informative and shows that the variance of c-index coefficients across industries is very large (standard deviation of more than 5 percentage points), thus confirming the preliminary analysis presented in Table 3. This standard deviation is as large as ten times the semi-elasticity value: it might well be therefore that global profit shifting is driven by few, very sensitive sectors. This poses an issue for policy makers, as anti-avoidance regulations may impose a burden in terms of compliance costs on all firms, while only some sectors truly engage in intensive shifting activities. Important to note is that the very large variance at the industry level remains even after controlling for firm heterogeneity (captured by the regressors for assets, employed workforce and intangibles) and group heterogeneity (captured by our vector of group-level controls for size, intangibles, and financial characteristics).

The sector-specific constant varies as much as the firm-level constant, meaning that differences across sectors are comparable in magnitude to differences across firms. The sum of sector and between-firm heterogeneity is more than half of the longitudinal heterogeneity of firms, the latter given by the value in the row *sd(Residuals)* in Table 4. Interestingly, the coefficients for the share of intangibles also vary substantially, in relative terms across sectors, pointing to the heterogeneous capabilities that different sectors have in generating and exploiting patents, trademarks, copyrights and other forms of intangible assets.

Additional interesting results concern the sector-level random effects for the proxies of labour and capital: the slopes of labour costs appear almost not to vary at all across sectors (while this is not the case for the slopes of fixed assets). The same result was obtained when transforming the reported variables by standardizing them. This might hint to the fact that using labour costs as a proxy for real economic activity in a nexus-based CIT system where revenues are split among countries based on an apportionment rule (as currently under discussion in the EU for the CCCTB reform proposal) might cause less inter-sectors behavioural distortions than one based on fixed assets. Also, c-indexes might be better calculated by using labour costs as weights instead of turnover, as the latter might be sensitive to profit shifting.

### **3.4 Multilevel hierarchical model robustness tests**

Several robustness checks were run (in addition to the usual tests). We used different definitions of the c-index (weighted by turnover as in Huizinga and Laeven 2008, non-weighted, and weighted using labour costs), but results were never affected meaningfully as the different c-indexes strongly correlate. Because it might be that industry variance could be partly capturing underlying country variance as industries are not evenly distributed geographically, we tested a different multilevel model where the nesting was done as time-firm-country, with industry dummies as controls at level 2. We found that the estimated elasticity is in that case about  $-.65$  when using profit and about  $-.66$  when using EBIT. Standard deviation at country level is about 5.2 when using either profit or EBIT. Two things are worth noticing. First, although the level 3 standard deviation is very similar when using either countries or industries, in relative terms because the estimated coefficient is smaller for industries it means that the variability is larger than across countries. Second, both the Akaike and the Bayesian information criteria indicate that the time-firm-industry model has larger explanatory power (they score 786,231 and 786,984, respectively, against 789,422 and 789,735 when using country-nesting; this ranking remains true even when omitting industry dummies in the time-firm-country models).

To account for possible omitted variable bias we followed the methodology outlined in Kim and Swoboda (2011) and compared our full model estimation with a multilevel model only using 2 hierarchical levels (in other words, we compared our results with the coefficients obtained from a classical fixed-effects panel model omitting country dummies and including Nace 2-digit sector-year dummies). We detect a difference in the coefficients found by means of multilevel regression and full range of controls, in comparison to classical fixed effects, of about  $.115$ , meaning that we cannot exclude that some omitted variable bias is present when using our full multilevel model. The produced

residuals, however, follow a distribution that fairly resembles a normal distribution. We conclude that the model in (2) is more efficient than the classical fixed effects panel model (as it uses more information from the data), but it brings a potential bias in the estimation of the c-index coefficient up to (an increase in absolute value of) .115. Given this potential bias and to further validate our estimates of industry-level variance in elasticities we built a different multilevel model following a methodology first proposed in Mundlak (1978; see Bell and Jones 2015 for a discussion on the merits of Mundlak's methodology). Basically, Mundlak's approach consists in substituting regressors with their mean across time and their differences to this mean. This is conceived as a solution to omitted variable bias endogeneity issues met in mixed effects models, because the between-effect component would be captured by the mean, while the within-effect component would be captured by the time-varying difference from the mean. In all our Mundlak-like specifications, the standard deviation of c-index coefficients at level 3 was always much larger than in our base multilevel models (up to more than 17 times the estimated elasticity value). We conclude that the obtained very large cross-industry variance is robust to possible omitted variable bias.

Comparing with other studies, we see that our elasticity estimates using EBIT position themselves below both older estimates (which find values well above 1) and most of the newest studies such as Lohse and Riedel (2013), Dischinger et al. (2014), Beer and Loeprick (2015), who find on average elasticities equal to -.53 when using EBIT. These results are closer to average coefficients found in Loretz and Mokkas (2015), whose mean is -.38 as reported in Heckemeyer and Overesch (2013).

## **4 Channels of profit shifting: transfer pricing versus financial shifting**

In this section we analyse separately transfer pricing through intangibles exploitation or financial shifting, using the multilevel model presented and validated in section 3. Companies can exploit different forms of profit shifting. Broadly speaking two main channels have been identified in the literature: transfer pricing, which also includes shifting by means of royalties and license fees for the use of intangible assets, and financial shifting. Transfer pricing alters the price of goods and services sold in intra-group transactions, and as such it affects the value of EBIT, but not the value of financial profit and losses. Financial shifting exploits the debt structure, either substituting equity capital for debt, or altering the interest rate paid on intra-group financial transactions. The latter affects the net financial cost (the difference between financial costs less

financial revenues) but it does not affect EBIT. It is just the case to remind that the overall profit before tax is obtained as the algebraic sum of EBIT less net financial costs.

## **4.1 Transfer pricing and intangible assets**

A growing body of the literature has focused on the relation between intangible assets and transfer pricing activities. Examples are Desai et al. (2006), Overesch and Schreiber (2009), Dischinger and Riedel (2011), Beer and Loeprick (2015), Griffith et al. (2014), Alstadsæter et al. (2015). Two main themes have been addressed: the fact that the ownership of intangibles can be moved between affiliates at a relatively low cost, and the fact that intangibles are often highly differentiated goods, in some cases truly unique, thus the search for an arm's length price is made particularly difficult for tax authorities. Here we focus on the second theme and look at the possible interactions between intangibles ownership and transfer pricing.

We follow the prevalent literature and add an interaction terms between c-index and a measure of intangibles intensity at the level of the subsidiary (in our case, this is the share of intangible over total assets). Previous studies using this approach (Overesch and Schreiber 2009, Beer and Loeprick 2015) have reported very large effects of the interaction term. For example, Beer and Loeprick (2015) conclude that "Increasing the ratio of intangible to total assets by one standard deviation translates into a 0.27 points higher semi-elasticity of taxable profits."<sup>7</sup>

We employ our full specification using EBIT as dependent variable, first testing a fixed-effects panel model as in (1), and then our multilevel model. The multilevel model is first run as per model (2), and then also having an industry-specific slope for the interaction term (either including, or not including, the share of intangibles together with c-index and the interaction term). Results are summarized in Table 4. The interaction term always produces small and non-significant coefficients using the fixed-effects model. From these results it would seem that intangibles do not play a major role at all, in direct contrast with results presented in previous studies.

Table 4, however, showed that the slope for intangibles varies greatly across industries, when using EBIT as dependent variable. It is important to bear in mind that no link must necessarily exist between the book value of the intangible asset (which, as stated before, cannot be at market value given the unique nature of most intangibles, and

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<sup>7</sup> It is important to note that the models tested in Beer and Loeprick (2015) are the closest and most comparable with our own, also given their use of Orbis data. Differences between our study and Beer and Loeprick (2015) exist, though, which make the results less comparable even when looking at classical fixed-effects models: they selected companies based on a 90% ownership rule, while we used 50%; they regressed the tax difference between parent and subsidiary, while we use c-indexes.

therefore often just equals development costs as per international accounting standard guidelines) and the actual price (royalties, or licence fees) paid for its use by third parties. In Beer and Loeprick (2015) the latter issue was partly accounted for by also looking at a dummy taking value 1 if the share of intangibles is above the sample median. However, it might still be the case that having more or less intangibles acts as a proxy for belonging to a high- or low-intensity sector in intangibles (for example, to an R&D-intensive sector where on average firms own several patents). Put in other words, if the latter were true, it would not be the case that a larger share of intangibles is a causal driver for more transfer pricing by individual firms, but rather, it would be true that belonging to a sector of activity rich in intangibles (or, rich in some types of intangibles) makes the company more prone to engage in profit shifting.

Table 5 reports results from the tests made by adding an interaction term between intangibles and c-indexes, either with logarithmic transformations of variables (as per previous section) or with standardized variables (this was done to reduce collinearity of the interaction term, and also to improve comparability with the results from earlier studies). The multilevel estimations in Table 5 report a small and statistically insignificant coefficient for the interaction term at level 2. When making the slope for the interaction term industry-specific (adding it at level 3), we find a standard deviation of .442 (with standard error .045). When using standardized variables the standard deviation at level 3 is .068 (with standard error .014) when adding both the interaction term and the share of intangibles at level 3, or .162 (with standard error .006) when omitting the share of intangibles at level 3. Thus, we can state that heterogeneity in industries definitely affects the use of intangibles for the purposes of transfer pricing. On average, belonging to a sector where intangible-driven transfer pricing is high (defined here as a sector that is at a one standard deviation positive distance from the across-industries mean) means a 100% to 700% larger semi-elasticity of EBIT, depending on the model specification. We conclude that intangible assets are associated with larger transfer pricing activities, but only conditional on the company belonging to specific industrial sectors.

One could possibly attribute this result to the different types of intangibles that are prevalent across sectors of activity. For instances patents might be more easily exploited than copyrights (or vice versa) for the purposes of transfer pricing, thus a technologically-intensive sector would be associated with more profit shifting. The latter hypothesis would be in line with studies that focus on the location choices of firms and find relevant industrial heterogeneity even just looking at the sensitivity of patent ownership (Griffith et al. 2014, Alstadsæter et al. 2015).

## 4.2 Financial shifting

We now use our multilevel model to produce estimates of financial shifting semi-elasticities. Sectors may differ w.r.t. the level of riskiness and the collaterals firms offer to lenders, thus the financial leverage and the possibility to exploit debt as a channel for profit shifting may also differ. We explore this possibility and to this end we repeat the same tests using the full model under (2), this time having as dependent variable either financial costs, or financial revenues (as before, values are transformed into logarithms).

Direct estimation using financial figures from the profit & loss account has, to our knowledge, never been used in previous studies (debt ratios are employed instead). We assume that the need for financing is roughly proportional to production, and therefore we may employ the same model used to explain pre-tax profit and EBIT. We expect to find that financial costs positively correlate with CIT rates, while the opposite should hold true for financial revenues.

As an alternative specification we employ "net" financial costs or revenues, obtained by subtracting financial revenues from costs (or vice versa). Thus, net values represent the profit margin due to financial activities and are separately regressed for firms having a negative margin (net costs) and then for firms having a positive margin (net revenues). Table 4 summarises the coefficients obtained.

The results in Table 6 produce very small sector-specific constants (less than .0001). This is in line with the idea that firm-specific and group-specific characteristics are more important in defining the access to external financing sources than sector-related characteristics. However, here again, the slopes for c-index relevantly differ across sectors, suggesting that the potential for profit shifting through financial channels is also heterogeneous across industries, as we previously argued for transfer pricing. Our tests obtain, as expected, a negative coefficient for financial revenues equal to  $-.270$ , but a coefficient for financial cost that is not statistically significant. Similarly, using net financial revenues we find a negative and significant coefficient ( $-.712$ ), while the coefficient for net financial costs obtain the opposite sign than expected. The coefficients for net financial costs and financial costs become insignificant when we exclude observations for financial (banks and insurance) companies, as a small number of companies in our data set belong to the financial macro-sector (looking at unprocessed data, a total of 14,109 observations out of 1,095,298, or equivalently, 1.29% of the sample belong to the financial macro-sector). The significance for financial revenues is lost as well when excluding financial companies, but it remains (at  $p\text{-value} < 1\%$ ) for net financial revenues.

We conclude that results are not robust for (net) financial costs. Coefficients obtained using financial revenues (but not using net revenues) remain significant even excluding financial companies. One interpretation is that non-financial companies rely often on external debt financing but they seldom have financial assets generating interests from unrelated parties. That is, it is likely that financial revenues are more often intra-group transactions in non-financial firms, than financial costs (which include genuine costs paid to external lenders). This would explain why costs are less significant in our estimates than revenues. However we cannot test this hypothesis as the data set does not allow distinguishing between intra-group and extra-group transactions.

A comparison of our results from using financial items is made harder by a lack of studies employing this measure. A comparison can still be made indirectly, by looking at differences between the obtained semi-elasticities from regressing EBIT and pre-tax profit. Heckemeyer and Overesch (2013) employ the following method: they multiply semi-elasticities from EBIT by a correcting factor of 1.25 which serves the purpose to make the semi-elasticities comparable with those obtained using pre-tax profit, as they empirically find that EBIT is on average 25% larger than pre-tax profit. The ratio of EBIT on pre-tax profit was calculated using consolidated accounts for the S&P 500 companies, thus clean from intra-group transactions and from effects ascribable to profit shifting. In this way they calculate a comparable semi-elasticity from "consensus" EBIT coefficients (-.594), and they derive a comparable semi-elasticity for the financial margin (differencing between semi-elasticities from pre-tax profit and comparable EBIT), equal to -.227. The latter is visibly smaller than the former, thus transfer pricing should be deemed more important than financial shifting. Note though that Loretz and Mokkas (2015) obtain the opposite result as their mean coefficient for pre-tax profit is much larger than for EBIT, thus pointing to financial shifting being more important than transfer pricing.

If we proceed similarly to Heckemeyer and Overesch (2013) and multiply our coefficient from EBIT (-.393) by 1.25 we obtain a comparable semi-elasticity of -.491, a value that is larger than the semi-elasticity obtained using pre-tax profit (-.475). Table 6 summarizes semi-elasticities from our multilevel estimations, the "consensus" estimates from Heckemeyer and Overesch (2013), and the mean estimates from Huizinga and Laeven (2008) and Loretz and Mokkas (2015) (these are, to our knowledge, the only other studies that exploit panel data using both EBIT and pre-tax profit as dependent variables). We employ the mean semi-elasticities for each study as calculated in Heckemeyer and Overesch (2013). All values for the EBIT elasticities in Table 6 are multiplied by 1.25 to make them directly comparable to pre-tax profit semi-elasticities.

The "Financial margin" semi-elasticities reported in Table 6 are derived by subtracting the value in row 2 from the value in row 1.

Again following Heckemeyer and Overesch (2013), if one extrapolates the semi-elasticity that would be needed for the financial margin to obtain our overall semi-elasticity of -0.475, given the comparable semi-elasticity for EBIT (-.491), then by simple algebraic computation it turns out that this derived comparable semi-elasticity is:  $.491 - .475 = .016$ , a positive value and (in absolute value) much smaller than -.491.

In summary, transfer pricing results in (much) larger semi-elasticities than those generated by financial shifting activities. Note that the latter result cannot be attributed to the use of multilevel methodology, as it is obtained as well by classical fixed-effects model estimation: the semi-elasticities in the latter tests were equal to -.359 for pre-tax profit and -.269 for EBIT, which means that the comparable EBIT semi-elasticity would be  $-.269 * 1.25 = -.336$ , and the derived comparable semi-elasticity for financial shifting just -.023.

## 5 Conclusions

We exploited firm-level data to document a relevant heterogeneity across industries in the response of pre-tax profit to CIT rates, suggesting that a multi-level econometric estimation is a useful complement to classical techniques to quantify the size of profit shifting. We motivate this heterogeneity pointing to cross-sector differences in the capabilities to engage in transfer pricing. Accounting for sector-heterogeneity in profit shifting has important normative and policy implications and this is the first time it is rigorously estimated. In theory profit shifting fosters internationally mobile investments and helps reduce the allocative inefficiencies represented by different national tax systems. However tax avoidance may be limited to a few sectors, such that generally loose control on profit shifting can act as a subsidy to some industries only, that is, to the ones capable to engage more easily in tax dodging.

Our study therefore contributes to the assessment of said welfare costs by explicitly estimating how profit shifting varies across industries. The larger the cross-industry variance in profit shifting activities, the larger distortions caused on the allocation of investments and the smaller the welfare costs expected from stopping them. We indeed find a very large variance as the estimated standard deviation of elasticities is about ten times the mean value of the elasticity across sectors. Such large variance remains even after controlling for firm and group specific characteristics that are known from the literature to be associated with different degrees of profit shifting. A message stemming from these results is that empirical analyses of profit shifting (including for the



calibration of macro-models) should probably pay attention to specific sectors of activities.

We further dissected the nature of our profit shifting estimates by looking at the role of intangible assets and at the relative magnitude of transfer pricing versus financial shifting. We found that, in our data and contrary to previous literature, intangibles do not affect elasticities directly at firm level, rather they seem to capture heterogeneity at the sectoral level. This result questions (the interpretation of) previous evidence reporting a sizable and statistically significant effect of intangibles on profit shifting elasticities, as it might be that those coefficients were merely proxying for unobserved industry characteristics (e.g. as we pointed out, arm's length pricing rules are less binding because of larger monopolistic rents). Our results also downplay the importance of financial shifting as we almost exclusively detect transfer pricing at play. It might be (though this is merely a speculation) that the proliferation of thin-capitalization and earning-stripping rules across the globe have hampered the financial channel for tax avoidance so that multinationals now rely more on transfer pricing alone.

## References

- Alstadsæter, A., Barrios, S., Nicodème, G., Skonieczna, A.M. and Vezzani, A. (2015), "Patent Boxes Design, Patents Location and Local R&D," WP No. 57. Directorate General Taxation and Customs Union, European Commission.
- Auerbach, A. (2010), "A modern corporate tax," The Hamilton Project.
- Becker, J. and N. Riedel (2012), "Cross-Border Tax Effects on Affiliate Investment – Evidence from European Multinationals," *European Economic Review*, 56, 436-450.
- Beer, S. and Loeprick, J. (2015), "Profit shifting: drivers of transfer (mis)pricing and the potential of countermeasures," *International tax and Public Finance*, 22, 426-451.
- Bell, A. and Jones, K. (2015), "Explaining Fixed Effects: Random Effects Modeling of Time-Series Cross-Sectional and Panel Data," *Political Science Research and Methods*, 3, 133-153.
- Blouin, J., L. Robinson and J. Seidman (2012), "Coordination of Transfer Prices on Intra-Firm Trade," Tuck School of Business Working Paper No. 2010-74, Dartmouth.
- Christopoulou, R. and P. Vermeulen (2012), "Markups in the Euro area and the US over the period 1981-2004: a comparison of 50 sectors", *Empirical Economics*, 42(1), 53-77.
- Cnossen, S. (2017). "Coordinating Corporation Taxes in the European Union: Slowly moving towards CBIT?," *International Tax and Public Finance* (forthcoming).
- Cristea, A.D. and D.X. Nguyen. "Transfer pricing by multinational firms: New evidence from foreign firm ownerships," *American Economic Journal: Economic Policy*, 8(3), 170-202.
- Desai, M.A., Foley, C.F. and Hines, J.J. (2006), "The demand for tax haven operations," *Journal of Public Economics*, 90(3), 513-531.
- Devereux, M.P. and de la Feria, R. (2014), "Designing and implementing a destination-based corporate tax," Oxford University Centre for Business Taxation, Working Paper 14/07.
- Dharmapala, D. (2014), "What Do We Know About Base Erosion and Profit Shifting? A Review of the Empirical Literature," CESifo Working Paper Series No. 4612.

- Dischinger, M. (2010) "Profit Shifting by Multinationals: Indirect Evidence from European Micro Data," Discussion Paper, Ludwig-Maximilians University Munich.
- Dischinger, M. and Riedel, N. (2011), "Corporate taxes and the location of intangible assets within multinational firms," *Journal of Public Economics*, 95(7-8), 691-707.
- Dischinger, M., B. Knoll and N. Riedel (2014) "The Role of Headquarters in Multinational Profit Shifting Strategies," *International Tax and Public Finance*, 21, 248-271.
- Egger, P., W. Eggert and H. Winner (2010), "Saving Taxes through Foreign Plant Ownership," *Journal of International Economics*, 81, 99-108.
- European Commission (2015), *A Fair and Efficient Corporate Tax System in the European Union: 5 Key Areas for Action*, Communication from the Commission to the European Parliament and the Council, COM(2015)302, June.
- Evers, L., Miller, H. and C. Spengel (2014), "Intellectual Property Box Regimes: Effective Tax Rate and Tax Policy Considerations," *International Tax and Public Finance*, 1-29
- Finke, K. (2013), "Tax Avoidance of German Multinationals and Implications for Tax Revenue Evidence from a Propensity Score Matching Approach," mimeo.
- Gelman, A. and Hill, J. (2006), *Data analysis using regression and multilevel/hierarchical models*. Cambridge University Press.
- Gumpert, A., Hines, J. R. Jr, and Schnitzer, M. (2016), "Multinational firms and tax havens," *Review of Economics and Statistics*, 98(4), 713-727.
- Griffith, R., Miller, H. and O'Connell, M. (2014), "Ownership of intellectual property and corporate taxation," *Journal of Public Economics*, 112, 12-23.
- Heckemeyer, J. and Overesch, M. (2013), "Multinationals' profit response to tax differentials: Effect size and shifting channels," ZEW-Centre for European Economic Research Discussion Paper, (13-045).
- Hox, J. and Roberts, J.K. eds. (2011), *Handbook of advanced multilevel analysis*. Psychology Press.
- Huizinga, H. and L. Laeven (2008), "International Profit Shifting within Multinationals: A Multi-Country Perspective," *Journal of Public Economics*, 92, 1164-1182.
- Kim, J.S. and Swoboda, C.M. (2011), "Handling omitted variable bias in multilevel models: Model specification tests and robust estimation," in *Handbook of advanced multilevel analysis* (Hox, J. and Roberts, J.K. eds.), 197-217.
- Lohse, T. and N. Riedel (2013) "Do Transfer Pricing Laws Limit International Income Shifting? Evidence from European Multinationals," CESifo Working Paper No. 4404.
- Markle, K. (2015), "A Comparison of the Tax-Motivated Income Shifting of Multinationals in Territorial and Worldwide Countries," *Contemporary Accounting Research*.
- Mundlak, Y. (1978), "Pooling of Time-series and Cross-section Data," *Econometrica*, 46(1), 69-85.
- OECD (2013), *Action Plan on Base Erosion and Profit Shifting*, Organisation for Economic Cooperation and Development, Paris.
- Overesch, M. and Schreiber, U. (2009), "R&D Intensities, International Profit Shifting, and Investment Decisions," University Of Mannheim Discussion Paper.
- Riedel, N. (2014), "Quantifying International Tax Avoidance: A Review of the Academic Literature," ETPF Policy Paper, 2.
- Tørsløv, T., Wier L. and Zucman, G. (2018), "The Missing Profits of Nations," NBER Working paper 24701.

## Tables

**Table 1: Summary statistics for the variables used in estimating Equation (1).**

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
C-index	713,319	-.0079	.0584	-.311078	.427540
Consolidated EBIT	725,101	476,993	1,736,573	-1.04e+07	2.24e+07
Consolidated financial costs	572,905	563,845	6,528,641	- 1,499,769	4.58e+09
Consolidated financial revenues	575,722	333,965	4,933,831	- 6,628,101	3.06e+09
Cost of labour	725,101	9,577	101,101	1	6.40e+07
EBIT	724,751	5,480	57,879	- 9,063,340	7,093,048
Financial costs	686,326	2,445	53,017	- 1,323,674	2.34e+07
Financial revenues	690,147	4,158	75,194	-1.17e+07	1.37e+07
Fixed assets	725,101	54,150	659,835	1	1.56e+08
Freedom Index (average of areas 2-4-5)	714,782	7.4356	.3563	5.45	8.52
GDP	724,313	1.61e+12	1.14e+12	5.43e+08	5.91e+12
GDP per capita	724,313	36,517	17,296	640	149,160
No. of companies in group	725,101	1,225	3,377	2	22,299
No. of countries	725,101	5.7048	4.4904	2	30
Pre-tax profit	724,737	7,129	81,390	-2.14e+07	1.27e+07
Share of intangibles	721,272	.0810	.1390	0	.86
Share of intangibles (group)	724,003	.0755	.0927	0	.50

**Table 2: Classical panel data regression by means of fixed-effects model estimation.**

<i>Dep. Var. is Pre-tax profit</i>	<b>Minimal model</b>	<b>Full model</b>	<b>Full model</b>	<b>Full model</b>
Cost of labour (log)	.325*** (.006)	.395*** (.010)	.407*** (.010)	.399*** (.010)
Fixed assets (log)	.088*** (.003)	.074*** (.005)	.075*** (.005)	.072*** (.005)
GDP per capita (log)	.616*** (.015)	.921 (.231)	-17.98 (43.03)	.510 (.265)
C-index	-.267*** (.070)	-.539*** (.104)	-.002 (.146)	-.451*** (.106)
Country and Company Group controls	<i>no</i>	<i>yes</i>	<i>yes</i>	<i>yes</i>
Year dummies	<i>no</i>	<i>no</i>	<i>yes</i>	<i>yes</i>
Country-year dummies	<i>no</i>	<i>no</i>	<i>yes</i>	<i>no</i>
Industry-year dummies	<i>no</i>	<i>no</i>	<i>no</i>	<i>yes</i>
No. of observations	563,710	257,147	257,147	256,531
R-squared	.04	.05	.06	.06

*Note: Significance at the 1%, 5%, and 10% levels is indicated by \*\*\*, \*\*, and \*, respectively.*

**Table 3: Summary of fixed effects model results for industry subsamples.**

<i>Industry sub-samples (fixed effects model)</i>						
Simple mean of coefficients:	with p-value $\leq 10\%$	<i>min.</i>	<i>max.</i>	with p-value $\leq 5\%$	<i>min.</i>	<i>max.</i>
Minimal model	-.71	-5.09	4.34	-.31	-3.96	4.34
Full Model	-1.12	-11.35	10.7	-1.47	-7.91	4.34
Weighted mean by no. of observations:	with p-value $\leq 10\%$			with p-value $\leq 5\%$		
Minimal model	-.52			-.55		
Full Model	-1.04			-1.09		

*Note: The table reports average, minimum and maximum coefficients for c-indexes.*

**Table 4: Multilevel model results (standard errors in parenthesis).**

	Pre-tax profit (log)	Pre-tax profit (log)	EBIT (log)	EBIT (log)
Cost of labour (log)	.451*** (.001)	.447*** (.003)	.487*** (.001)	.474*** (.002)
Fixed assets (log)	.221*** (.001)	.265*** (.002)	-.195*** (.001)	.240*** (.002)
GDP per capita (log)	.259*** (.005)	.565*** (.183)	.167*** (.004)	.519*** (.171)
C-index	-.891*** (.050)	-.475*** (.080)	-.945*** (.047)	-.393*** (.076)
Country and Company Group controls	no	yes	no	yes
Year dummies	no	yes	no	yes
Country dummies	no	yes	no	yes
<i>Random effects, Firm level:</i>				
sd(Constant)	.758	.281	.720	.242
<i>Random effects, Industry level:</i>				
sd(Cost of labour)	<.0001	<.0001	<.0001	<.0001
sd(Fixed assets)	.089	.045	.080	.043
sd(GDP per capita)	.005	.088	<.0001	.085
sd(C-index)	5.46	5.21	5.48	5.24
sd(Share of Intangibles)		.096		.089
sd(Constant)	.757	.281	.719	.244
sd(Residual)	.758	.866	.861	.810
No. of observations	672,203	256,531	675,968	260,696
No. of distinct companies	132,015	66,599	131,648	66,875

*Note: Random effects are reported as standardized deviations from the group mean, and sd(Residual) indicates the standard deviation at level 1 (that is, across different times for the same firm). Significance at the 1%, 5%, and 10% levels is indicated by \*\*\*, \*\*, and \*, respectively.*

**Table 5: Results for the multilevel model adding an interaction term for intangibles.**

<i>Dep. Var. is EBIT</i>	<b>Fixed-effects model</b>	<b>Multilevel model</b>	<b>Multilevel model + level-3 slope</b>	<b>Multilevel model + level-3 slope (standardized variables)</b>	<b>Multilevel model + level-3 slope (standardized variables)</b>
Cost of labour (log)	.443*** (.010)	.474*** (.002)	.474*** (.002)	1.069*** (.006)	1.066*** (.006)
Fixed assets (log)	.078*** (.005)	.239*** (.001)	.238*** (.001)	.624*** (.006)	.630*** (.006)
GDP per capita (log)	.571** (.247)	.520*** (.171)	.547*** (.171)	.418*** (.111)	.372*** (.112)
C-index	-.372*** (.142)	-.413*** (.108)	-.406*** (.107)	-.023*** (.004)	-.023*** (.004)
Share of Intangibles*C-index	-.013 (.032)	-.006 (.024)	-.002 (.023)	-.0006 (.003)	-.001 (.003)
Share of Intangibles (log)					-.009** (.006)
Country and Company Group controls	yes	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes	yes
Country dummies	no	yes	yes	yes	yes
Industry-year dummies	yes	no	no	no	no
<i>Random effects, Firm level:</i>					
sd(Constant)		.238	.375	.630	.600
<i>Random effects, Industry level:</i>					
sd(Cost of labour)		<.0001	<.0001	.513	.502
sd(Fixed assets)		.043	.056	.562	.531
sd(GDP per capita)		.085	.076	.198	.190
sd(C-index)		5.24	5.09	.258	.272
sd(Share of Intangibles*C-index)			.442	.162	.068
sd(Share of Intangibles)		<.0001			.352
sd(Constant)		.245	.385	.609	.594
sd(Residual)		.810	.816	.785	.775
No. of observations	260,696	260,696	260,696	260,696	260,696
No. of distinct companies	66,875	66,875	66,875	66,875	66,875

*Note: For the multilevel model random effects are reported as standardized deviations from the group mean, and sd(Residual) indicates the standard deviation at level 1 (that is, across different times for the same firm). Significance at the 1%, 5%, and 10% levels is indicated by \*\*\*, \*\*, and \*, respectively.*

**Table 6: Multilevel model results (standard errors in parenthesis) for financial shifting.**

	Financial costs (log)	Net Financial costs (log)	Financial revenues (log)	Net Financial revenues (log)
Cost of labour (log)	.261*** (.003)	.240*** (.003)	.338*** (.003)	.227*** (.005)
Fixed assets (log)	.531*** (.002)	.537*** (.002)	.381*** (.002)	.514*** (.003)
GDP per capita (log)	3.28*** (.031)	.815*** (.231)	.292 (.219)	-1.31*** (.355)
C-index	-.254*** (.093)	-.145 (.099)	-.270** (.107)	-.712*** (.141)
Country and Company Group controls	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes
Country dummies	yes	yes	yes	yes
<i>Random effects, Firm level:</i>				
sd(Constant)	<.0001	<.0001	<.0001	<.0001
<i>Random effects, Industry level:</i>				
sd(Cost of labour)	.069	.012	.037	<.0001
sd(Fixed assets)	.057	<.0001	.134	.083
sd(GDP per capita)	.103	.103	.096	.106
sd(C-index)	8.68	6.34	8.89	5.45
sd(Share of Intangibles)	.140	.110	.165	.117
sd(Constant)	<.0001	<.0001	<.0001	<.0001
sd(Residual)	.953	.939	1.13	1.11
No. of observations	320,891	204,543	296,715	124,863
No. of distinct companies	73,723	59,497	69,186	42,936

*Note: Random effects are reported as standardized deviations from the group mean, and sd(Residual) indicates the standard deviation at level 1 (that is, across different times for the same firm). Significance at the 1%, 5%, and 10% levels is indicated by \*\*\*, \*\*, and \*, respectively.*



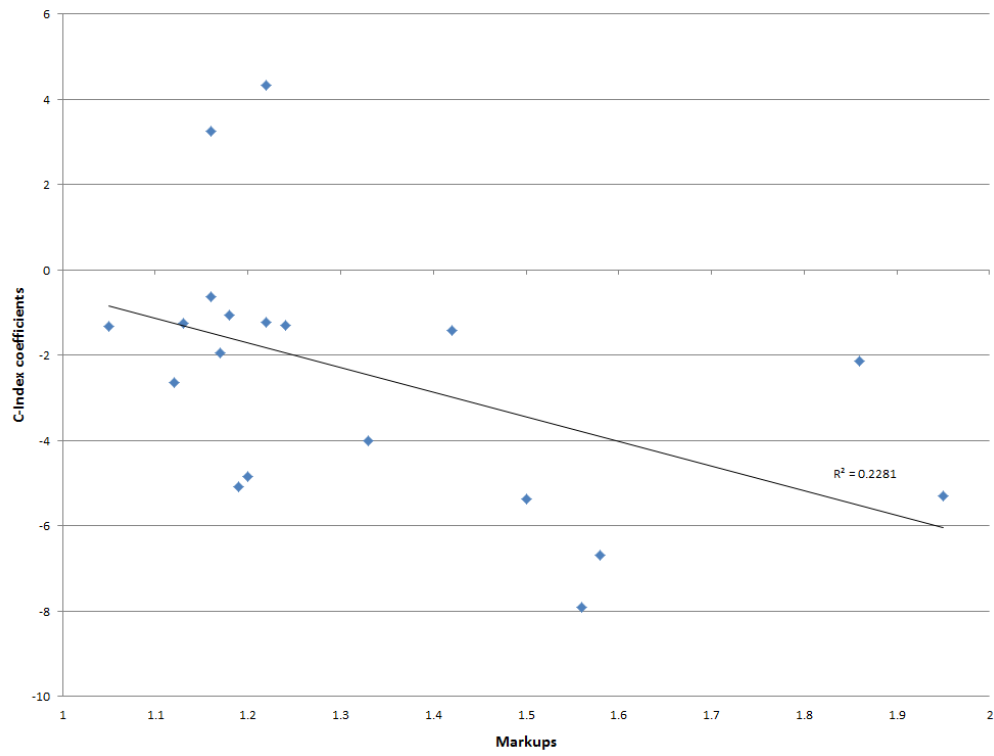
**Table 7: Comparable semi-elasticities obtained using pre-tax profit or EBIT as dependent variable, from different studies.**

	Own estimates - Full Multilevel model	Huizinga and Laeven (2008)	Heckemeyer and Overesch (2013)	Loretz and Mokkas (2015)
Pre-tax profit	-.475	-1.210	-.821	-1.01
EBIT (comparable value)	-.491	-1.562	-.594	-.475
Financial margin (comparable value)	.016	.352	-.227	-.535

*Note: The values in the last row for financial shifting are derived differencing the previous two values.*

## Figures

Figure 1: Scatter plot between mark-up prices and elasticities, by industry.



## **List of abbreviations and definitions**

BEPS - Base Erosion and Profit Shifting

CIT - Corporate Income Tax

EBIT - Earnings Before Interests and Taxes

EU - European Union

GDP - Gross domestic Product

GUO - Global Ultimate Owner

NACE - Nomenclature statistique des Activités économiques dans la Communauté Européenne (classification of economic activities)

OLS - Ordinary Least Squares

SD - Standard Deviation

USD - United States dollars





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