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The Tax-Elasticity of Tangible Fixed Assets: Evidence from Novel Corporate Tax Data*

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Abstract

This paper develops a new approach to calculate country-industry-year-specific forward-looking effective tax rates (FLETRs) based on a panel of 19 industries, 221 countries, and the years 2001 to 2020. Beside statutory tax rate and tax base determinants, the FLETRs account for typical country-industry-specific financing structures as well as asset compositions. We show that effective tax rates suffer from significant measurement error when the latter information is neglected, owing primarily to inappropriately assigned asset weights to statutory depreciation allowances. Our empirical analysis exploits the substantial variation in FLETRs over time to provide estimates of the tax semi-elasticity of corporate investment in tangible fixed assets. Based on more than 24 million firm entity observations, our results suggest a statistically significant tax semi-elasticity of -0.41, which is at the lower end of previous findings. We further show that different sub-groups of firms respond very heterogeneously to tax incentives.

Keywords: Corporate taxation, depreciation allowances, effective marginal tax rates, investment responses, predictive mean matching

JEL classification: H25, H32, F23

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1. Introduction

One of the main objectives of fundamental tax reforms such as the 2017 US "Tax Cuts and Jobs Act" is to raise corporate investment and thereby economic growth. Whether such reforms are successful in this regard depends in large parts on the extent to which firms' real investments respond to changes in tax incentives. A central measure of the relationship between corporate taxation and investment is the tax-elasticity of corporate investment. Despite its policy relevance, there is disagreement as to the responsiveness of real assets to changes in corporate taxation, which is underlined by the heterogeneity in previous estimates. This paper contributes to the literature by providing estimates on the tax-elasticity of firms' tangible fixed assets that are based on a broad panel of novel forward-looking corporate effective tax rates (FLETRs).

The aim of FLETRs is to capture incentives of the corporate tax code (statutory tax rate and tax base determinants) by depicting the tax burden of a hypothetical investment project, which makes FLETRs particularly suitable for the analysis of investment responses (Sørensen, 2004).[1] The key distinction from the previous literature regarding the way we calculate FLETRs is that we account for typical country-industry-specific financing and asset structures. Accounting for these country-industry-specific characteristics plays an important role in determining the magnitude of the FLETRs, as interest payments on debt are generally tax-deductible and depreciation allowances differ between asset categories. In other words, using country-industry-level financing and asset structures allows us to correctly capture the general heterogeneity in investment incentives that a country's tax code implicitly offers to the different industries. At the same time, as our FLETRs rely on typical country-industry-specific weights, we ensure that tax measures are exogenous and primarily capture

[1] Note that quantifying the tax burden using forward-looking measures goes back to the seminal contribution of King and Fullerton (1984) and was substantially advanced by Devereux and Griffith (1998b) as well as Devereux and Griffith (2003). So-called backward-looking measures (calculated as taxes paid relative to pre-tax profit), in contrast, not only fail to capture current and future investment incentives but are also prone to severe endogeneity concerns as both taxes paid and pre-tax profit may be driven by tax-planning decisions of a firm (Devereux and Griffith, 2002).

incentive effects from tax law. Most previous studies do not account for country-industry heterogeneity, but instead calculate FLETRs using identical financing and asset structures for all countries and industries, often due to a lack of adequate data.[2] Our analysis shows that disregarding country-industry-level heterogeneity for calculating FLETRs leads to a systematic measurement error.

Regarding the country-industry-specific financing structures, we aggregate firm-entity level data from Bureau van Dijk's *Orbis* database. For the calculation of the country-industry-specific asset structures, we distinguish a total of seven different asset types for which we derive weights from the *EUKLEMS & INTANProd* database and *Orbis*. If these data sources are not available for country-industry combinations or do not provide sufficient information, we impute the financing and asset structures using *Predictive Mean Matching (PMM)*, which we run on extensive sets of both country- and industry-specific matching co-variates. Combining the country-industry-specific financing and asset structures with statutory information on the tax rates and depreciation regimes yields FLETRs for virtually the entire world and all industries. More precisely, our almost perfectly balanced panel includes FLETRs for 221 countries,[3] 19 industries, and 20 years (2001 to 2020). For the time span covered by our panel, we observe a total of close to 700 reforms of national tax codes, i.e., changes to the statutory tax rate and/or depreciation allowances.

We exploit the substantial variation in our FLETRs to estimate tax semi-elasticities of firms' tangible fixed assets using the *Orbis* dataset with over 24 million firm entity level observations. Our preferred model yields a statistically significant tax semi-elasticity of

[2]See, e.g., Devereux and Griffith (1998a), Egger et al. (2014), Spengel et al. (2016a), Spengel et al. (2016b), Spengel et al. (2016c), Steinmüller et al. (2019). Note that most contributions use the constant financing and asset structures proposed in the seminal publication *Taxing Profits in a Global Economy: Domestic and International Issues* by the OECD from 1991. Notable exemptions are Egger et al. (2009) as well as Egger and Loretz (2010), who use *Orbis* to calculate firm-year-specific financing and asset structures, and Steinmüller et al. (2019), who use a combination firm-specific financing structures based on *Orbis* and industry-specific asset structures that are equal for all countries. Using time-varying and/or firm-level financing and asset weights would lead to endogenous FLETRs, though, as such structures capture endogenous responses to the tax incentives.

[3]Our dataset primarily comprises UN member states but also non-member states, e.g., Taiwan, as well as self-governing territories that formally are part of other states, e.g., Greenland. For the sake of clarity and simplicity, we shall henceforth refer to all included tax-jurisdictions as "countries".

-0.41, which is at the lower end of previous findings. We also show that our main finding – a negative elasticity that is small in magnitude – is highly robust to alternative model specifications. We additionally conduct a set of group-specific tax-elasticity estimations. This part of the paper is motivated by different strands of both theoretical and empirical contributions to the literature suggesting that certain groups of firms respond particularly (in-)sensitive to changes in tax incentives. For instance, the tax-sensitivity of investment should depend on the degree to which a firm is financially constraint.[4]

While our group-specific results are consistently in line with the hypotheses derived from the literature, let us highlight one interesting finding, illustrating that firm entities' tax-sensitivity is highly correlated with firms' ability to avoid taxes through relocating profits to low-tax countries. The idea is to examine how firm entities respond to changes in the marginal tax rate given the group-wide (or multinational-firm-wide) minimum statutory corporate tax rate.[5] The reasoning behind this exercise is the following: firms that can access low-tax or tax haven countries may be able to shift profits there, and are thus less responsive to tax incentives at the other locations. While we generally find negative elasticities, the tax response becomes steadily stronger for those groups where the firm-group-specific minimum tax rate is high. In fact, we find that only after a threshold of a minimum tax rate of 24%, the tax-elasticities turn statistically significant. This finding allows for an interpretation in light of the profit-shifting literature, as large multinational corporations are able to shift profits to entities located in low-tax jurisdictions to avoid taxes. The latter makes these firms less responsive to tax incentives at all other locations.

Beside the new approach of calculating FLETRs, this paper adds to the literature in several ways. We primarily contribute to previous research on investment responses to tax incentives. Some recent estimates suggest quite substantial tax effects in this context. For

[4]See, e.g., Keuschnigg and Ribi (2013).

[5]That is, the minimum tax rate that they are exposed to within their firm group. This minimum tax rate is defined as the group-wide (or multinational-firm-wide) minimum statutory tax rate or, in the case of stand-alone entities, the tax rate of the country they are located in. We then group all observations according to the respective minimum tax rate.

example, Ohrn (2018) shows that a 1 percentage point reduction in firms' effective corporate tax rate (through additional tax-base deductions) is associated with a 4.7 percent increase in installed capital. Based on a large sample of US firms, Zwick and Mahon (2017) investigate the impact of temporary bonus depreciation rules on firms' investments, distinguishing between eligible and non-eligible capital and industries. They find a substantial increase of investment into eligible equipment. A seminal empirical paper quantifying investment responses to taxes at the level of firms is that of Chirinko et al. (1999). This study suggests a user cost of capital elasticity of about -0.25. Earlier work of Cummins et al. (1994, 1995, 1996) exploits tax reforms to learn about the consequences of changes in the user cost of capital. Their findings indicate substantial investment effects of tax policy. Using German data, Harhoff and Ramb (2001) estimate a long-run user cost of capital elasticity of -0.56.[6] Our semi-elasticity estimates, based on our large sample including about 24 million observations, are substantially smaller.

Some previous contributions study investment responses and specific channels through which investment is affected. For example, Chaney et al. (2012) analyze the effect of real estate price shocks that affect the collateral value of firms, which is a significant driver of investment. Edgerton (2010) accounts for financing constraints as well as loss carrybacks and carryforwards leading to asymmetries in tax responses. Early work of Fazzari et al. (1987) highlights that investment responses depend on the extent to which firms are financially constrained. As mentioned above, in Section 6.5, we add to these findings by providing group-specific estimates on the tax-elasticity of the tangible fixes assets. While this paper

[6] There is also a large literature that uses international investment data (foreign direct investments) to identify tax effects from country-year-specific variation in taxes. De Mooij and Ederveen (2003) perform a meta-analysis to estimate the tax-elasticity of corporate investment. They find substantial heterogeneity in elasticities across studies with a median value of -3.3. Similarly, De Mooij and Ederveen (2008) illustrate that corporate taxation has a substantial impact on the choice of the legal form, financing structure, profit shifting, as well as (intensive and extensive margin) investment decisions. Additionally, they demonstrate that the tax elasticities along these different decision margins vary substantially. Feld and Heckemeyer (2011) conduct a meta-analysis and estimate a median tax semi-elasticity of corporate investment of -2.49 and illustrate that employing firm-level data and (country-specific) effective tax measures yields more accurate estimations of the semi-elasticity. In contrast to this literature, our novel FLETR data allow us to adequately capture and exploit variation within and across different industries and countries in a unified estimation and data context.

is not primarily interested in one particular heterogeneity, it illustrates that our approach of measuring tax incentives is very consistent with how we expect taxes to affect heterogeneous firms' decisions.

The remainder of the paper is structured as follows. Section 2 derives the country-industry-year-specific FLETR measure. Section 3 describes the various data sources that are used for the calculation of the FLETRs and the estimation of the tax-elasticities of investment. The calculation of country-industry-specific financing and asset structures is detailed in Section 4. Section 5 describes the country-industry-year-specific FLETRs. The tax semi-elasticities of investment are estimated in Section 6. Finally, Section 7 concludes and presents policy implications.

2. Forward-looking Effective Tax Measures

For the empirical estimation of the tax semi-elasticity of investment, it is crucial to model the incentive effects of the corporate tax code in an adequate way. The literature recommends the use of forward-looking measures in such a context, as the incentive to invest depends on current and expected taxation (Sørensen, 2004). In this paper, we distinguish two different kinds of FLETRs: the effective marginal tax rate (EMTR) and the effective average tax rate (EATR). The EMTR captures incentives of the tax code at the intensive margin – i.e., the tax burden a firm would face on a marginal investment that just breaks even. This property makes it particularly suitable for the calculation of tax semi-elasticities. The EATR, on the other hand, depicts the effective tax burden of all infra-marginal units invested. It is primarily used for the analysis of discrete investment choices, such as location decisions (Devereux and Griffith, 2003). Consequently, the EATR plays only a minor role in our analysis. Since our estimation of the tax semi-elasticities is based primarily on the EMTR, this section focuses on providing intuition for this measure and the role that country-industry-specific financing and asset structures play for its computation. A brief discussion of the EATR is provided in Appendix 1.

The theoretical framework of the EMTR is developed in the seminal contributions by Devereux and Griffith (1998b), Hall and Jorgenson (1967), King (1974), King and Fullerton (1984), and OECD (1991). A simple formal representation of the EMTR is

$$EMTR = \frac{(\tau - \tau\delta)}{(1 - \tau\delta)}, \tag{1}$$

where τ and δ denote the statutory tax rate and the net present value (NPV) of depreciation allowances, respectively. A detailed derivation of this formula is provided in Appendix 2. Note that one goal of the simple representation in (1) is that it measures tax incentives in a tractable way and allows us to observe all statutory tax code determinants and incentives.[7]

From (1), it is evident that the marginal investment is not affected (i.e., $EMTR = 0$) if $\delta = 1$, i.e., in the case where the tax law allows a firm to immediately deduct the full purchase price of an asset (e.g., a machine) for tax purposes. A feature of the EMTR is that it may easily become negative (the tax system then effectively subsidizes investments) if governments allow for generous investment tax credits and bonus depreciation (Zwick and Mahon, 2017).

For the sake of illustration, let us look at a specific example for the EMTR. In 2010, France levied a corporate tax rate of 34.4%, and granted a NPV of depreciation allowance for equity financed machinery of 0.81. Plugging these values into equation (1) yields an EMTR of 9.1% (for marginal investments in machinery).[8] Our goal, however, is not to calculate FLETRs of investments in a single asset type that are purely equity financed. Instead, our goal is to depict the tax burden of country-industry-typical investments in different asset

[7]Calculating FLETRs involves a number of trade-offs. On the one hand, our goal is to capture incentive effects from tax law in a very detailed way, so we aim at including both the tax rate and tax base determinants. On the other hand, the more details we model, the more assumptions we need to accept. We believe that the parsimonious EMTR shown in (1) is ideal for the purpose of this paper, as it accounts for the most important tax code information and heterogeneity in tax-base effects. In fact, the major advantage we see is that, with some assumptions, we are able to observe all parameters that allow us to calculate adequate EMTRs.

[8]The corresponding EATR equals 27.4%.

categories that are financed using a combination of equity and debt.[9] In total, we distinguish between seven asset categories: *Buildings, Machinery, Office equipment, Computer equipment, Intangible fixed assets, Vehicles* and *Inventory.* The distinction of different asset categories is important, as different assets are subject to varying depreciation allowances, e.g., buildings depreciate over a substantially longer period than computer equipment. The distinction between equity and debt financing is relevant as interest payments on debt are usually tax deductible, which results in higher NPVs of depreciation allowances for debt financing compared to financing through retained earnings.[10] Let us denote the NPV of depreciation allowances per unit of investment in asset type a in country c in year t by A^E_{act} and A^D_{act}, with the superscripts E and D indicating financing through retained earnings and debt, respectively.[11] It is important to note that the NPVs of depreciation allowances are purely determined by national tax codes, and tax law applies equally to all industries in a country. Hence, the only reason why different industries located in the same country have a different overall NPV of depreciation allowances is that they use different financing and asset compositions when carrying out investment projects. This is reflected in the formal depiction of the country-industry-year-specific NPV:

$$\delta_{cit} = ES_{ci} \sum_{a=1}^{7} w_{aci} \cdot A^E_{act} + DS_{ci} \sum_{a=1}^{7} w_{aci} \cdot A^D_{act}, \tag{2}$$

where w_{aci} denotes the share of asset a in a typical investment carried out in industry i in country c.[12] ES_{ci} and DS_{ci} denote the country-industry-specific shares of retained earnings and debt used to finance the investment, respectively, which add up to unity. The procedures to obtain w_{aci} as well as ES_{ci} and DS_{ci} are explained in greater detail in Section 4.

[9] Note that using time-constant rather than time-varying financing and asset weights for the empirical analysis of investment avoids endogeneity issues that may arise due to changes in the financing and asset structures in response to changes in the tax code.

[10] Note that we disregard the possibility of issuing new equity.

[11] Note that since we disregard inflation, inventories are not depreciable, i.e., $A^E_{invent,ct} = A^D_{invent,ct} = 0 \ \forall \ c, t$ (see Hanappi, 2018).

[12] The sum of the asset weights equals one for each country-industry pair, i.e., $\sum_{a=1}^{7} w_{aci} = 1$.

Finally, using (2), we obtain country-industry-year-specific EMTRs:

$$EMTR_{cit} = \frac{(\tau_{ct} - \tau_{ct}\delta_{cit})}{(1 - \tau_{ct}\delta_{cit})}. \tag{3}$$

Expression (3) is used to calculate the EMTRs we present in Section 5.

3. Data

Throughout this paper, we use data from a total of five different databases to (i) calculate and impute country-industry-specific financing and asset weights (see Section 4); (ii) calculate FLETRs (see Section 5); and to (iii) estimate tax semi-elasticities of investment (see Section 6). In the following, we briefly describe the databases, which data they provide, and how we use the data for our purposes.

3.1. RSIT International Tax Institutions (ITI) Database

The statutory corporate tax regime data that we use to calculate FLETRs is taken from the Research School of International Taxation's (RSIT) *International Tax Institutions (ITI)* database (Wamser et al., 2023). More precisely, we use the data on statutory corporate tax rates (τ_{ct}) as well as NPVs of depreciation allowances for the six asset categories *Buildings, Machinery, Office equipment, Computer equipment, Intangible fixed assets,* and *Vehicles.* This panel includes 3,954 year-specific data points that span over a total of 221 countries over the years 2001 to 2020.[13] Additionally, we obtain the count variable of the number of double taxation treaties that a country has in a given year ($NDTT_{ct}$), which serves as a control variable in the estimation of the tax semi-elasticity of investment (see Section 6).

[13]For a detailed description of the dataset and data sources, see Wamser et al. (2023).

3.2. EUKLEMS & INTANProd

The country-industry-specific asset weights that we derive in this paper are – with the exception of the asset type inventory – based on the 2021 release of the *EUKLEMS & INTANProd* database provided by the Luiss Lab of European Economics. For our purpose, we use the net capital stocks at current replacement costs in million units of the respective national currency that the database provides at the NACE Rev. 2 (ISIC Rev. 4) section level.[14] In detail, we use the capital stock variables for *Dwellings, Other buildings and structures, Computer hardware, Research and development, Computer software and databases, Other machinery equipment and weapon systems, Telecommunications equipment*, and *Transport equipment*. Note that these asset categories, which are based on the European System of Accounts (ESA) 2010, do not directly match the ones for which the *ITI* database provides the depreciation allowances which we use for the calculation of the FLETRs. In Section 4.2, we therefore regroup the ESA 2010 based variables from *EUKLEMS & INTANProd*, to obtain industry-specific net stock values of all considered asset categories for 18 EU countries, as well as for the UK, Japan, and the US.[15] The data coverage ranges from 1995 to 2019, though 2019 is scarcely covered. With the exception of Japan and the US, data for 19 NACE Rev. 2 (ISIC Rev. 4) sections are provided.[16]

3.3. Orbis Dataset

For our firm-level analysis of the tax semi-elasticity of investment in Section 6, we use Bureau van Dijk's *Orbis* database. *Orbis* contains yearly balance sheet and income statement data as well as general information on the firm entities, such as industry affiliation, year of incorporation, and ownership structure. The definition of variables and a more detailed

[14] For the descriptions of all sections, see Appendix 3. Note that since NACE Rev. 2 was created based on ISIC Rev. 4, these two classification systems are identical at the section level.

[15] Note that, since in Section 4.2 we obtain asset weights by summing up all capital stock variables and then taking shares, we only consider observations for which all variables are non-missing.

[16] Note that the sections *T* and *U* are not covered in the *EUKLEMS & INTANProd* database. For Japan, additionally the sections *M* and *N* are not covered and for the US the sections *D*, *E*, and *O*. For the descriptions of all sections, see Appendix 3.

description of the data for the purpose of the investment elasticity estimation is provided in Section 6.2.

We further use *Orbis* information to obtain the financing structure and the weight of the asset type inventory at the country-industry level, both of which we need for the calculation of the FLETRs. More precisely, for the calculation of the financing structure (see Section 4.1), we use the variables non-current liabilities ($NCLI_{jt}$, with j and t denoting firm entity and year, respectively) and total assets ($TOAS_{jt}$). The calculation of the inventory shares is based on the stocks of current assets (i.e., inventories) (INV_{jt}), tangible fixed assets ($TFAS_{jt}$), and intangible fixed assets ($IFAS_{jt}$),

3.4. World Development Indicators and Worldwide Governance Indicators

In our analysis of the tax semi-elasticity of investment (see Section 6), we condition on a number of country-level factors that possibly influence investment behavior. Furthermore, we feed the matching algorithm for the imputation of missing financing and asset weights with country-level variables (Section 4.3). Our sources for the country-level controls are the World Bank's *World Development Indicators (WDI)* and *Worldwide Governance Indicators (WGI)* databases.

From the *WDI* database, we obtain the GDP measures GDP in constant PPP US\$ (GDP_{ct}), GDP per capita in constant PPP US\$ ($GDP\ p.c._{ct}$), and GDP growth ($GDP\ growth_{ct}$). Additional variables taken from the *WDI* data are inflation ($Inflation_{ct}$), domestic credit to the private sector in percent of a country's GDP ($DCPS_{ct}$), and the real interest rate ($Real\ interest\ rate_{ct}$).[17]

From the *WGI* database, we use the *Rule of Law* indicator (ROL_{ct}), which captures "perceptions of the extent to which agents have confidence in and abide by the rules of

[17] Note that the real interest rate variable is not as well covered as the other variables we control for in our analysis of the tax-elasticity in Section 6. To be able to control for the interest rate without reducing the sample size, we impute missing observations as follows. If for a given country one or more years are covered, then missing values of that country are imputed with the mean over these observed values. For countries without any coverage in the *WDI* database, we impute using a mean over all values of the countries for which values are observed.

society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence" as well as a *Control of Corruption* variable ($Corruption_{ct}$) measuring "the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as 'capture' of the state by elites and private interests" (Kaufmann et al., 2011, p. 223).[18] Note that both measures are varying in an interval of -2.5 to 2.5. The Worldwide Governance indicators are defined such that a higher value corresponds to better governance, i.e., a higher value of $Corruption_{ct}$ indicates less corruption (Kaufmann et al., 2011).

3.5. Eora Global Supply Chain Database

Finally, we obtain a set of industry-specific variables from the *Eora26* database, which is part of the *Eora Global Supply Chain* database (Lenzen et al., 2012; Lenzen et al., 2013). These variables are solely used for imputing financing and asset weights (see Section 4.3). Note that the *Eora26* industry classification system is different from the NACE Rev. 2 (ISIC Rev. 4) classification that we use throughout this paper.[19]

The industry-specific variables (in basic prices in $1,000$ current year US$) that we take from the *Eora26* database are: Gross output (GO_{cit}), gross input (GI_{cit}), compensation of employees (COE_{cit}), net taxes on production (calculated as the difference between taxes on production and subsidies on production) ($net\ TOP_{cit}$), net operating surplus (NOS_{cit}), net mixed income (NMI_{cit}), and consumption of fixed capital ($COFC_{cit}$). Additionally, the *Eora26* database records sector-specific information on greenhouse gas emissions associated with production (Kanemoto et al., 2014; Kanemoto et al., 2016). For our purpose, we use the variable total CO_2 emissions in gigagrams ($CO2_{cit}$). In total, all variables are covered for 189 countries over the time span 1990 to 2016.

[18] Note that since the *WGI* database was only updated biennially between 1996 and 2002, we impute the missing 2001 values by taking the mean of the respective variables of the years 2000 and 2002.

[19] Appendix 4 provides detailed information on how we convert the *Eora26* classification along with general information on the structure of the database.

4. Calculating Country-Industry-Specific Weights

In this section, we detail how we calculate the country-industry-specific financing (i.e., the DS_{ci}'s and ES_{ci}'s) and asset weights (i.e., the w_{aci}'s) that are needed to compute the country-industry-year-specific FLETRs that we use for the estimation of the tax semi-elasticity of investment. More precisely, the industry levels we distinguish are the NACE Rev. 2 (ISIC Rev. 4) *sections*.[20]

The derivation of the weights is undertaken in two steps. First, we compute (or impute) country-industry-year-specific weights for years within the time horizon for which we want to calculate the FLETRs.[21] Second, we obtain the time-constant weights by taking averages over all year-specific weights belonging to a certain country-industry combination.

Depending on the respective data availability, a certain country-industry-specific weight may either be obtained (i) directly from data, (ii) by imputation using a matching algorithm, or (iii) by imputation using weights from countries in geographical proximity. The preferred approach is (i); approach (ii) is only implemented in the case where (i) does not yield a single year-specific weight; approach (iii) is used only when also approach (ii) does not yield a single year-specific weight due to lack of data for matching. Note that by requiring an approach to only yield a minimum of one year-specific data point, we obtain final time-constant weights that are averages over varying numbers of years.[22]

[20]Note that we can only calculate weights and therefore FLETRs for 19 of the 21 sections. We cannot calculate weights for the sections *T activities of households as employers; undifferentiated goods- and services-producing activities of households for own use*, and *U activities of extraterritorial organisations and bodies*, due to lack of data.

[21]Note that we generally only consider data for the years 2001 to 2018 for the calculation of the weights. The year 2001 is chosen as first year as it is also the first year for which we calculate FLETRs. The year 2018 is the latest year for which sufficient capital stock information from the *EUKLEMS & INTANProd* is available.

[22]The reason for not combining the different approaches to maximize the number of year-specific observations is that we perceive having possibly few but very precise yearly weights preferable to having a larger number of yearly weights out of which some are imputed with less precision.

4.1. Financing Structure

For the derivation of the country-industry-specific financing structures, we start by calculating debt ratios at the firm entity level using data from *Orbis*. Following Steinmüller et al. (2019), we define the debt ratio of firm entity j in year t, DS_{jt}, as long-term debt over total assets.[23] More specifically, for long-term debt we use the *Orbis* variable non-current liabilities ($NCLI_{jt}$).[24] Formally, we get

$$DS_{jt} = \frac{NCLI_{jt}}{TOAS_{jt}}. \tag{4}$$

We proceed by aggregating the entity-level data points from (4) to the final country-industry-specific debt shares in two steps. First, we create year-specific debt shares for country c and industry i, DS_{cit}, by taking unweighted means over all firm entities belonging to a given country-industry-year bin.[25] Second, we obtain the final time-constant debt shares, DS_{ci}, by taking unweighted means over all available year-specific debt shares, DS_{cit}, corresponding to the given country-industry pair. Respective equity shares are then obtained by subtracting these debt shares from unity, i.e., $ES_{ci} = 1 - DS_{ci}$.

4.2. Asset Structure

For the calculation of the country-industry-specific asset weights, we use data from two different sources. For the asset categories *Buildings, Machinery, Office equipment, Computer equipment, Intangible fixed assets,* and *Vehicles*, we use data from the *EUKLEMS & INTANProd* database. Information on the asset category *Inventory* is obtained from *Orbis*. Since the coverage of these two data sources differs, we first calculate time-constant asset

[23] Steinmüller et al. (2019) argue that only long-term debt can be harnessed to finance investment projects and is therefore the relevant measure to be considered when assessing an entity's investment opportunities, even if it underestimates its actual (total) debt ratio.

[24] Note that we exclude observations with non-positive total assets and set ratios that are negative due to negative long-term debt equal to zero. As we do not allow weights to exceed unity, we set debt ratios exceeding unity to one.

[25] To obtain meaningful values, we set the minimum number of firm entities per bin to five.

weights using only the *EUKLEMS & INTANProd* data, without taking inventory into account, i.e., the weights for *Buildings, Machinery, Office equipment, Computer equipment, Intangible fixed assets,* and *Vehicles* initially sum up to unity without inventory. Then, we determine time-constant inventory weights and rescale the weights of the other asset types such that the weights of all assets – including inventory – add up to unity. The advantage of separating the calculations this way is that we are not limiting the data usage to years that are covered by both sources, but instead are able to use all available information. As noted in the data section above, we regroup the capital stock variables that we obtain from *EUKLEMS & INTANProd* to match the ones that we distinguish for the calculation of the FLETRs.[26]

Next, for each country-industry-year combination, we sum up the six asset stock figures and take shares for the individual asset types denoted by w^*_{acit}. The superscript asterisk indicates that the weights are not yet re-scaled with the inventory share. We then obtain the respective time-constant, country-industry-specific weights, w^*_{aci}, by taking unweighted means over all available year-specific weights w^*_{acit}.

For the calculation of the inventory shares we follow Egger et al. (2009) and Egger and Loretz (2010), who define the firm entity j-specific inventory share in year t as

$$w_{\text{invent},jt} = \frac{INV_{jt}}{TFAS_{jt} + IFAS_{jt} + INV_{jt}}, \tag{5}$$

where $TFAS_{jt}$, $IFAS_{jt}$, and INV_{jt} denote tangible fixed assets, intangible fixed assets, and stocks of current assets (i.e., inventories), respectively. The aggregation to country-industry-year-specific inventory weights, $w_{\text{invent},cit}$, and then the final time-constant weights, $w_{\text{invent},ci}$, is identical to the one used for the debt shares in Section 4.1.

Finally, we re-scale the time-constant asset weights obtained from *EUKLEMS & INTANProd* by multiplying each of them with the factor $(1 - w_{\text{invent},ci})$. So, for instance, the final

[26]For details on the mapping of the capital stock variables to the asset categories used in this paper see Appendix 5.

weights for the asset type *Buildings*, $w_{\text{build},ci}$, are obtained as $w_{\text{build},ci} = w^*_{\text{build},ci} \cdot (1 - w_{\text{invent},ci})$. This ensures that the sum over all seven asset types equals unity.

4.3. Imputation

Using the *Orbis* and *EUKLEMS & INTANProd* databases does not yield financing and asset structures for all country-industry combinations for which we intend to calculate FLETRs. Therefore, we implement an imputation strategy that matches observed weights from country-industry pairs that are covered in the data to those that are missing.

The matching algorithm that we use for the imputation is *Predictive Mean Matching* (PMM) (Rubin, 1986; Little, 1988). The PMM-based imputation of a single missing weight corresponding to country k, industry l, and year m, denoted by $y^{miss}_{c=k,i=l,t=m}$, is carried out as follows.[27] In a first step, we estimate a linear model, using all observations corresponding to the same industry l. Formally, this model can be written as

$$\boldsymbol{y}^{obs}_{c,i=l,t} = \boldsymbol{\beta}_{i=l}\boldsymbol{X}^{obs}_{c,i=l,t} + \boldsymbol{\varepsilon}^{obs}_{c,i=l,t}. \tag{6}$$

$\boldsymbol{y}^{obs}_{c,i=l,t}$ denotes the vector of all observed weights for industry l. $\boldsymbol{X}^{obs}_{c,i=l,t}$ denotes a matrix of covariates that are used for the matching (including a vector of ones, i.e., a constant is always included) and $\boldsymbol{\beta}_{i=l}$ denotes the corresponding coefficient vector. The model errors are collected in the vector $\boldsymbol{\varepsilon}^{obs}_{c,i=l,t}$. Estimating (6) yields the coefficient estimate vector $\widehat{\boldsymbol{\beta}}_{i=l}$ that is then used to form predictions for all complete cases that were used to estimate (6), i.e.,

$$\widehat{\boldsymbol{y}}^{obs}_{c,i=l,t} = \widehat{\boldsymbol{\beta}}_{i=l}\boldsymbol{X}^{obs}_{c,i=l,t}. \tag{7}$$

[27] We follow the notation of van Buuren (2018).

Furthermore, $\widehat{\boldsymbol{\beta}}_{i=l}$ is used to calculate an estimate for the case we want to impute, i.e.,

$$\widehat{y}^{miss}_{c=k,i=l,t=m} = \widehat{\boldsymbol{\beta}}_{i=l}\boldsymbol{X}^{miss}_{c=k,i=l,t=m}, \tag{8}$$

with $\boldsymbol{X}^{miss}_{c=k,i=l,t=m}$ denoting the covariates for the missing observation. The missing weight $y^{miss}_{c=k,i=l,t=m}$ is imputed with the observed weight (the so-called donor), $y^{obs}_{c=o,i=l,t=p}$, for which

$$|\widehat{y}^{miss}_{c=k,i=l,t=m} - \widehat{y}^{obs}_{c=o,i=l,t=p}| \tag{9}$$

is minimal. We require the donor to be from the same industry that we are looking to impute (here industry l). However, the donor must not necessarily stem from the same year of the data point we are looking to impute, i.e., m and p in (9) may be different.[28]

An advantage that PMM holds over other so-called "hot deck" imputation methods, i.e., methods that use values observed elsewhere for imputation, is that the covariates are summarized into one matching metric using a weighting scheme, i.e., the $\widehat{\boldsymbol{\beta}}_i$ that reflects the importance of the different covariates for predicting financing and asset weights.[29] Another advantage of PMM is that it is implicit (Little and Rubin, 2019), i.e., there is no need to define an explicit model for the distribution of the missings. Instead, the only assumption that has to be invoked is that the distribution of a missing entry is identical to the observed data of the donor (Van Buuren, 2018).

We first impute the financing weights. The dependent variable is the observed yearly debt share, which we get from Orbis, DS_{cit} (see Section 4.1). The country-level covariates used for the matching largely follow the ones used by Goldbach et al. (2021), and broadly aim at capturing the condition of a country's financial market, the strength of its institutions,

[28] Alternatively, instead of using just the donor for which the corresponding prediction is closest to the prediction of the missing data point, the mean of the d closest matches can be considered for imputation. As robustness check, we graphically provide imputation results for $d = 5, 10$, and 15 in Appendix 6.

[29] In contrast, for instance with the widely used k-Nearest Neighbor (k-NN) matching, all included covariates are assigned the same importance for finding a match (Hastie et al., 2009). In Appendix 6, we provide graphical evidence, using k-NN for imputation and compare the results to the ones obtained using PMM.

as well as its overall economic development. More specifically, we control for the *Rule of Law* indicator (ROL_{ct}), the *Control of Corruption* indicator ($Corruption_{ct}$), the logarithm of the variable measuring domestic credit provided to the private sector relative to a country's GDP ($log\ DCPS_{ct}$), annual inflation ($Inflation_{ct}$), as well as GDP growth ($GDP\ growth_{ct}$). As described above, all these variables are taken from the World Bank's WDI database. Furthermore, we include the statutory tax rate τ_{ct} as a proxy for the generosity of a country's corporate tax code. Additionally, we condition on a set of country-industry-level variables to account for the size and characteristics of industries. These variables are the logarithm of gross output ($log\ GO_{cit}$), gross input ($log\ GI_{cit}$), compensation of employees ($log\ COE_{cit}$), net operating surplus ($log\ NOS_{cit}$), net mixed income ($log\ NMI_{cit}$), paid net taxes on production ($log\ net\ TOP_{cit}$), and consumption of fixed capital ($log\ COFC_{cit}$). As described above, all country-industry-level variables are taken from the *Eora26* database. Finally, we include year indicators to control for year-specific effects that are common to all countries.[30] Once we have imputed the yearly debt ratios, DS_{cit}, for country-industry combinations that are not covered in *Orbis*, we proceed to compute time-constant debt and retained earnings shares as described in Section 4.1.

Next, we proceed to impute the asset weights. As discussed above in Section 4.2, we calculate the asset weights for inventory and the six other asset types separately using two different databases with different coverage. As a result, in many cases, we only need to impute the inventory share or the composition of the other asset types, but not both. To optimally use all available data and to be able to sensibly combine imputed and observed asset weights into one structure, we disregard inventory when imputing the asset categories *Buildings*, *Machinery*, *Office equipment*, *Computer equipment*, *Intangible fixed assets*, and *Vehicles*. That is, we use the yearly weights derived from the *EUKLEMS & INTANProd* database that have not yet been rescaled with the inventory share (denoted by w^*_{acit} in Section

[30] Descriptive statistics of the matching covariates are presented in Appendix 7. Note that we can only impute yearly financing weights for the years 2001 to 2016, as 2016 is the last year for which the industry-specific matching covariates are available.

4.2). By construction, these w^*_{acit}'s add up to unity in each year for a given country-industry combination. For the imputed equivalents, however, this is not necessarily the case, as different donors may be drawn for each asset type. We therefore rescale the imputed w^*_{acit}'s such that they add up to unity at the year level for each country-industry combination. Thereafter, the derivation of the final time-constant asset structures is identical to the procedure described in Section 4.2.

For the imputation of the asset weights, we again use a combination of country-specific and country-industry-specific covariates to control for market size and market conditions, economic development, as well as the industry-specific structure of primary inputs and production.[31] At the country level, we control for the logarithm of GDP ($log\ GDP_{ct}$) and GDP per capita ($log\ GDP\ p.c._{ct}$). At the industry level, we control for the logarithm of the compensation of employees ($log\ COE_{cit}$), the net operating surplus ($log\ NOS_{cit}$), the net mixed income ($log\ NMI_{cit}$), the consumption of fixed labour ($log\ COFC_{cit}$), as well as the logarithm of CO_2 emissions ($log\ CO2_{cit}$). Finally, we control for year-specific effects by including time dummies.[32]

Due to a lack of data on covariates, missing financing structures in 53 countries and asset structures in 56 countries cannot be imputed using the PMM procedure. In order to calculate FLETRs for these countries, they are assigned the time-constant observed and/or PMM-imputed weights of their geographical neighbors. For instance, San Marino is assigned the weights from Italy and Andorra is assigned the mean of the weights of France and Spain. More than half of the countries that we are missing are small islands in the Caribbean region or Oceania. In these cases, missing asset and/or financing weights are replaced by the region-specific mean of all non-missing weights.[33] [34]

[31]Note that we use the same covariates for the imputation of each asset type.

[32]Descriptive statistics of the covariates used for the matching of asset weights are presented in Appendix 7. Again, note that we can only impute yearly weights for the years 2001 to 2016 due to covariate coverage.

[33]The exact imputation using geographically close countries is detailed in Appendix 8.

[34]Note that we have collected statutory tax rates and tax base rules for these countries. As the variation in EMTRs is largely driven by statutory tax determinants, we prefer to make somewhat stricter assumptions on asset and financing weights, but instead are able to keep these countries in our sample.

4.4. *Descriptive Statistics of Asset and Financing Weights*

Table 1 presents summary statistics of the time-constant, country-industry-specific financing and asset structures that we use for the calculation of the FLETRs. The summary statistics are grouped by the different approaches we use obtain the weights. Panel A only depicts information on weights that are directly derived from the primary data sources. The Panels B and C describe weights we have imputed using the PMM procedure or values from geographically proximate countries, respectively.

A key result that holds for each panel is that there is substantial variation between the mean values of the debt ratios and in particular the asset weights of the different industries.

Table 1: *DESCRIPTIVES ON IMPUTED COUNTRY-INDUSTRY-SPECIFIC FINANCING AND ASSET WEIGHTS*

The table depicts means (expressed in %) and standard deviations (in brackets) of the financing and asset weights by NACE Rev. 2 (ISIC Rev. 4) sections. Panel A depicts weights that are derived directly from data sources (see Sections 4.1 and 4.2). Panels B and C depict weights that are imputed using PMM with $d = 1$ donor and weight values of geographically proximate countries, respectively (see Section 4.3). The last row of each panel gives the number of the country-industry-specific weights across all industries. Descriptions for the different NACE Rev. 2 (ISIC Rev. 4) sections are provided in Table A.1.

Panel A: Weights derived directly from data sources

	DS_{ci}	$w_{\mathrm{build},ci}$	$w_{\mathrm{comp},ci}$	$w_{\mathrm{ifas},ci}$	$w_{\mathrm{mach},ci}$	$w_{\mathrm{office},ci}$	$w_{\mathrm{vehic},ci}$	$w_{\mathrm{invent},ci}$
A	18.0 (0.098)	51.6 (0.116)	0.2 (0.002)	0.5 (0.007)	18.7 (0.088)	0.3 (0.007)	5.0 (0.030)	26.4 (0.096)
B	17.8 (0.093)	47.7 (0.148)	0.3 (0.003)	1.9 (0.020)	28.3 (0.135)	0.5 (0.009)	2.9 (0.025)	21.0 (0.089)
C	15.1 (0.096)	24.4 (0.102)	0.5 (0.003)	10.9 (0.086)	25.5 (0.057)	0.6 (0.008)	1.4 (0.007)	37.4 (0.102)
D	24.4 (0.120)	64.9 (0.166)	0.3 (0.002)	1.7 (0.022)	23.9 (0.135)	0.9 (0.015)	0.8 (0.011)	11.6 (0.107)
E	17.7 (0.110)	73.0 (0.100)	0.2 (0.002)	0.9 (0.008)	9.8 (0.075)	0.4 (0.007)	1.9 (0.010)	16.5 (0.102)
F	14.6 (0.110)	35.6 (0.115)	0.7 (0.006)	1.8 (0.021)	18.8 (0.096)	0.5 (0.005)	9.7 (0.048)	33.2 (0.145)
G	11.8 (0.091)	29.1 (0.066)	0.9 (0.006)	2.6 (0.021)	10.2 (0.031)	0.6 (0.006)	4.5 (0.024)	54.3 (0.129)
H	18.3 (0.106)	56.3 (0.140)	0.4 (0.002)	1.3 (0.015)	7.4 (0.042)	0.9 (0.010)	26.8 (0.143)	9.8 (0.077)
I	20.4 (0.124)	59.9 (0.096)	0.7 (0.006)	1.3 (0.023)	15.4 (0.073)	1.1 (0.011)	2.5 (0.024)	18.8 (0.142)
J	12.7 (0.086)	40.9 (0.136)	3.1 (0.022)	15.1 (0.103)	10.1 (0.065)	11.1 (0.093)	3.3 (0.082)	18.2 (0.099)
K	14.0 (0.082)	54.4 (0.188)	3.9 (0.025)	15.4 (0.114)	8.0 (0.063)	1.7 (0.027)	4.4 (0.047)	11.8 (0.096)
L	22.8 (0.127)	85.9 (0.080)	0.0 (0.001)	0.1 (0.001)	0.4 (0.005)	0.0 (0.001)	0.1 (0.002)	18.1 (0.144)
M	11.6 (0.072)	36.8 (0.128)	3.1 (0.026)	27.9 (0.152)	11.4 (0.041)	1.7 (0.024)	4.4 (0.017)	16.9 (0.091)
N	14.3 (0.085)	28.5 (0.144)	2.1 (0.014)	4.5 (0.061)	19.1 (0.082)	2.3 (0.029)	30.7 (0.131)	15.7 (0.087)
O	14.3 (0.124)	76.0 (0.087)	0.5 (0.003)	1.9 (0.012)	8.0 (0.066)	0.3 (0.003)	1.7 (0.021)	14.9 (0.107)
P	14.0 (0.115)	68.1 (0.136)	0.8 (0.005)	14.3 (0.104)	5.4 (0.032)	0.5 (0.006)	0.8 (0.007)	10.1 (0.080)
Q	16.3 (0.110)	66.1 (0.139)	1.1 (0.009)	4.1 (0.040)	17.7 (0.103)	1.0 (0.018)	1.7 (0.007)	11.7 (0.077)
R	16.8 (0.120)	68.7 (0.143)	1.1 (0.010)	3.0 (0.038)	12.6 (0.119)	1.5 (0.018)	1.7 (0.016)	12.4 (0.079)
S	14.7 (0.103)	50.7 (0.100)	1.5 (0.016)	4.9 (0.069)	12.1 (0.075)	1.2 (0.017)	3.8 (0.028)	25.6 (0.127)
Obs	1,321	394	394	394	394	394	394	1,261

Panel B: Weights imputed using PMM

	DS_{ci}	$w_{\mathrm{build},ci}$	$w_{\mathrm{comp},ci}$	$w_{\mathrm{ifas},ci}$	$w_{\mathrm{mach},ci}$	$w_{\mathrm{office},ci}$	$w_{\mathrm{vehic},ci}$	$w_{\mathrm{invent},ci}$
A	14.7 (0.050)	33.7 (0.108)	0.2 (0.001)	2.3 (0.013)	30.4 (0.080)	2.5 (0.013)	4.4 (0.025)	26.1 (0.050)
B	14.9 (0.048)	57.9 (0.085)	0.3 (0.003)	1.3 (0.011)	13.6 (0.082)	0.5 (0.010)	2.3 (0.016)	25.0 (0.045)
C	14.3 (0.042)	33.0 (0.057)	0.6 (0.004)	1.7 (0.034)	24.3 (0.041)	0.9 (0.009)	2.4 (0.005)	36.5 (0.026)
D	18.9 (0.048)	64.0 (0.071)	0.2 (0.002)	1.3 (0.007)	19.5 (0.053)	0.3 (0.010)	0.5 (0.006)	14.6 (0.037)
E	9.4 (0.050)	65.9 (0.106)	0.4 (0.003)	0.8 (0.007)	12.6 (0.081)	0.4 (0.008)	3.1 (0.010)	16.8 (0.059)
F	12.9 (0.050)	40.7 (0.092)	0.7 (0.003)	1.1 (0.009)	17.9 (0.052)	0.3 (0.004)	7.2 (0.048)	31.9 (0.037)
G	12.0 (0.041)	27.3 (0.060)	0.4 (0.006)	1.2 (0.015)	8.7 (0.037)	0.8 (0.003)	4.4 (0.015)	58.7 (0.046)
H	12.1 (0.055)	52.4 (0.121)	0.4 (0.001)	0.4 (0.004)	4.7 (0.024)	0.6 (0.005)	27.1 (0.142)	16.1 (0.065)
I	13.5 (0.072)	56.4 (0.092)	0.4 (0.004)	1.0 (0.013)	14.7 (0.060)	2.4 (0.010)	1.8 (0.010)	25.0 (0.052)
J	9.1 (0.036)	42.4 (0.104)	1.5 (0.017)	8.4 (0.049)	9.5 (0.054)	8.4 (0.049)	3.6 (0.074)	29.5 (0.096)
K	10.6 (0.037)	29.2 (0.202)	6.8 (0.046)	28.0 (0.162)	9.7 (0.034)	5.2 (0.067)	8.8 (0.064)	12.6 (0.071)
L	17.3 (0.080)	72.5 (0.145)	0.0 (0.001)	0.2 (0.003)	1.2 (0.008)	0.1 (0.001)	0.2 (0.001)	28.7 (0.129)
M	9.4 (0.033)	48.9 (0.113)	1.4 (0.023)	12.4 (0.117)	13.5 (0.041)	2.2 (0.031)	3.3 (0.017)	18.7 (0.054)
N	12.6 (0.038)	44.4 (0.119)	2.1 (0.010)	1.8 (0.013)	16.5 (0.064)	2.7 (0.029)	14.1 (0.113)	19.1 (0.078)
O	8.5 (0.049)	68.6 (0.089)	0.7 (0.003)	0.7 (0.008)	11.6 (0.079)	0.3 (0.005)	1.8 (0.028)	16.0 (0.050)
P	9.3 (0.056)	70.9 (0.091)	1.7 (0.006)	9.9 (0.091)	6.4 (0.027)	0.7 (0.004)	0.8 (0.004)	9.4 (0.040)
Q	11.6 (0.040)	39.8 (0.179)	1.7 (0.008)	4.5 (0.032)	37.2 (0.177)	2.9 (0.018)	2.3 (0.007)	11.0 (0.070)
R	8.5 (0.061)	52.2 (0.141)	1.5 (0.009)	2.0 (0.014)	24.0 (0.120)	1.9 (0.024)	6.7 (0.040)	11.4 (0.053)
S	9.9 (0.056)	41.3 (0.113)	0.9 (0.007)	1.7 (0.029)	12.0 (0.073)	1.0 (0.006)	7.6 (0.033)	38.7 (0.112)
Obs	1,921	2,741	2,741	2,741	2,741	2,741	2,741	1,930

Panel C: Weights imputed using values of geographically proximate countries

	DS_{ci}	$w_{\mathrm{build},ci}$	$w_{\mathrm{comp},ci}$	$w_{\mathrm{ifas},ci}$	$w_{\mathrm{mach},ci}$	$w_{\mathrm{office},ci}$	$w_{\mathrm{vehic},ci}$	$w_{\mathrm{invent},ci}$
A	17.1 (0.046)	39.7 (0.096)	0.1 (0.001)	2.1 (0.008)	26.8 (0.055)	2.2 (0.010)	4.6 (0.013)	24.3 (0.058)
B	16.0 (0.035)	58.4 (0.060)	0.3 (0.001)	1.2 (0.012)	15.9 (0.055)	0.3 (0.001)	1.4 (0.010)	22.5 (0.047)
C	14.1 (0.054)	30.3 (0.061)	0.6 (0.002)	4.0 (0.060)	24.3 (0.031)	0.7 (0.004)	2.2 (0.005)	37.8 (0.043)
D	21.9 (0.058)	62.1 (0.078)	0.3 (0.001)	1.6 (0.017)	21.1 (0.070)	0.5 (0.009)	0.7 (0.008)	13.8 (0.039)
E	13.5 (0.054)	70.8 (0.080)	0.3 (0.002)	0.7 (0.005)	10.0 (0.055)	0.2 (0.003)	2.2 (0.007)	15.0 (0.057)
F	14.8 (0.048)	42.6 (0.076)	0.6 (0.002)	1.0 (0.008)	15.3 (0.028)	0.4 (0.002)	7.5 (0.029)	31.9 (0.053)
G	13.7 (0.047)	25.9 (0.034)	0.5 (0.003)	1.5 (0.011)	8.7 (0.020)	0.7 (0.002)	4.4 (0.008)	58.3 (0.060)
H	14.1 (0.064)	46.7 (0.088)	0.4 (0.001)	0.7 (0.006)	6.2 (0.026)	0.6 (0.004)	34.0 (0.102)	11.4 (0.049)
I	16.1 (0.070)	57.3 (0.060)	0.5 (0.002)	0.9 (0.010)	16.2 (0.035)	1.9 (0.006)	2.0 (0.006)	21.2 (0.068)
J	10.2 (0.051)	42.2 (0.073)	3.0 (0.016)	10.3 (0.078)	9.4 (0.028)	9.6 (0.043)	3.1 (0.020)	22.4 (0.067)
K	13.1 (0.043)	28.4 (0.162)	9.4 (0.037)	32.7 (0.128)	10.4 (0.037)	3.4 (0.024)	6.0 (0.040)	9.6 (0.053)
L	21.2 (0.066)	76.7 (0.103)	0.1 (0.000)	0.2 (0.001)	1.2 (0.005)	0.0 (0.001)	0.2 (0.001)	21.2 (0.083)
M	10.6 (0.040)	44.9 (0.076)	1.6 (0.014)	19.4 (0.114)	13.7 (0.034)	1.5 (0.011)	3.2 (0.007)	15.5 (0.049)
N	13.7 (0.038)	41.1 (0.092)	2.2 (0.005)	2.3 (0.019)	18.9 (0.052)	2.4 (0.012)	17.5 (0.096)	15.5 (0.058)
O	9.6 (0.033)	68.6 (0.050)	0.6 (0.002)	1.4 (0.008)	11.2 (0.042)	0.2 (0.003)	1.8 (0.015)	16.2 (0.049)
P	11.8 (0.044)	68.8 (0.052)	1.5 (0.004)	13.9 (0.057)	6.1 (0.014)	0.7 (0.003)	0.9 (0.003)	8.3 (0.034)
Q	14.0 (0.052)	42.8 (0.133)	1.8 (0.006)	4.5 (0.015)	36.9 (0.104)	2.3 (0.009)	2.4 (0.005)	9.1 (0.049)
R	12.4 (0.058)	54.1 (0.109)	1.5 (0.005)	2.0 (0.009)	23.8 (0.085)	1.7 (0.010)	6.0 (0.025)	10.7 (0.038)
S	12.5 (0.053)	43.4 (0.066)	1.3 (0.007)	3.0 (0.045)	12.9 (0.034)	1.0 (0.008)	6.1 (0.021)	32.2 (0.084)
Obs	957	1,064	1,064	1,064	1,064	1,064	1,064	1,008

Intuitively, this heterogeneity seems plausible. For instance, section *C manufacturing* exhibits a noticeably higher share of *machinery* in its mean asset composition than the service industries, e.g., *P education*. Additionally, there is substantial variation in every weight within each industry, irrespective of the method used to derive it, as indicated by the standard deviations. The fact that the variation is strong not only for the weights derived directly from the data but also for the PMM imputed weights (Panel B) indicates that for the latter approach, a wide range of observed values was drawn for the matching.[35] Overall, the strong variation both between and within industries corroborates our approach of estimating country-industry-specific financing and asset compositions for the calculation of FLETRs. Conversely, assuming symmetric asset and financing structures across all countries and industries, as done by most of the previous literature, most likely leads to imprecise tax measures and introduces additional measurement error. We finally provide a number of plausibility checks also by looking at single data points in Appendix 6.

5. Country-industry-year-specific FLETRs

In this section, we calculate and describe the new country-industry-year-specific FLETRs using the time-constant, country-industry-specific financing and asset weights we have calculated and estimated in the previous section. In a first step, we compute the NPV of depreciation allowances, δ_{cit}, by plugging the financing shares, ES_{ci} and DS_{ci}, as well as the asset shares, w_{aci}, into equation (2). The country-industry-year-specific EMTRs are then obtained by inserting δ_{cit} as well as the statutory tax rate, τ_{ct}, into (3). For the calculation of the country-industry-year-specific EATRs we use the same NPV of depreciation allowances, δ_{cit}. For details on the calculation of the EATR as well as descriptions, refer to Appendix 9.

For the sake of comparison, we additionally calculate EMTRs that are based on symmetric financing and asset weights for all countries and industries, which is the common approach

[35]In Appendix 6, we illustrate graphically that this result is robust to increasing the number of donors considered for the imputation of a single year-specific data point.

in the existing literature. More precisely, we use the parameterization by Steinmüller et al. (2019) that matches the asset types that are also used in the paper at hand.[36] We denote the EMTRs and NPVs of depreciations allowances based on these symmetric weights as $EMTR_{ct}$ and δ_{ct}, respectively.

In a first step of analyzing the new country-industry-specific EMTRs, we plot year-specific means over all countries for each industry. For the sake of comparison, we add year-specific means of the country-year specific EMTR over all countries to the plot. The resulting Figure 1 suggests that the country-industry-year-specific EMTRs follow, on average, the same downward trend as their country-year-specific counterparts. There is, however, substantial variation in the average EMTRs across industries implying that the country-year-specific average EMTRs significantly over-/underestimate the tax burden for certain industries. For example, firms operating in the sections *Construction*, *Manufacturing*, as well as *Wholesale and retail trade* face among highest average EMTRs.[37] On the other hand, firms engaged in *Arts, entertainment, and recreation*, *Financial and insurance activities*, as well as *Human health and social work activities* face the lowest effective tax burden. Overall, the findings in Figure 1 suggest that disregarding country-industry-level heterogeneity for calculating EMTRs leads to a systematic measurement error.

To further explore the heterogeneity from using country-industry-year-specific versus country-year-specific EMTRs, we take the difference between the levels of these two measures ($EMTR_{cit} - EMTR_{ct}$) and plot the corresponding distribution (Figure 2). It can be seen that most of the mass of the density plot is located on an interval of plus/minus five percentage points with a steep spike on the interval of plus/minus one percentage point. This suggests that the additional variation in $EMTR_{cit}$ that is introduced by the country-industry-specific financing and asset weights does not lead to a large structural deviation

[36] In detail, the asset structure is composed as follows: *Buildings* 38%, *Computer equipment* 2%, *Intangible fixed assets* 11%, *Inventory* 26%, *Machinery* 2%, *Office equipment* 1%, *Vehicles* 2%. The debt-financing share and the equity-financing share are assumed to amount to 1/3 and 2/3, respectively (Steinmüller et al., 2019).

[37] Note that the on average by far largest EMTRs are the ones for *Wholesale and retail trade*. This can in large parts be explained with the high inventory shares that we find for this industry and the fact that inventories are not subject to depreciation, as we disregard inflation.

Figure 1: *DEVELOPMENT OF MEAN COUNTRY-YEAR AND COUNTRY-INDUSTRY-YEAR-SPECIFIC EMTRs*

The figure depicts the development of the mean country-year and country-industry-year-specific EMTRs calculated in 5. The grey dots represent the mean country-industry-year-specific EMTRs across countries for each year. The black dots that are connected by black lines represent the mean country-year-specific EMTRs across countries for each year. Calculations are based on a sample of 75,126 observations.

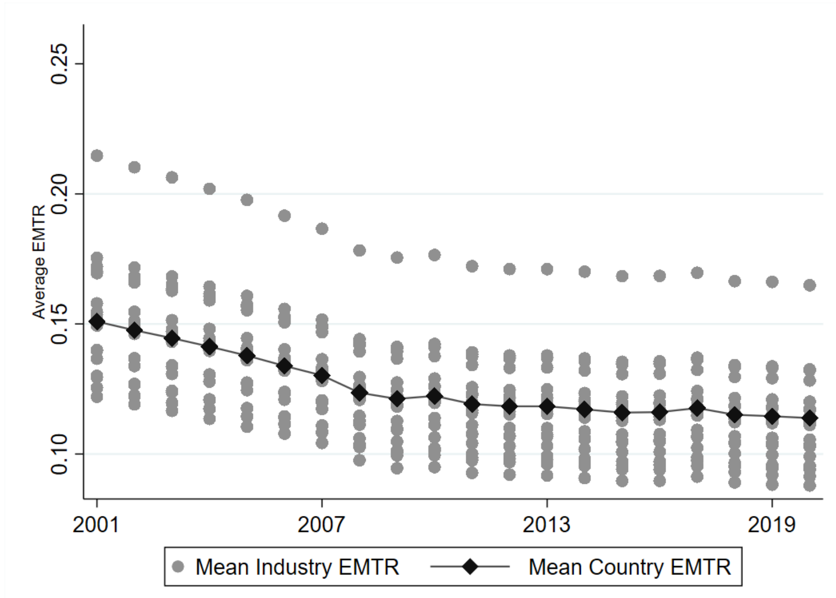
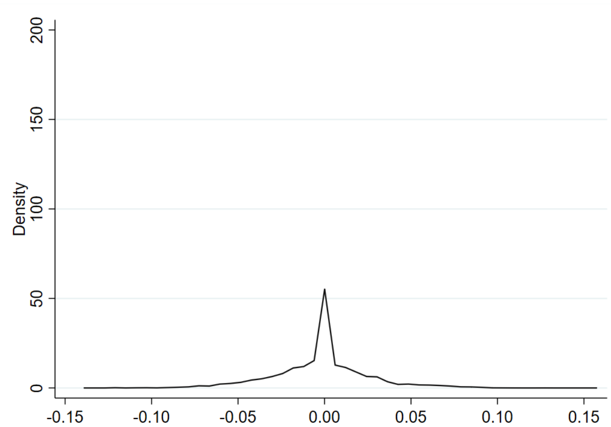


Figure 2: *DISTRIBUTION OF DEVIATIONS FROM THE COUNTRY-YEAR EMTRs*

The figure depicts the distribution of the differences between country-industry-year-specific and country-year-specific EMTRs calculated in Section 5. The distribution is calculated based on 75,126 observations using a triangle kernel with a bandwidth of 0.0022.



from EMTR measures where this heterogeneity is neglected. In other words, the finding suggests that the magnitude in the country-industry-specific EMTRs is mainly determined by the national tax code and only to a comparably smaller part by the country-industry-specific characteristics.

Finally, to quantify how much of the overall variance in our country-industry-year-specific EMTRs is due to the country level (i.e., the countries' tax codes) versus the industry level (i.e., the country-industry-specific weights), we carry out an analysis of variance (ANOVA). For this purpose, we propose a simple model of the form[38]

$$EMTR_{cit} = \alpha + \mu_c + \lambda_i + \theta_t + \eta_{cit}. \tag{10}$$

Here, α denotes a constant. Country-, industry-, and year-specific sets of dummy variables are contained in μ_c, λ_i, and θ_t, respectively; η_{cit} is the error component. We denote the total variance in $EMTR_{cit}$ as SS_{EMTR} and the partial sums of squares of the country-, industry-, and year effects as SS_μ, SS_λ, and SS_θ, respectively. The model's residual sum of squares is SS_η. Note that it holds that $SS_{EMTR} = SS_\mu + SS_\lambda + SS_\theta + SS_\eta$.[39] The results of the ANOVA in Table 2 suggest that the sums of squares of the country effects, SS_μ, contribute to SS_{EMTR} in a major way ($SS_\mu/SS_{EMTR} = 68.63\%$). Compared to that, the industry effects play a smaller – nonetheless non-neglible – role with $SS_\lambda/SS_{EMTR} = 7.92\%$. These findings are in line with the graphical evidence shown above and indicate that the national tax codes are the main contributors to the variation in our country-industry-year-specific EMTRs. However, the ANOVA also shows that the country-industry-specific financing and asset weights account for a substantial amount of variation in the EMTRs.

When analyzing the EATR in a similar way as the EMTR in this section, it can be seen that the EATR exhibits much less industry-specific variation when applying the same country-industry-year-specific NPVs of depreciation allowances. A detailed analysis of the

[38]Note that the setup of the ANOVA broadly follows Egger et al. (2009).

[39]Further note that the R^2 is given by $(SS_\mu + SS_\lambda + SS_\theta)/SS_{EMTR}$.

Table 2: *ANALYSIS OF VARIANCE OF COUNTRY-INDUSTRY-YEAR-SPECIFIC EMTRs*

The table depicts analysis of variance (ANOVA) results of the country-industry-year-specific effective marginal tax rates ($EMTR_{cit}$) that are calculated in Section 5. The ANOVA is based on 75,126 observations.

	Partial sum of squares	Degrees of freedom	F-statistic	p-value
Country effects	246.558	220	1131.18	0.000
NACE Rev. 2 section effects	28.450	18	1595.28	0.000
Year effects	10.757	19	571.45	0.000
Model	285.081	257	1119.61	0.000
Residual	74.176	74,868		
Total	359.256	75,125		
R^2	0.794			

EATR can be found in Appendix 9.

6. Tax Semi-Elasticity of Firms' Tangible Fixed Assets

6.1. Empirical Approach

In this section, we calculate the tax semi-elasticity of investment, using the EMTRs calculated in Section 5. Following Steinmüller et al. (2019), we use the logarithm of firm entity j's tangible fixed assets ($log\ TFAS_{jt}$) as dependent variable to capture real investment behavior. This outcome has been used regularly in the literature and is also common in studies examining the effect of (corporate) taxation on foreign investments. We provide more discussion on this measurement and the empirical specification below. We implement the following estimation equation

$$log\ TFAS_{jt} = \gamma EMTR_{cit} + \boldsymbol{\psi X_{jt-1}} + \boldsymbol{\zeta X_{ct}} + \theta_t + c_j + \varepsilon_{jt}. \tag{11}$$

The coefficient γ measures the semi-elasticity of investment[40] with respect to the marginal tax rate, $EMTR_{cit}$. We control for a set of lagged affiliate-specific variables, denoted by

[40] Note that we use "investment" in our micro-level panel data approach interchangeably for "investment in tangible fixed assets".

$\boldsymbol{X_{jt-1}}$, and a set of country-specific variables, denoted by $\boldsymbol{X_{ct}}$, both of which are described in more detail below. The corresponding parameter estimates are contained in the vectors $\boldsymbol{\psi}$ and $\boldsymbol{\zeta}$, respectively. Furthermore, we control for year- and firm entity-specific effects, which we denote by θ_t and c_j, respectively.[41] Finally, ε_{jt} denotes the error component.

Note that, given specification (11), the role of the financial and asset weights becomes less important (but of course not irrelevant) since we condition on firm entity j-specific heterogeneity c_j, and focus on the substantial variation in the EMTRs over time. The aim of the analysis is to identify changes in the investment behavior, driven by changes in the tax code.

6.2. Sample and Control Variables

The control variables that we use largely follow Steinmüller et al. (2019). At the firm entity level (indicated by index j), we include the one-period lag of the logarithm of sales ($log\ SALES_{jt-1}$) and cost of employees ($log\ STAF_{jt-1}$). Additionally, we include three entity-level ratios proposed by Liu (2020): the cash flow rate ($CF\ rate_{jt}$), defined as the cash flow in year t divided by the sum of tangible and intangible fixed assets in $t-1$; the one period lag of the sales growth rate ($SALES\ growth_{jt-1}$), i.e., the sales growth rate from $t-2$ to $t-1$; and the one period lag of the profit margin ($Profit\ margin_{jt-1}$), with the profit margin in t being defined as $EBIT_{jt}/SALES_{jt}$. To minimize the influence of obvious outliers, we winsorize all three ratio variables at the top and bottom 1 percentiles.

At the country level, we control for host country c's GDP ($log\ GDP_{ct}$), GDP per capita ($log\ GDP\ p.c._{ct}$), and the GDP growth rate ($GDP\ growth_{ct}$) as proxies for market size, the state of a country's economic development, and the general economic situation, respectively. Additionally, we control for inflation ($Inflation_{ct}$) to capture investment risk. In particular, following the arguments in Aggarwal and Kyaw (2008), as well as Huizinga et al. (2008), countries with higher inflation usually exhibit a higher risk premium and higher general

[41] Note also that we provide an extensive discussion on different types of fixed effects we might include in the estimations (see Section 6.4).

business risk. Furthermore, we include the real interest rate ($Real\ interest\ rate_{ct}$) to control the cost of debt financing.[42] The variable domestic credit to private sector relative to a country's GDP ($log\ DCPS_{ct}$) is included as a measure for capital market depth. The corruption ($Corruption_{ct}$) and rule of law (ROL_{ct}) indicators capture the strength of institutions such as creditor rights. We finally control for the number of double taxation treaties ($NDTT_{ct}$) that a country has.

For our sample, we consider *Orbis* observations for the time span 2001, i.e., the first year for which we calculate FLETRs, to 2018, which is the last year for which all control variables are available. Following the literature (e.g., Steinmüller et al., 2019; Liu, 2020), we exclude a number of industries from our analysis (as tax treatment of these industries differs from the standard one).[43] We finally impose the requirement that a firm entity must be observed at least twice in the sample period. Descriptive statistics for our final sample of over 24 million observations as well as a correlation matrix for selected variables are provided in Table 3.

6.3. Basic Results

Table 4 presents the basic estimation results of the tax semi-elasticity of investment.[44] The results presented in columns (1) to (4) are based on the largest possible sample of more than 24 million observations with 4,787,866 individual firm entities in 70 countries.

[42] Note that, depending on the theoretical concept of expressing the ETR formally, a benchmark interest rate might also feature in the tax formula. However, for the sake of measurability, we aim at keeping the EMTR formula as simple as possible, but condition on the interest rate.

[43] In detail, these industries are denoted by the section codes A, B, K, O, P, Q, T, and U. For a description on these sections, see Appendix 3.

[44] Note that we report robust standard errors that are clustered at the country-industry-year level, i.e., the level at which we merge the tax measures to the firm entity-level data (Moulton, 1990).

Table 3: ***DESCRIPTIVES ON DATA SET USED FOR THE ESTIMATION OF THE TAX-ELASTICITY OF CORPORATE INVESTMENT***

The table depicts descriptive statistics on all the variables used for the estimation of the tax-elasticity of investment. Panel A reports descriptives on the different tax measures applied. Panel B reports descriptives on the firm entity level variables. Panel C depicts Pearson correlation coefficients for key variables. Definitions of the variables are provided in Section 6.2.

Panel A: Tax measures

	Observations	Mean	(sd)
$EMTR_{cit}$	24,144,916	0.160	(0.063)
$EATR_{cit}$	24,144,916	0.234	(0.068)
τ_{ct}	24,144,916	0.266	(0.076)
δ_{cit}	24,144,916	0.473	(0.148)

Panel B: Firm entity level variables

	Observations	Mean	(sd)
$log\ TFAS_{jt}$	24,144,916	10.780	(2.462)
$log\ SALES_{jt-1}$	24,144,916	13.192	(1.889)
$log\ STAF_{jt-1}$	24,144,916	11.514	(1.938)
$CF\ rate_{jt}$	24,144,916	1.808	(11.006)
$SALES\ growth_{jt-1}$	24,144,916	0.278	(1.507)
$Profit\ margin_{jt-1}$	24,144,916	-0.025	(0.541)

Panel C: Country level variables

	Observations	Mean	(sd)
$log\ GDP_{ct}$	24,144,916	27.605	(1.146)
$log\ GDP\ p.c._{ct}$	24,144,916	10.475	(0.333)
$GDP\ growth_{ct}$	24,144,916	1.471	(2.408)
$Inflation_{ct}$	24,144,916	1.700	(2.338)
$Real\ interest\ rate_{ct}$	24,144,916	2.857	(1.864)
$log\ DCPS_{ct}$	24,144,916	4.450	(0.462)
$Corruption_{ct}$	24,144,916	0.779	(0.726)
ROL_{ct}	24,144,916	0.934	(0.591)
$NDTT_{ct}$	24,144,916	90.172	(22.611)

Panel D: Correlation matrix (24,144,916 observations)

	$log\ TFAS_{jt}$	$EMTR_{cit}$	$EATR_{cit}$	τ_{ct}	δ_{cit}
$log\ TFAS_{jt}$	1.000				
$EMTR_{cit}$	0.052	1.000			
$EATR_{cit}$	0.054	0.873	1.000		
τ_{ct}	0.051	0.793	0.989	1.000	
δ_{cit}	0.000	-0.495	-0.038	0.098	1.000

Our benchmark specification in column (1) suggests an EMTR semi-elasticity of about -0.41, i.e., a 1 percentage point higher EMTR results in 0.41% less investment in tangible fixed assets. The corresponding elasticity equals -0.065 which is a very small effect compared to the previous literature.

Column (2) illustrates that the effect of the EATR is not only smaller but also slightly less statistically significant. This result is in line with expectations as discrete investment

Table 4: *BENCHMARK ESTIMATES*

The table presents OLS estimates. The dependent variable is the logarithm of firm entity j's tangible fixed assets, $log\ TFAS_{jt}$. Robust standard errors are reported in parentheses (clustered at the country-industry-year level). *** denotes significance at the 1% level; ** denotes significance at the 5% level; * denotes significance at the 10% level. The last rows report elasticities corresponding to the tax measure(s) used in the respective model. Corresponding standard errors are obtained using the Delta method. Definitions and descriptive statistics on the explanatory variables are provided in Section 6.2.

	(1)	(2)	(3)	(4)
$EMTR_{cit}$	-0.405**			
	(0.166)			
$EATR_{cit}$		-0.298**		
		(0.138)		
τ_{ct}			-0.248**	-0.253**
			(0.122)	(0.122)
δ_{cit}				0.273**
				(0.113)
$log\ SALES_{jt-1}$	0.266***	0.266***	0.266***	0.266***
	(0.005)	(0.005)	(0.005)	(0.005)
$log\ STAF_{jt-1}$	0.087***	0.087***	0.087***	0.087***
	(0.002)	(0.002)	(0.002)	(0.002)
$CF\ rate_{jt}$	-0.004***	-0.004***	-0.004***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
$SALES\ growth_{jt-1}$	-0.010***	-0.010***	-0.010***	-0.010***
	(0.000)	(0.000)	(0.000)	(0.000)
$Profit\ margin_{jt-1}$	-0.067***	-0.067***	-0.067***	-0.067***
	(0.003)	(0.003)	(0.003)	(0.003)
$log\ GDP_{ct}$	1.602***	1.603***	1.603***	1.603***
	(0.285)	(0.286)	(0.286)	(0.286)
$log\ GDP\ p.c._{ct}$	-0.504*	-0.508*	-0.508*	-0.509*
	(0.261)	(0.261)	(0.262)	(0.262)
$GDP\ growth_{ct}$	-0.007***	-0.007***	-0.007***	-0.007***
	(0.002)	(0.002)	(0.002)	(0.002)
$Inflation_{ct}$	-0.008***	-0.008***	-0.008***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)
$Real\ interest\ rate_{ct}$	-0.004**	-0.004**	-0.004**	-0.004**
	(0.002)	(0.002)	(0.002)	(0.002)
$log\ DCPS_{ct}$	0.101***	0.100***	0.099***	0.099***
	(0.030)	(0.030)	(0.030)	(0.030)
$Corruption_{ct}$	-0.067***	-0.068***	-0.068***	-0.068***
	(0.024)	(0.024)	(0.024)	(0.024)
ROL_{ct}	-0.067*	-0.069*	-0.068*	-0.067*
	(0.039)	(0.040)	(0.040)	(0.040)
$NDTT_{ct}$	0.008***	0.008***	0.008***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)
Entity fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Adjusted R^2	0.898	0.898	0.898	0.898
Observations	24,144,916	24,144,916	24,144,916	24,144,916
Elasticities				
$EMTR_{cit}$	-0.065**			
	(0.027)			
$EATR_{cit}$		-0.070**		
		(0.032)		
τ_{ct}			-0.066**	-0.067**
			(0.032)	(0.032)
δ_{cit}				0.129**
				(0.053)

decision may be less responsive to changes in tax incentives in the short-run. Moreover, the fixed effects approach removes all cross-sectional variation in the tangible fixed assets and identification is based on marginal changes in the EMTR over time. In this sense, the EMTR should be the best measure to explain changes in outcome. Column (3) employs the statutory tax rate (τ_{ci}) as an alternative tax measure, which neither accounts for tax base effects nor for appropriate asset and financing weights. While the coefficient is still negative and statistically significant, it is substantially smaller compared to the EMTR. Column (4) distinguishes between τ and the weighted δ – to differentiate between tax rate and tax base effects. The coefficients are both statistically significant and have the expected signs. An interesting finding here is that the corresponding elasticity for δ is relatively high (0.13).[45] Given these results, the newly calculated EMTRs capture tax incentives in the most appropriate way by incorporating both statutory tax policy changes and country-industry-specific firm characteristics.

Let us briefly discuss the findings for the other control variables. We may distinguish between different groups of variables. First, $log\ SALES$ and $log\ STAF$ are positively related to investments in fixed assets. These two variables, thus, seem to capture size effects. Second, $CF\ ratio$, $SALES\ growth$, and $Profit\ margin$ are all negatively associated with the outcome variable. All three variables may be interpreted as proxies for investment opportunities. In fact, all three variables may be positively correlated with firm age, as well as firm and industry maturity, which explains the negative effect on investment in fixed assets. Third, of the different GDP indicators, it is mainly $log\ GDP$ that has a positive and economically significant impact on investment. Fourth, the negative coefficient on $Inflation$ is in line with the investment risk argument presented above. Fifth, the negative coefficient on $Real\ interest\ rate$ suggests that a high cost of debt financing hampers investment. Sixth,

[45]When including the EMTR and the statutory tax rate (or the EATR) at the same time, the EMTR becomes slightly insignificant, but is still negative, while the other coefficients on the two tax measures are insignificant, positive and close to zero. Since the variation – especially the variation over time – in all tax measures is mainly driven by changes in statutory rules (which is, however, what we are mainly interested in), there is not sufficient distinct variation that allows us to properly identify the respective effects jointly.

log DCPS, a measure of capital market depth, facilitates investment, which is what we expect. We may finally highlight the positive impact of *NDTT*, which confirms earlier findings (see, e.g., Egger and Merlo, 2011).[46]

To test for robustness, we also also run (1) dynamic regressions, (2) regressions using the gross investment rate as an alternative outcome following the setup used by Liu (2020) (see Appendix 10), as well as (3) specifications that are based on a balanced panel. This does not substantially change the EMTR effects.[47]

6.4. Alternative Fixed Effects Specifications

We now estimate equation (11) for alternative fixed effects specifications to test the robustness and sensitivity of the benchmark results. Table 5 demonstrates that we find a negative and highly significant tax effect, irrespective of the choice of alternative fixed effects.

The estimates closest to our benchmark result in Table 4 are those that condition on firm entity (group) as well as industry-year effects, see columns (1) and (2).[48] The largest coefficient is found in specification (4), which is conditional on a country-year-specific fixed effect. Note that country-year-specific EMTRs would not be identified in this specification, but the country-industry-year specific ones ($EMTR_{cit}$) are.

A last, but very powerful test (last column in Table 5), relates to an estimate including entity-specific as well as country-industry-year-specific fixed effects.[49] The effect of the EMTR is then only identified when using an interaction term between a time-varying entity-j-specific variable and the EMTR. We thus suggest an alternative firm-specific effective

[46] As a general remark, let us add that the estimates are not biased through time-constant country- or industry-specific effects per se, as these are captured by the entity-j-specific fixed effects.

[47] Note that the respective results are available upon request. The estimated coefficients are relatively close to the ones of the preferred model: (1) suggests a short-run effect of -0.217 (std. err.: 0.103) and a long-run effect of -0.49; (2) a number of results following the specification of Liu (2020) are shown in more detail in Table (Appendix 10); (3) leads to a substantially smaller sample and a coefficient of -0.307 (std. err.: 0.174).

[48] Note that we identify groups using the information on the global ultimate owner (GUO) of a firm entity that is provided by *Orbis* for a subset of our sample. In the case where no information on the GUO is available, we treat an observed entity as a stand-alone firm.

[49] Of course, this set of fixed effects nests country- and group fixed effects.

Table 5: ***FIXED EFFECTS SPECIFICATIONS***

The table presents OLS estimates. The dependent variable is the logarithm of firm entity j's tangible fixed assets, $log\ TFAS_{jt}$. The firm entity level and country level control variables are the same that are used in Table 4, column (1).Robust standard errors are reported in parentheses (clustered at the country-industry-year level). *** denotes significance at the 1% level; ** denotes significance at the 5% level; * denotes significance at the 10% level. The last rows report elasticities corresponding to the EMTR. Corresponding standard errors are obtained using the Delta method.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$EMTR_{cit}$	-0.402***	-0.485***	-1.523***	-4.752***	-1.847***	-1.449***	
	(0.151)	(0.142)	(0.299)	(0.495)	(0.384)	(0.301)	
$EMTR^{A}_{cit}$							-0.328***
							(0.037)
Firm entity level controls	YES	YES	YES	YES	YES	YES	YES
Country level controls	YES	YES	YES	NO	YES	YES	YES
Entity fixed effects (fe)	YES	NO	NO	NO	NO	NO	YES
Group fe	NO	YES	YES	NO	NO	YES	NO
Country fe	NO	NO	NO	NO	YES	YES	NO
Year fe	NO	NO	YES	NO	NO	YES	NO
Industry-year fe	YES	YES	NO	NO	YES	NO	NO
Country-year fe	NO	NO	NO	YES	NO	NO	NO
Country-industry-year fe	NO	NO	NO	NO	NO	NO	YES
Adjusted R^2	0.898	0.855	0.849	0.395	0.447	0.850	0.899
Observations	24,144,916	24,205,343	24,205,343	25,332,567	25,332,663	24,205,341	24,144,274
Elasticity $EMTR_{cit}$	-0.064***	-0.077***	-0.243***	-0.757***	-0.294***	-0.231***	-0.038***
	(0.024)	(0.023)	(0.048)	(0.079)	(0.061)	(0.048)	(0.004)

tax measure, which we define as $EMTR^{A}_{cit} = EMTR_{cit} \times NOLOSS_{jt}$. $NOLOSS_{jt}$ is a time-varying j-specific binary variable indicating whether entity j suffers a loss or not ($NOLOSS_{jt} = 1$ if a positive value for $EBIT$ is observed, 0 otherwise).

The logic behind this approach is that the EMTR should only have an effect when profits are positive, so that an interaction allows us to identify the EMTR effect. Assuming that tax incentives apply only to firms with positive profits, $EMTR^{A}_{cit}$ is just a version of a firm-specific effective tax measure. The estimate on $EMTR^{A}_{cit}$ equals -0.328 (std. err.: 0.037), which is relatively close to our benchmark estimate and highly statistically significant.[50]

Altogether, the alternative fixed effects specifications suggest the following: It is important to condition on entity-specific heterogeneity; the country-industry-specific EMTRs offer substantial value-added compared to country-year-specific measures; the findings are very

[50]Detailed results are available upon request.

robust to various fixed effects specifications.

6.5. Heterogeneous Tax Responses

Finally, we exploit the substantial cross-country and industry variation of our new EMTRs to analyze the heterogeneous impact of statutory tax policy changes on the investment behavior of different subgroups of firms. Note that we basically motivate the heterogeneity analysis as well as the definition of subgroups along different contributions to the literature, providing arguments or evidence for heterogeneous tax responses. Let us start with a literature suggesting that *(i)* the tax-responsiveness of investment should be reduced if firms make losses (for similar arguments in the context of financial choices, see MacKie-Mason, 1990, or Goldbach et al., 2021); *(ii)* Egger et al. (2014) show that a small group of *tax-avoiding* multinationals do not respond to taxes at all. This result is consistent with the argument that the tax-sensitivity of investment declines in the extent to which firms are able to avoid being taxed (Overesch, 2009, as well as Goldbach et al., 2019, provide evidence on such effects); *(iii)* the theoretical contribution of Keuschnigg and Ribi (2013) argues that the tax-sensitivity of investment depends on the degree to which a firm is financially constraint; *(iv)* Zwick and Mahon (2017) empirically show that small firms respond more to depreciation incentives compared to large firms, which is in line with the hypothesis that small firms are often financially constraint; *(v)* Overesch and Wamser (2009) suggest that the tax-elasticity of foreign direct investment (FDI) depends on the type of FDI, the underlying business model, as well as the internationalization of a multinational group (see also Stöwhase, 2005). We may thus focus on different industries, which we expect to be more or less tax-responsive.

Note that it is not a particular goal of our analysis to learn about a specific heterogeneity. We want to document, however, that we can adequately capture heterogeneous tax-responses using our new tax data in combination with a large micro-level dataset. As the following will show, the heterogeneous effects we find are consistent with what has been shown before

Table 6: ***TAX-RESPONSIVENESS FOR DIFFERENT SUBGROUPS***

The table presents OLS estimates. The dependent variable is the logarithm of firm entity j's tangible fixed assets, $log\ TFAS_{jt}$. The point estimates correspond to firm entity j-specific subgroups and are estimated using the approach described in Section 6.5. In terms of control variables and fixed effects, the setup is identical to Table 4, column 1. Robust standard errors are reported in parentheses (clustered at the country-industry-year level). *** denotes significance at the 1% level; ** denotes significance at the 5% level; * denotes significance at the 10% level. Note that except for the specification *Profitable firm entity*, we use samples that exclude firm entities j with a non-positive EBIT in more than 25% of the time in our panel. The subgroups are defined as follows. *Profitable firm entity*: Firm entity j reports strictly positive EBIT in at least 75% over time. *Stand-alone firm*: j is not part of a group (note that only firm entities with information on the global ultimate owner are considered for this regression, which reduces the sample size considerably). *Young firm entity age*: j's age (age is calculated as difference between current year and the year of incorporation) is lower than the 25 percentile of the age variable of the overall sample. *Manufacturing*: j operates in the section *C Manufacturing*. *Transportation and storage*: j operates in the section *H Transportation and storage*. *Construction*: j operates in the section *F Construction*. *Wholesale and retail*: j operates in the section *G Wholesale and retail trade; repair of motor vehicles and motorcycles*. *High GDP growth*: j is located in a country where half or more than half of the country-specific entity-year observations exhibit a GDP growth rate that is equal to or higher than the 75 percentile of the GDP growth rate of the overall sample. *Weak capital market*: j is located in a country where more than half of the country-specific entity-year observations exhibit a logarithm of the domestic credit to the private sector as share of the GDP that is lower than the 25 percentile of this variable of the overall sample. *Low GDP per capita*: j is located in a country where more than half of the country-specific entity-year observations exhibit a GDP per capita that is lower than the 25 percentile of this variable of the overall sample.

	Subgroup semi-elasticity	(se)
Profitable firm entity	-1.904***	(0.331)
Stand-alone firm	-1.243***	(0.265)
Young firm entity age	-1.418***	(0.238)
Manufacturing	-1.226**	(0.567)
Transportation and storage	-2.628***	(0.798)
Construction	-1.130**	(0.474)
Wholesale and retail	-0.165	(0.218)
High GDP growth	-1.715***	(0.352)
Weak capital market	-1.543***	(0.321)
Low GDP per capita	-1.508***	(0.327)

in the above-mentioned literature. The subgroups that we use for the heterogeneity analysis are defined according to industry-, country- or firm-characteristics. For the purpose of this heterogeneity analysis, we introduce indicator variables for a specific subgroup and then, based on our large sample, report only the results from the interaction terms for the specific group we are interested in.[51]

Table 6 depicts the results for the different subgroups. For the precise definitions of the subgroup indicators, see also the table notes. We find a semi-elasticity of -1.90 for firm entities that report strictly positive profits in most years. This estimate is significantly larger than the benchmark estimate of -0.41, which is consistent with *(i)*.[52] Next, we find that stand-alone firms are more responsive, which is in line with the arguments presented in *(ii)* and *(iv)*. Furthermore, we find that comparably younger firm entities as well as firm entities located in countries with weak capital markets, high GDP growth, and countries with low GDP per capita are more responsive to tax policy changes compared to the benchmark result. These results may be explained with the financial constraint arguments *(iii)* and *(iv)*. Finally, we find that that different industries respond differently to changes in the EMTR, as suggested in *(v)*. In detail, we find that the most responsive industry is *Transportation and storage* with a statistically significant EMTR semi-elasticity of about -2.6. The *Manufacturing*- and *Construction*-industry entities are less than half as sensitive but also statistically significant with an EMTR semi-elasticity of about -1.2 and -1.1, respectively. Tax incentives matter less for entities in *Wholesale and retail trade* with a coefficient of -0.17, which is statistically insignificant.

Let us finally focus on a specific type of heterogeneity which we find particularly interesting. It relates to a large literature showing that some firms can avoid taxes by relocating profits to low-tax countries (see the reasoning in *(ii)*). In our basic analysis we include three types of firm entities: stand-alone entities, entities that belong to a domestic firm group, and

[51] Complete estimation results are available upon request.

[52] Note that since profitability is a key factor for explaining tax-responses, we carry out the remainder of the subgroup analysis using samples that only include firm entities that are mostly profitable

entities that belong to a multinational firm group. While we exploit this information to estimate a coefficient on those that are not part of a firm group, the idea is now to examine how firm entities respond to changes in the EMTR given the group-wide (or multinational-firm-wide) minimum statutory corporate tax rate ($Minimum\ tax_j$).[53] For stand-alone entities and national groups, this minimum tax rate equals the statutory rate of the country that they are located in.[54]

For an entity that is part of a multinational group, $Minimum\ tax_j$ is calculated by taking the lowest tax rate among all countries that the multinational is operating in according to *Orbis*. The reasoning behind this approach is that multinationals are generally able to shift profits to entities located in low-tax countries to avoid taxes. Therefore, we expect that those entities facing a very high "minimum" tax should be more responsive, compared to others where $Minimum\ tax_j$ is relatively low. The latter suggests that these firms have access to a low-tax country and may shift profits towards related entities in this low-tax country. Alternatively, if the entity is itself the low-tax affiliate, then it faces a very low corporate tax rate. Figure 3 plots semi-elasticities for various values of $Minimum\ tax_j$.

The pattern we find is highly consistent with the profit-shifting argument. It seems that the negative tax effect only kicks in when the minimum tax rate is 24% or higher. For estimates where the minimum tax is lower, the estimated coefficients are close to zero and statistically insignificant. The increase in tax-responsiveness then increases in the minimum tax (in a not fully monotonic way).[55]

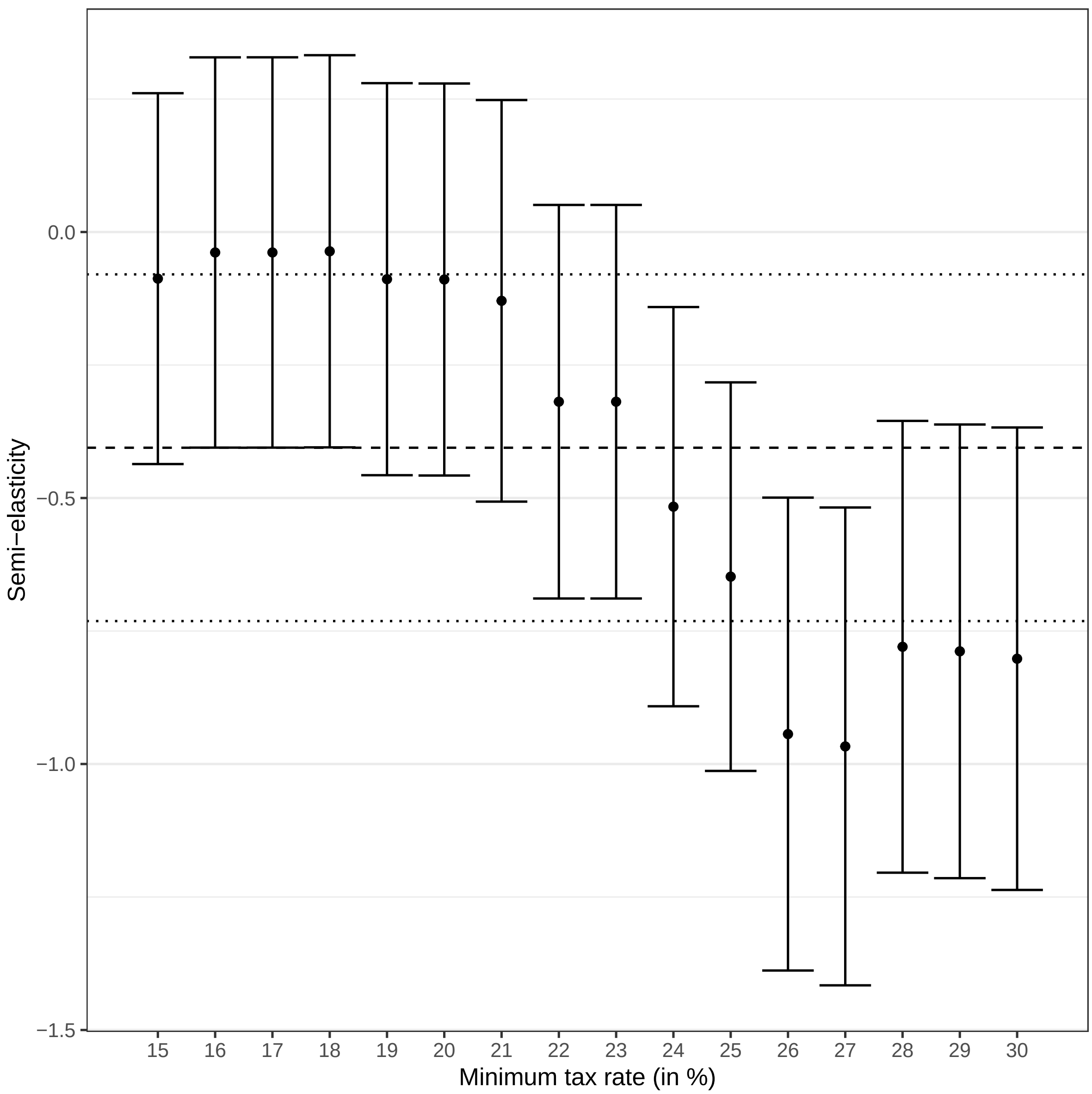
[53]Note that we calculate the minimum for the whole firm group (all entities observed) over all years in our sample.

[54]For firm entities for which we do not have any information on the global ultimate owner, we set the minimum tax rate as if they were stand-alone entities.

[55]Note that we cannot estimate the EMTR responses for groups where the minimum tax is below 15% or above 30% in a sufficiently precise way. Group sizes are too small and the variation over time in EMTRs is limited, introducing too much noise.

Figure 3: *TAX-RESPONSIVENESS AND MINIMUM TAX RATES*

The figure presents OLS estimates on $EMTR_{cit}$, and the corresponding 95% confidence intervals. The dependent variable is the logarithm of firm entity j's tangible fixed assets, $log\ TFAS_{jt}$. The point estimates correspond to subgroups of firm entities that are exposed to a within-firm minimum statutory tax rate that is equal to or higher than the tax rate depicted on the horizontal axis. For the definition of the minimum tax rate, see Section 6.5. The confidence intervals are based on robust standard errors (clustered at the country-industry-year level). In terms of control variables and fixed effects, the setup is identical to Table 4, column 1. The dashed line gives the semi-elasticity of the benchmark model (Table 4, column 1) and the dotted lines the corresponding confidence bounds.



7. Conclusions

This paper suggests a new approach to calculate country-industry-year-specific forward-looking effective tax rates (FLETRs) for 19 industries, 221 countries and the years 2001 to 2020. Beside statutory tax rate and tax base information, the FLETRs account for typical country-industry-specific financing- and asset structures. These financing- and asset structures are – depending on the data coverage – calculated directly from different data sources or imputed using Predictive Mean Matching. By accounting for the heterogeneity in financing and asset structures, we ensure that our FLETRs adequately capture the variation in the tax incentives that a country's tax code implicitly grants to different industries. We further show that effective tax rates suffer from significant measurement error when this country-industry-specific heterogeneity is neglected. Our empirical analysis exploits the substantial variation in FLETRs over time to provide estimates of the tax semi-elasticity of investment. Based on more than 24 million firm entity observations, our results suggest a tax semi-elasticity of about -0.41, which is at the lower end of previous findings. We further show that different sub-groups of firms respond very heterogeneously to tax incentives. For example, when focusing on firm entities operating in the manufacturing sector, we find a substantially bigger semi-elasticity of -1.23. Country-specific economic circumstances as well as profit shifting opportunities also have a significant impact on the tax semi-elasticity. All in all, the estimated semi-elasticities range from values close to zero up to -2.63.

Our study implies that policymakers should be careful when designing tax reforms or when using incentives such as bonus depreciation programs to stimulate corporate investment. The extent to which this leads to more real firm activity depends significantly on the type of business and several other firm- and/or country-specific conditions.

Appendix 1. Derivation of the EATR

This section briefly outlines the calculation of the forward-looking effective average tax rate (EATR). For the calculation of the EATR we follow Devereux and Griffith (2003) and Steinmüller et al. (2019). The EATR depicts the effective tax burden of all infra-marginal units invested in a hypothetical investment project. It is the scaled difference between the pre-tax net present value, R^*, and the post-tax net present value, R, of the hypothetical investment that has a given pre-tax rate of return p. This results in a *tax wedge*, reflecting the excess return to investment necessary to compensate for taxation. To obtain the EATR, the tax wedge is divided by the discounted rate of return (using the market interest rate for equity i for discounting), yielding

$$EATR_{cit} = \frac{R^* - R}{p/(1+i)} = \frac{\tau\big(p - i\delta\big)}{p}. \tag{A.1}$$

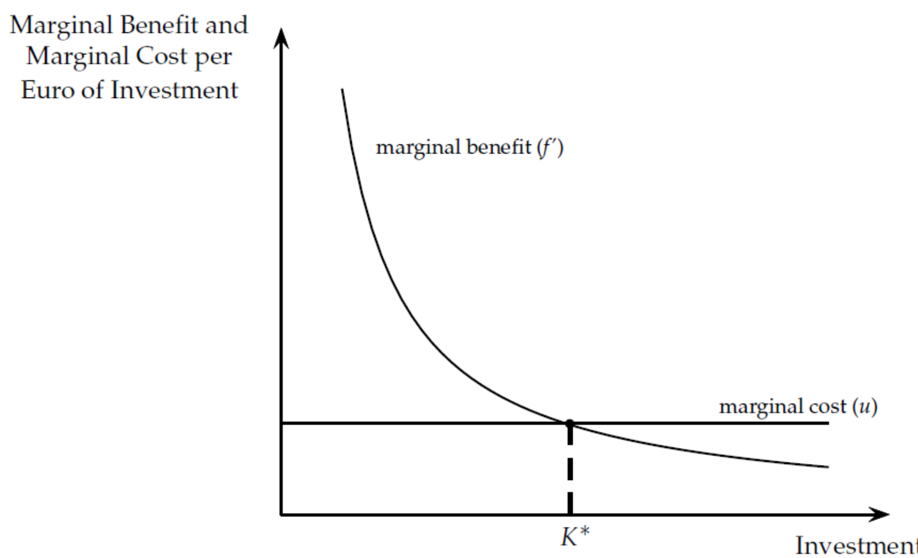
τ represents the statutory corporate tax rate and δ the NPV of depreciation allowances. From (A.1) it is evident that the NPV of depreciation allowances is less relevant for the size of the EATR compared to the EMTR. In fact, the size of the EATR crucially depends on the profitability of the investment as well as the statutory corporate tax rate (see also Devereux and Griffith, 2003). Country-industry-year-specific EATRs can then be calculated using the country-industry-year-specific NPVs of depreciation allowances, δ_{cit}, that are formally depicted in Section 2 of the main text:

$$EATR_{cit} = \frac{R^*_{cit} - R_{cit}}{p/(1+i)} = \frac{\tau_{ct}\big(p - i\delta_{cit}\big)}{p}. \tag{A.2}$$

Appendix 2. Derivation of the EMTR

Suppose a firm produces output following the production function $f(K)$ (with properties $f'(K) > 0, f''(K) < 0$) using capital K as the only input. Output is strictly increasing in K, for example investment in machinery, with $\partial f(K)/\partial K > 0$ denoting the marginal product of K. A profit-maximizing firm in a perfectly competitive environment compares marginal benefit of additional investment to marginal cost and increases or decreases K until the two equalize. Let us denote the marginal cost by $u = \sigma + i$, where σ is the economic depreciation rate of K, and i is the cost of equity.[56] We may interpret i as the after-tax return of a risk-free investment and, thus, as opportunity cost.[57] By assuming decreasing returns (a diminishing marginal product) to investment, the profit-maximizing investment K^* is determined by setting marginal benefit equal to marginal cost, i.e., $f'(K) = u$. Thus, in the absence of taxes, optimal investment is given by K^* (see Figure A.1).

Figure A.1: *OPTIMAL INVESTMENT*

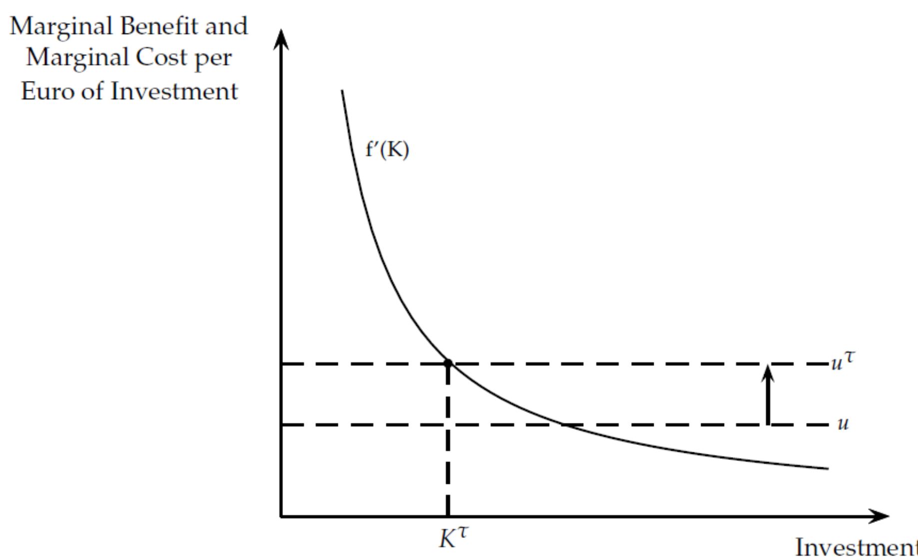


[56]Here, K is equity financed and financing cost are fully taxed (not tax-deductibility); prices are kept constant and equal to one.

[57]We may think of i also as a dividend payout. Note, however, that we are interested in calculating the effective tax burden at the corporate level. Thus, we are abstracting from taxes on dividends.

Introducing a tax τ in this simple model implies that some output is taxed away and the marginal earnings per unit of investment reduce to $f'(K)(1-\tau)$. This suggests a parallel downward shift in the marginal benefit curve and a new equilibrium where investment falls to K^{τ}, as illustrated in Figure A.2. Solving for $f'(K)$, we obtain $f'(K) = \frac{1}{(1-\tau)}(\sigma + i) \equiv u^{\tau}$. Note that the expression on the right-hand side of the equation is the *user cost of capital* (u^{τ}). With $\tau \in [0,1]$, the tax increases the required rate of return such that $u^{\tau} > u$. In order for the new optimality condition to hold, the firm invests less ($K^{\tau} < K$), leading to an increase of $f'(K)$ by a sufficient amount to just break even. The reduction in K and the concavity of the production function ensure that the pre-tax return with taxation is higher so that the firm is not making a loss.

Figure A.2: ***OPTIMAL INVESTMENT WITH TAXATION***



We can now account for the fact that governments typically grant tax deductions for the cost of financing and depreciation by introducing *depreciation allowances* into this model. While we only consider the period of the investment, investments generate future returns, and machines or other investments depreciate over time. Accordingly, we need to account for the future stream of depreciation allowances by considering the net present value (NPV) of depreciation allowances, which we denote by δ. Depreciation allowances reduce a firm's tax base, suggesting that for each unit of depreciation allowance subtracted from the tax base, the tax payment equals zero. Thus, there is a tax saving of $\tau \cdot \delta$ per unit of investment. Consequently, the depreciation allowance reduces the user cost of capital:

$$\widehat{u}^{\tau} = \frac{1}{(1-\tau)}(\sigma + i) \cdot (1 - \tau\delta).$$

Note that in a graphical illustration, this would shift the horizontal line of the user cost down. As Figure A.2 illustrates, a corporate tax τ drives a *wedge* between marginal benefit and marginal cost. The effective marginal tax rate (EMTR) is a measure of the relative size of this tax wedge between user cost of capital with and without taxation. Formally, we thus have

$$EMTR = \frac{\widehat{u}^{\tau} - u}{\widehat{u}^{\tau}} = \frac{\frac{1}{(1-\tau)}(\sigma + i) \cdot (1 - \tau\delta) - (\sigma + i)}{\frac{1}{(1-\tau)}(\sigma + i) \cdot (1 - \tau\delta)} = \frac{(\tau - \tau\delta)}{(1 - \tau\delta)}. \tag{A.3}$$

Appendix 3. NACE REV. 2 (ISIC REV.4) Section Description

Table A.1: *NACE REV. 2 (ISIC REV.4) SECTION DESCRIPTIONS*

The table depicts the descriptions of the sections of the *Statistical classification of economic activities in the European Community (NACE) Rev. 2* and the *International Standard Industrial Classification of All Economic Activities (ISIC) Rev. 4* that are used throughout this paper. Note that since NACE Rev. 2 was created based on ISIC Rev. 4, the classification systems are equal at the section level.

Section code	section description
A	Agriculture, forestry and fishing
B	Mining and quarrying
C	Manufacturing
D	Electricity, gas, steam and air conditioning supply
E	Water supply; sewerage, waste management and remediation activities
F	Construction
G	Wholesale and retail trade; repair of motor vehicles and motorcycles
H	Transportation and storage
I	Accommodation and food service activities
J	Information and communication
K	Financial and insurance activities
L	Real estate activities
M	Professional, scientific and technical activities
N	Administrative and support service activities
O	Public administration and defence; compulsory social security
P	Education
Q	Human health and social work activities
R	Arts, entertainment and recreation
S	Other service activities
T	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use
U	Activities of extraterritorial organizations and bodies

Appendix 4. Structure and Preparation of the Eora26 database

To provide a deeper understanding of the structure of the *Eora26* database, we start out by describing the *Eora Global Supply Chain* database (Lenzen et al., 2012; Lenzen et al., 2013), from which *Eora26* is derived. At the centre of the *Eora Global Supply Chain* database are the yearly multi-region input-output tables (MRIOs). For the countries in the MRIOs, generally either commodities or industries are included, but not both. This results in a mix of different input-output (IO) tables. In detail, three different types of IO tables are distinguished: Industry-by-Industry IO tables, Commodity-by-Commodity IO tables, and Supply-Use tables (SUTs). The latter category includes Commodity-to-Industry as well as Industry-to-Commodity transactions.[58] Furthermore, the industry and commodity classification systems that are used differ strongly between countries. To facilitate between-country analyses, a simplified version of the *Eora* MRIOs is provided, the so-called *Eora26* MRIOs. In this version, all industries and commodities are aggregated to a common 26-sector classification and the SUTs from the full resolution *Eora* MRIOs are converted to symmetric sector-by-sector IO tables using the *Eurostat manual of supply, use and input-output tables* (2008).[59] For our purpose, we translate this 26-sector classification of the *Eora26* database to the NACE Rev. 2 (ISIC Rev. 4) sections that we use throughout the paper. In doing this, we rely on the concordance table provided on the webpage of the *Eora26* database that documents how the different industries and commodity categories from the full resolution *Eora* were transformed to the 26-sector system of *Eora26*.[60] More precisely, we string-search the industry descriptions of the full resolution *Eora* database for the closest matches to the different NACE Rev. 2 (ISIC Rev. 4) section descriptions. Then, we look at how a chosen industry from the full *Eora* was converted to the 26-sector system and reverse this transformation for all countries. The precise assignment is depicted in Table A.2.

[58]For a graphical illustration of the MRIO layout, see Lenzen et al. (2013, p. 25).

[59]Eurostat (2008). Eurostat manual of supply, use and input-output tables. Office for Official Publications of the European Communities. Eurostat methodologies and working papers. Luxembourg. For more details, see the webpage of Eora26, *https://worldmrio.com/eora26/*.

[60]See *https://worldmrio.com/eora26/*.

Table A.2: *CONCORDANCE OF EORA26 SECTORS TO NACE REV. 2 (ISIC REV. 4) SECTIONS*

The table depicts the assignment that is used to translate the 26-sector classification of the *Eora26* database to the NACE Rev. 2 (ISIC Rev. 4) sections that we use throughout this paper. The aggregation is based on the concordance table that translates the different industry and commodity categories of the full *Eora* to the 26 sectors used in *Eora26* which can be found on the website of the *Eora26* database (*https://worldmrio.com/eora26/*). Descriptions for the different NACE Rev. 2 (ISIC Rev. 4) sections are provided in Table A.1.

NACE/ISIC	Eora26 sector(s)
A	0.873377 · Agriculture +
	0.126623 · Fishing
B	Mining and Quarrying
C	0.089343 · Food & Beverages +
	0.181663 · Textiles and Wearing Apparel +
	0.045522 · Wood and Paper +
	0.246543 · Petroleum, Chemical and Non-Metallic Mineral Products +
	0.122740 · Metal Products +
	0.229526 · Electrical and Machinery +
	0.025101 · Transport Equipment +
	0.043395 · Other Manufacturing +
	0.016167 · Recycling
D	Electricity, Gas and Water
E	0.181818 · Electricity, Gas and Water +
	0.818182 · Education, Health and Other Services
F	Construction
G	0.023499 · Maintenance and Repair +
	0.302872 · Wholesale Trade +
	0.673629 · Retail Trade
H	Transport
I	Hotels and Restaurants
J	Post and Telecommunications
K	Finacial Intermediation and Business Activities
L	Finacial Intermediation and Business Activities
M	Finacial Intermediation and Business Activities
N	Finacial Intermediation and Business Activities
O	Public Administration
P	Education, Health and Other Services
Q	Education, Health and Other Services
R	Education, Health and Other Services
S	0.071197 · Education, Health and Other Services +
	0.928803 · Others
T	Private Households
U	Others

Appendix 5. Assignment of EUKLEMS & INTANProd Asset Types

Table A.3: *ASSIGNMENT OF EUKLEMS & INTANProd RELEASE 2021 ASSET TYPES TO THE ASSET TYPES USED FOR CALCULATIONS OF FLETRs*

The table depicts the assignment of the asset categories from the *EUKLEMS & INTANProd* release 2021 to the asset categories used for the calculations of FLETRs in this paper (excluding the asset type *Inventory*).

Asset type	Assigned EU Klems 2019 asset types
Buildings	N111 Dwellings
	N112 Other buildings and structures
Computer equipment	N11321 Computer hardware
Intangible fixed assets	N1171 Research and development
	N1173 Computer software and databases
Machinery	N11O Other machinery equipment and weapons systems
Office equipment	N11322 Telecommunications equipment
Vehicles	N1131 Transport equipment

Appendix 6. Imputation

For the PMM imputation in Section 4.3, we impute a missing year-specific weight using the observed value corresponding to the data point (the so-called donor) for which the predicted value is closest to the predicted value of the missing data point that we were looking to impute. Alternatively, instead of using just one donor, the mean of the $d > 1$ donors that are closest may be chosen (Van Buuren, 2018). In the extreme case of setting d to the number of available complete cases, one would obtain identical imputed values for all missing data points, that is, the mean over all donor candidates. To not lose variation among the imputed values, typically small d's are chosen.[61] In Figure A.3, we depict asset weight structures for the section *C Manufacturing* that are imputed as described in Section 4.3 but with a varying number of donors d.[62]

It is evident that the imputed asset structures look similar for $d = 1$, 5, 10, and 15. In particular, the reduction in variation between countries when increasing d is small. We therefore conclude that our imputation results are robust to other commonly used choices for the number of donors d.

An algorithm that is heavily used in the literature for matching purposes is k-Nearest Neighbor (k-NN) matching. With k-NN matching, each covariate used for the matching is standardized to have an overall mean of zero and variance of one. A missing data point is then imputed with the mean of the k observed data points for which the Euclidean distance of the covariates to those of the missing is minimal. The key difference between PMM and k-NN matching is that PMM takes into account the importance of each covariate for predicting the dependent variable, whereas k-NN matching assigns each covariate the same weight. For the sake of completeness, we carry out the imputation of asset structures for the sector *C Manufacturing* with k-NN matching using the same covariates that we used with PMM.[63]

[61] See Van Buuren (2018) for a thorough literature review on the optimal choice of donors.

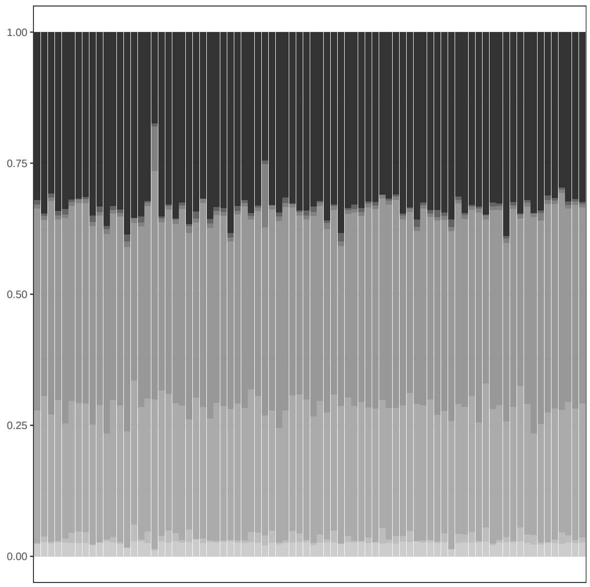
[62] Note that the same countries are depicted in the same order as in Panel B of Figure A.5.

[63] Note, however, that we do not include time dummies, as k-NN matching does not allow for categorical variables. Further note that no logs of the variables are taken.

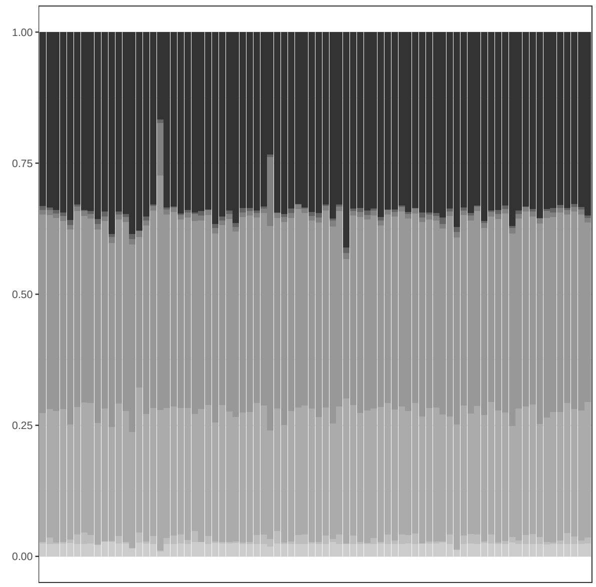
Figure A.3: *COUNTRY-SPECIFIC ASSET STRUCTURES OF SECTION C MANUFACTURING IMPUTED USING PMM WITH DIFFERENT NUMBER OF DONORS*

The figure depicts asset structures for the NACE Rev. 2 (ISIC Rev. 4) section *C Manufacturing* by country. The structures of the depicted countries are fully imputed using PMM (see Section 4.3). The panels correspond to imputation using a different number of donors d. Each bar corresponds to the asset structure of a different country. The order of the countries is the same in all panels and identical to the one in Panel B of Figure A.5. The asset types are indicated by the different shadings of the bars. The asset types are – from dark to bright shading – as follows: buildings, computer equipment, intangible fixed assets, inventory, machinery, office equipment, and vehicles.

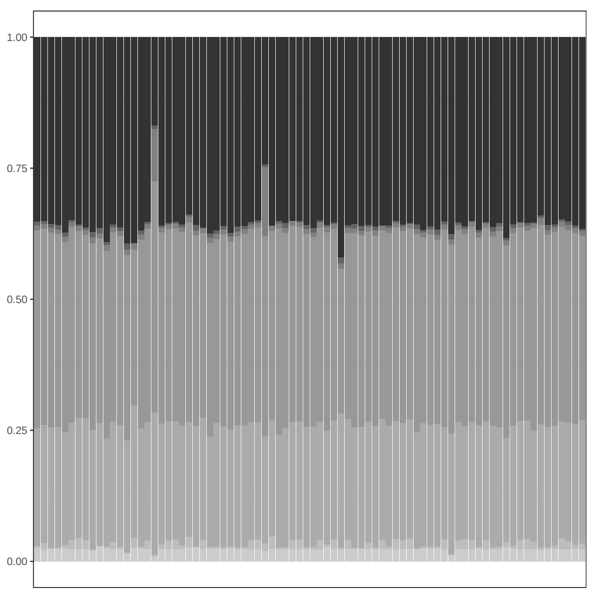
Panel A: $d = 1$



Panel B: $d = 5$



Panel C: $d = 10$



Panel D: $d = 15$

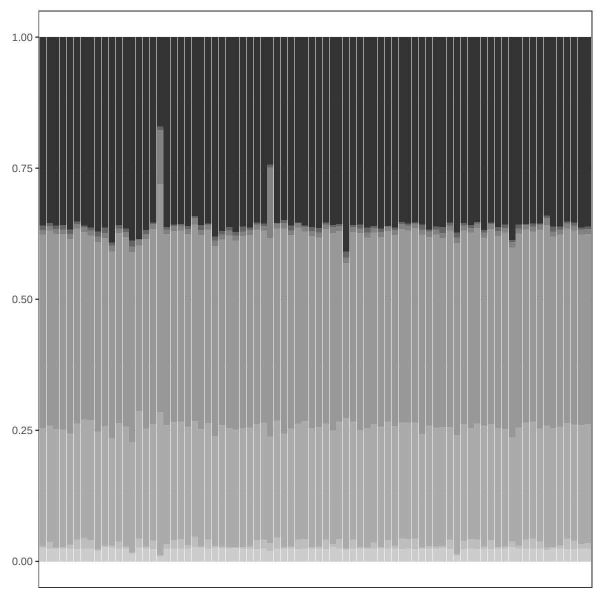
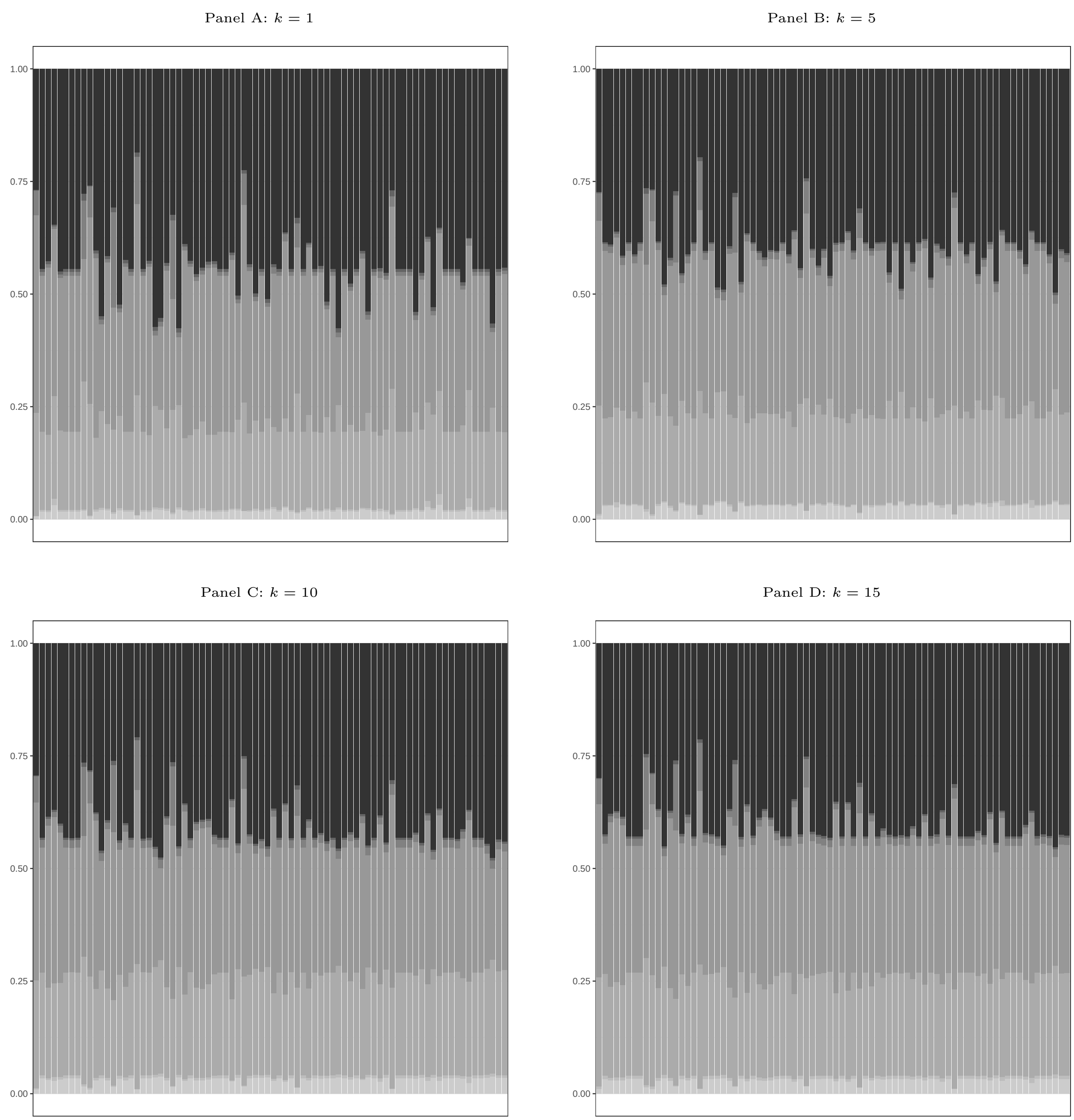


Figure A.4: ***COUNTRY-SPECIFIC ASSET STRUCTURES OF SECTION C MANUFACTURING IMPUTED USING k-NN WITH DIFFERENT NUMBER OF k***

The figure depicts asset structures for the NACE Rev. 2 (ISIC Rev. 4) section *C Manufacturing* by country. The structures of the depicted countries are fully imputed using k-NN (see Hastie et al., 2009, ch. 13.3). The panels correspond to imputation using a different number of neighbors k. Each bar corresponds to the asset structure of a different country. The order of the countries is the same in all panels and identical to the one in Panel B of Figure A.5. The asset types are indicated by the different shadings of the bars. The asset types are – from dark to bright shading – as follows: buildings, computer equipment, intangible fixed assets, inventory, machinery, office equipment, and vehicles.



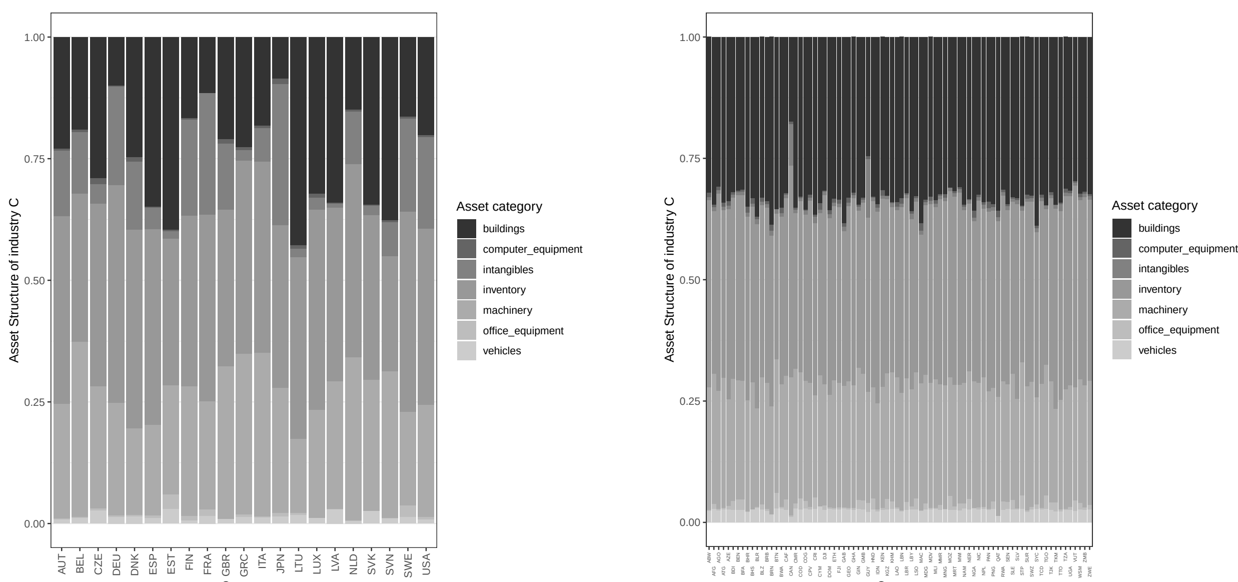
The results are depicted in Figure A.4.

It can be seen that, irrespective of k, the imputed asset structures are often identical or extremely similar between countries. Furthermore, it shows that the imputed asset structures seem to be highly dependent on the chosen k, as the amount of variation between countries decreases strongly as k is increased.

Finally, let us also provide some more in-depth plausibility checks of the country-industry-specific asset structures of section *C Manufacturing*. Panel A in Figure A.5 depicts the asset structures of countries that are fully covered by the primary data sources. Panel B in Figure A.5 shows the asset structures of countries that were entirely imputed using the PMM procedure.

Figure A.5: *COUNTRY-SPECIFIC ASSET STRUCTURES FROM PRIMARY DATA SOURCES OF SECTION C MANUFACTURING*

The figure depicts depicts asset structures for the NACE Rev. 2 (ISIC Rev. 4) section *C Manufacturing* by country. In Panel A, the structures of the depicted countries are fully derived from the primary data sources *EUKLEMS & INTANProd* release 2021 and *Orbis* (see Section 4.2). In Panel B, the structures of the depicted countries are fully imputed using PMM with $d = 1$ donor (see Section 4.3).



Panel A: Observed weights

Panel B: Imputed weights

Comparing these two figures, it can be seen that the imputed results exhibit somewhat less variation. However, as shown in Table 1, this is not a result that is representative of the imputation of all weights in all industries. In fact, there are several sections where there is more variation among the group of PMM imputed countries than in the one with observed data. One country that stands out in Panel B of Figure A.5 is Canada that exhibits the lowest share of buildings among the depicted imputed countries. Taking a look at Panel A of Figure A.5, it can be seen that the imputed asset structure of Canada is similar to the asset structures of other highly developed nations such as Germany, France, Japan, the Netherlands, Sweden, or the USA. Conversely, the imputed less developed countries in Panel B of Figure A.5 exhibit similarities to the less developed countries that were used for the matching, such as Lithuania or Slovakia.

Another interesting observation that can be made when looking at Panel B of Figure A.5 is the fact that the different PMM imputed asset structures appear to not be identical. This indicates that the unique weighting of the covariates for the matching of each asset type yielded a mix of different donors matched for the imputation of a single asset structure.

Appendix 7. Descriptive Statistics of Imputation Covariates

Table A.4: ***DESCRIPTIVES ON COVARIATES USED FOR IMPUTATION***

The table depicts descriptive statistics on all the covariates used for the imputation of financing (Panel A) and asset structures (Panel B). The time span that is covered in the sample is 2001 to 2016. Definitions of all variables are provided in Section 3.

Panel A: Covariates for financing structure imputation (36,214 observations)		
	Mean	(sd)
τ_{ct}	0.253	(0.094)
ROL_{ct}	0.077	(0.995)
$Corruption_{ct}$	0.094	(1.022)
$log\ DCPS_{ct}$	3.607	(0.980)
$Inflation_{ct}$	5.417	(10.570)
$GDP\ growth_{ct}$	3.638	(4.410)
$log\ GO_{cit}$	15.229	(2.421)
$log\ GI_{cit}$	15.174	(2.440)
$log\ COE_{cit}$	13.519	(2.817)
$log\ NOS_{cit}$	13.055	(3.103)
$log\ NMI_{cit}$	9.335	(4.969)
$log\ net\ TOP_{cit}$	10.217	(3.260)
$log\ COFC_{cit}$	11.954	(3.180)

Panel B: Covariates for asset structure imputation (49,811 observations)		
	Mean	(sd)
$log\ GDP_{ct}$	25.152	(2.006)
$log\ GDP\ p.c._{ct}$	9.288	(1.218)
$log\ COE_{cit}$	13.355	(2.689)
$log\ NOS_{cit}$	12.902	(2.991)
$log\ NMI_{cit}$	9.514	(4.834)
$log\ COFC_{cit}$	11.849	(3.017)
$log\ CO2_{cit}$	6.423	(2.527)

Appendix 8. Imputation of countries without Covariate Data

Table A.5: *IMPUTATION OF COUNTRIES WITHOUT COVARIATE DATA*

The table depicts the assignment of countries for which we obtain weights (either directly through data sources or through the imputation algorithm) to countries for which we do not obtain weights. If two more countries are assigned, then the unweighted average of these countries' weights are used for imputation.

Panel A: Financing structure (53 countries with missing weights)	
Countries with missing weights	Countries used for imputation
AIA;ANT;BES;CUW;CYM;DMA;GLP;GRD;KNA;LCA;MSR;MTQ;PRI;SXM; TCA;VCT;VGB;VIR	ABW;ATG;BHS;BRB;DOM;JAM;TTO
ASM;COK;FSM;KIR;MHL;MNP;NCL;NIU;NRU;PLW;PYF;SLB; TLS;TON	AUS;FJI;NZL;PNG;VUT;WSM
AND	ESP; FRA
ARG	BOL; BRA; CHL; PRY; URY
BLZ	GTM; MEX
BMU	ABW;ATG;BHS;BRB;DOM;JAM;TTO;USA
COM	MDG; MDV; MUS; SYC
ERI	DJI; ETH; SDN
GGY	FRA; GBR
GIB	ESP
GNB	SEN; GIN
GNQ	GAB; CMR
GRL	CAN; ISL
IMN	GBR
JEY	FRA; GBR
LIE	CHE; AUT
MCO	FRA
PRK	CHN; KOR
SMR	ITA
TKM	AFG; IRN; KAZ
UZB	AFG; KAZ; KGZ; TJK
XKX	SRB
YUG	MNE; SRB

Panel B: Asset structure (56 countries with missing weights)	
Countries with missing weights	Countries used for imputation
AIA;ANT;BES;CUW;DMA;GLP;GRD;KNA;LCA;MSR;MTQ;PRI;SXM; TCA;VCT;VGB;VIR	ABW;ATG;BHS;BRB;CYM;DOM;JAM;TTO
ASM;COK;FSM;KIR;MHL;MNP;NCL;NIU;NRU;PLW;PYF;SLB; TLS;TON	AUS;FJI;NZL;PNG;VUT;WSM
AND	ESP; FRA
COM	MDG; MDV; MUS; SYC
ERI	DJI; ETH
GGY	FRA; GBR
GIB	ESP
GNB	SEN; GIN
GNQ	GAB; CMR
GRL	CAN; ISL
IMN	GBR
JEY	FRA; GBR
LIE	CHE; AUT
MCO	FRA
MKD	ALB; BGR; GRC; SRB
MNE	ALB; BIH; HRV; SRB
PRK	CHN; KOR
PSE	EGY; ISR; JOR
SDN	CAF; EGY; ETH; LBY; TCD
SMR	ITA
SSD	CAF; COD; ETH; KEN; UGA
SYR	IRQ; ISR; JOR; LBN; TUR
TWN	CHN; JPN; KOR; PHL
VEN	BRA; COL; GUY
XKX	SRB
YEM	OMN; SAU
YUG	SRB

Appendix 9. Country-industry-year-specific EATRs

The country-industry-year-specific EATRs are obtained by plugging the country-year-specific statutory tax rate, τ_{ct}, as well as the country-industry-year-specific NPVs of depreciation allowances, δ_{cit}, which are calculated using the financing and asset weights from Section 4, into equation (A.2). Note that for the parameterization of the pre-tax rate of return, p, and the market interest rate, i, we follow Steinmüller et al. (2019) and set $p = 0.2$ and $i = 0.05$ across all countries, industries, and years. Similar to Section 5 of the main text, we additionally calculate country-year-specific EATRs for the sake of comparison using the same symmetric financing and asset weights from Steinmüller et al. (2019).

In the following, we redo the graphical analysis as well as ANOVA from Section 5 of the main text using the EATR instead of the EMTR as tax measure of interest. The EATRs in Figure A.6 exhibit a similar downward trend as the EMTRs in Figure 1. However, when comparing these two figures, two things stand out. First, the yearly means of the country-year-specific EATR (i.e., the black line) are around 8 percentage points higher each year. Second, the deviation of the yearly means of the country-industry-year-specific EATRs from the respective country-year-specific counterparts is a lot smaller compared to the EMTR figure. Both results can be explained with the fact that the NPV of depreciation allowances plays a relatively small role in determining the magnitude of EATRs compared to the statutory corporate tax rate. This also explains the strong centering of the distribution of $(EATR_{cit} - EATR_{ct})$ right around the zero mark in Figure A.7. Finally, looking at the ANOVA of the country-industry-year-specific EATR in Table A.6, it can be seen that the country-industry-specific variation from the financing and asset weights almost does not contribute to the total variance in $EATR_{cit}$ at all and that almost all of the variation can be explained with country effects (i.e., the tax codes). Again, this finding can be explained with the – compared to the EMTR – much smaller impact of the NPV of depreciation allowances on the EATR overall.

Figure A.6: *DEVELOPMENT OF MEAN COUNTRY-YEAR AND COUNTRY-INDUSTRY-YEAR-SPECIFIC EATRs*

The figure depicts the development of the mean country-year and country-industry-year-specific EATRs calculated in Appendix 9. The grey dots represent the mean country-industry-year-specific EATRs across countries for each year. The black dots that are connected by black lines represent the mean country-year-specific EATRs across countries for each year. Calculations are based on a sample of 75,126 observations.

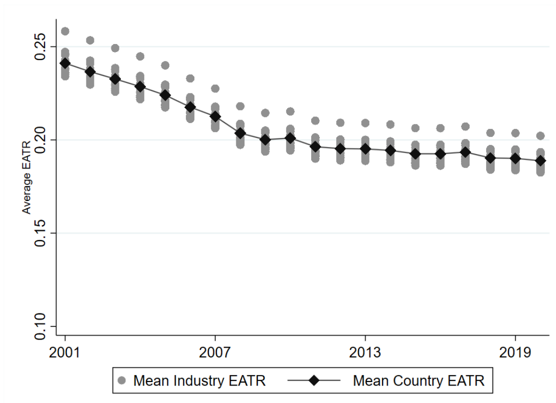


Figure A.7: *DISTRIBUTION OF DEVIATIONS FROM THE COUNTRY-YEAR EATRs*

The figure depicts the distribution of the differences between country-industry-year-specific and country-year-specific EATRs calculated in Appendix 9. The distribution is calculated based on 75,126 observations using a triangle kernel with a bandwidth of 0.0005.

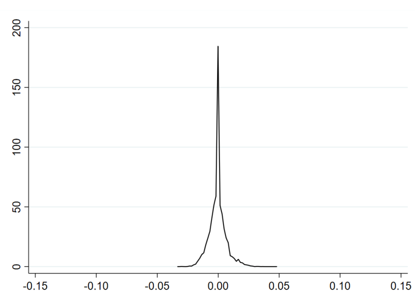


Table A.6: ***ANALYSIS OF VARIANCE OF COUNTRY-INDUSTRY-YEAR-SPECIFIC EMTRs***

The table depicts analysis of variance (ANOVA) results of the country-industry-year-specific effective average tax rates ($EATR_{cit}$) that are calculated in Appendix 9. The ANOVA is based on 75,126 observations.

	Partial sum of squares	Degrees of freedom	F-statistic	p-value
Country effects	540.787	220	2305.31	0.000
NACE Rev. 2 section effects	1.829	18	95.30	0.000
Year effects	22.563	19	1113.72	0.000
Model	562.991	257	2054.44	0.000
Residual	79.831	74,868		
Total	642.821	75,125		
R^2	0.876			

Appendix 10. Analysis of Investment Responses using Investment Rates

In the following, as robustness check, we analyze the sensitivity of firm entities' investment with respect to our country-industry-year-specific EMTRs using gross investment rates into fixed assets instead of the logarithm of the asset stock as dependent variable. The setup we use is derived from Liu (2020), who investigates the investment behavior of UK multinationals after the UK's switch from a worldwide to a territorial tax system in 2009. In detail, the gross investment rate into fixed assets ($Gross\ investment\ K_{jt}$) is obtained by adding year t's depreciation and amortization to the net change in the fixed asset stock from the previous to the current year. Then, this term is scaled by the previous year's fixed asset stock.[64] As control variables at the firm entity level, Liu (2020) uses the one-period lag of the logarithm of sales ($log\ SALES_{jt-1}$) as well as the cash flow rate ($CF\ rate_{jt}$), the one period lag of the sales growth rate ($SALES\ growth_{jt-1}$), and the one period lag of the profit margin ($Profit\ margin_{jt-1}$).[65] To minimize the influence of outliers, following Liu (2020), we winsorize all ratios – including the investment rate – at the top and bottom 1 percentiles. At the country-level, we control for the GDP per capita growth rate, population size, unemployment rate, the *Rule of Law* indicator, as well as a financial institution stability indicator.[66] Note that, as above in the main body of the paper, we exclude certain industries and require a firm entity to appear in the sample at least two times.

Following Liu (2020), we estimate a set of models using a variety of control variable and fixed effects combinations. The results of the analysis are depicted in Table A.7. Note

[64] Formally, we get $Net\ investment\ K_{jt} = (K_{jt} - K_{jt-1} + DEPR_{jt})/K_{jt-1}$, with $K_{jt} = TFAS_{jt} + IFAS_{jt}$, denoting the fixed asset stock of firm entity j in year t, calculated as the sum of tangible and intangible fixed assets. $DEPR_{jt}$ denotes the depreciation and amortization of j's assets in year t. Note that since the *Orbis* database depicts depreciation and amortization jointly using a single variable, we are not able to sensibly compute gross investment rates for the tangible fixed asset stock.

[65] For the definition of the ratio variables, see Section 6.2.

[66] See Section 3.4 for a detailed description of the data. The financial institution stability indicator is the *Bank Z-score* from the World Bank's *Global Financial Development* database and estimates the likelihood of country's banking system to default.

Table A.7: ***TAX-RESPONSIVENESS USING GROSS INVESTMENT RATES***

The table presents OLS estimates. The dependent variable is the gross investment rate in fixed assets ($Gross\ investment\ K_{jt}$). Robust standard errors are reported in parentheses (clustered at the country-industry-year level). *** denotes significance at the 1% level; ** denotes significance at the 5% level; * denotes significance at the 10% level. Details on the variables are provided in Appendix 10.

	(1)	(2)	(3)	(4)	(5)	(6)
$EMTR_{cit}$	-0.653***	-0.560***	-0.550***	-0.399**	-0.382**	-1.000*
	(0.240)	(0.191)	(0.181)	(0.179)	(0.169)	(0.543)
Firm entity level controls	NO	YES	YES	YES	YES	YES
Country level controls	NO	NO	NO	YES	YES	YES
Entity fixed effects	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	NO	YES	NO	NO
Industry-year fixed effects	NO	NO	YES	NO	YES	NO
Country-year fixed effects	NO	NO	NO	NO	NO	YES
Adjusted R^2	0.068	0.135	0.135	0.136	0.136	0.136
Observations	27,228,920	27,228,920	27,228,920	27,228,920	27,228,920	27,228,788

that the use of different variables compared to the analysis in the main text leads to a larger sample size of over 27 million observations. All models yield negative and statistically significant coefficients on $EMTR_{cit}$. In terms of the magnitude of the investment response, we find that – with the exception of columns (1) and (6) – all models yield coefficients that are roughly comparable with the benchmark estimates depicted in Table 4.

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